



The relationship between ventilation practices and indoor environmental quality in British homes.

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I, Cairan Alexander Van Rooyen, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Europeans spend most of their time indoors at home, and the indoor environmental quality (IEQ) in homes plays an important role in occupants' comfort, well-being, and physical health. Ventilation modifies IEQ, subsequently impacting occupant exposure to indoor temperatures, air quality, and noise. In homes with space conditioning, ventilation also influences heat transfer, energy use, and carbon emissions - thus ventilation lies at the intersection of health, energy, and the climate.

Despite the importance of ventilation, there is a lack of understanding of conditions experienced in real homes and its relationship with ventilation, particularly when considering all components of IEQ together. This research employed an empirical, mixed-methods design in seven occupied case study dwellings in England to investigate ventilation practices, air exchange rates (AER), and their relationship with IEQ and decay times of pollutant peaks.

A novel method was developed to determine window positions (open, ajar, and closed) using simultaneous sound measurements inside and outside dwellings. This method was validated in two test cases, achieving an accuracy of up to 96%.

Measurements revealed substantial variability in ventilation practices and AER across different homes and seasons, highlighting the challenge of generalising findings. Windows and doors were closed most of the occupied time, particularly during the winter. Most homes had AER below the commonly accepted healthy threshold during occupied periods. Opening windows generally reduced indoor temperature, humidity, CO_2, CO, and total volatile organic compounds (TVOC), although noise levels and, unexpectedly, particulate matter increased. A novel analysis technique provides insights into the decay times of pollutant peaks and presents a method for informing practical public health advice for reducing exposure to peaks.

This thesis enhances our understanding of how ventilation impacts the indoor environment and enables us to better evaluate the potential health implications of interventions that modify IEQ.

Impact statement

This thesis builds on the existing literature by advancing our understanding of the complex relationships between ventilation, indoor environmental quality, and health in homes. The research addressed five key gaps in empirical evidence on: ventilation practices in occupied homes (RQ1), air exchange rates and their relationship with ventilation practices and season (RQ2), the relationship between ventilation and exposure to pollutant peaks (RQ3), a method to infer window and door positions using sound measurements (RQ4), and how ventilation impacts different components of IEQ (RQ5).

Academic contributions:

This research addresses gaps in the literature by providing a comprehensive, longitudinal dataset on ventilation practices, AER, and IEQ in occupied homes. The dataset includes building surveys, laboratory analysis of VOCs, and participant questionnaires. The data was collected entirely remotely using the postal service, demonstrating this data collection method for complex long-term IEQ monitoring campaigns. A novel noise measurement platform and method for inferring window positions from sound measurements was developed, enabling more detailed measurements of ventilation and sound in varied contexts. A number of new analysis techniques and concepts were developed to analyse and understand the large, multivariable, timeseries dataset. These data, algorithms, methods, and techniques will be shared on an open source platform and through publications, which will contribute to refining research methods and enable further research in this field.

Public Health Implications:

This research highlights the impacts of ventilation on IEQ, providing evidence for estimating exposure and burden of disease in the population and enabling the development of targeted interventions to promote healthy IEQ. Additionally, the new data driven method for analysing decays of pollutant peaks offers a practical framework for informing public health advice with the aim of reducing exposure to pollutants.

Policy and Building design:

Many homes in this research had ventilation provision that was not compliant with standards at the time of construction, which supports other evidence, suggesting the need to reform the building control process to ensure homes are constructed in accordance with standards. Most homes kept windows closed during occupied times and experienced poor ventilation rates, particularly during the winter. These findings suggest that existing ventilation provision and standards are not enabling homes to

achieve healthy levels of ventilation, and this supports other evidence to revise standards, such as Part F of the Building Regulations to promote healthy indoor environments. Evidence from this research can inform policy makers of the critical impacts of ventilation on IEQ, especially in light of Net-Zero, decarbonising the existing stock, urbanisation, and densification. Another key finding is the large variability in ventilation practices, AER, and the impact of ventilation on IEQ, which underline the need for context specific and flexible building design standards which account for different occupant practices, occupancy patterns and environmental conditions.

This research enhances our understanding of the relationship between ventilation and IEQ. This thesis provides evidence to support academic research, changes to policy and public health messaging, with the aim of improving IEQ, protecting occupant health, and ultimately contributing to a healthier and more sustainable future.

Inclusion of published works

This thesis contains data, text, and figures that are available in another format or have been prepared for publication with the assistance of other authors. There are two relevant papers that are declared here. The first declaration is for the published paper 'Ventilation provision and use in homes in Great Britain: a national survey.' (Van Rooyen and Sharpe, 2024), which does not form a core component of this thesis but is used for comparison and context throughout. The second declaration is for an unpublished paper 'Using outdoor and indoor sound measurements in an occupied dwelling to infer if a window is open, ajar or closed', which is described throughout Chapter 4.

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Nomenclature

Acronyms

ACH	Air changes per hour
ADF	Building Regulations Approved Document Part F
AER	Air Exchange Rate
AH	Absolute humidity
ASHRAE	American society of heating, refrigeration and air conditioning engineers
BREEAM	Building Research Establishment's Environmental Assessment Method
BSEER	Bartlett School of Environment Energy and Resources
CIBSE	Chartered Institution of Building Services Engineers
CMO	Chief Medical Officer
CO	Carbon monoxide
COPD	Chronic Obstructive Pulmonary Disease
CREDS	The Centre for Research into Energy Demand Solutions
d-MEV	Decentralised Mechanical Extract Ventilation
DALY	Disability-Adjusted Life Year
DCLG	Department for Communities and Local Government
dMEV	Decentralised mechanical extract ventilation
EPA	U.S. Environmental Protection Agency
EPC	Energy Performance Certificate
EPSRC	Engineering and Physical Sciences Research Council
EWD	Excess winter deaths
GDPR	General Data Protection Regulation
HDM	House dust mites
HIU	Heat Interface Unit
HVAC	Heating, ventilation and air conditioning
Hz	Hertz
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
IOR	Indoor to outdoor ratio

IQR	Interquartile range
kHz	Kilohertz
LOD	Level of detection
MAE	Mean absolute error
MBE	Mean bias error
MEV	Mechanical extract ventilation
MVHR	Mechanical ventilation with heat recovery
NDIR	Nondispersive infrared
NNG	WHO Night Noise Guidelines
NSWWS	National Severe Weather Warning Service
O-ISLD	Outdoor to indoor sound level difference
OCC	Oxford City Council
P1/2/3/4/5/6/7	Participant 1/2/3/4/5/6/7
PAHs	Polycyclic Aromatic Hydrocarbons
PCA	Principal component analysis
PCB	Polychlorinated biphenyls
PFTs	Perflourocarbon tracers
PHE	Public Health England
PHPP	Passive House Planning Package
PID	Photo-Ionisation Detector
PID	Photo-ionisation detector
PMV	Predicted mean vote
PPB	Parts Per Billion
PPM	Parts Per Million
RH	Relative Humidity
RMSE	Root mean squared error
RPi	Raspberry Pi
SAP	Standard Assessment Procedure
SBS	Sick building syndrome
SD	Standard deviation
SES	Socio Economic Status
SFS	Sequential forward feature selection
SLM	Sound level meter

SMA	Simple moving average
SMS	Sound monitoring system
TVOC	Total Volatile Organic Compounds
UCL	University College London
UKHSA	UK Health Security Agency
VOC	Volatile Organic Compounds
WHO	World Health Organisation
WMO	World Meteorological Organization

Definitions

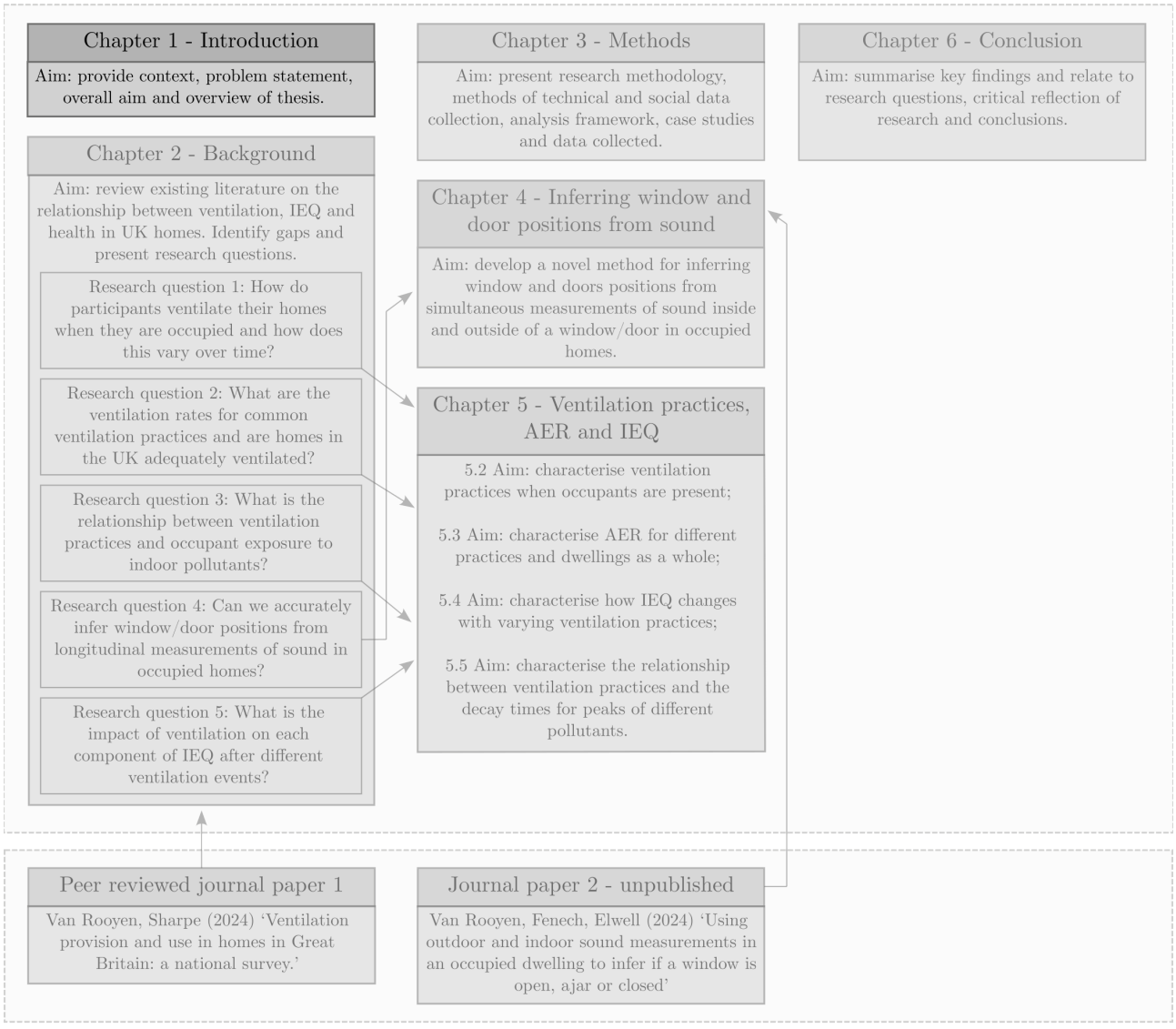
A-weighted sound pressure	Value of overall sound pressure, measured in pascals (Pa), after the electrical signal derived from a microphone has been passed through an A-weighting network (BSI, 2014)
Octave band	Band of frequencies in which the upper limit of the band is twice the frequency of the lower limit. (BSI, 2014)

Symbols

CO_2	Carbon Dioxide	(ppm)
CO	Carbon Monoxide	(ppm)
dB(A)	A-weighted sound pressure level	
dBL_{Aeq}	A-weighted equivalent continuous sound level	
dBL_{Amax}	A-weighted maximum continuous sound level	
$dBL_{night,outside}$	A-weighted long term average sound during the night (23:00 to 07:00)	
L_{10}	10th percentile	
L_{50}	50th percentile (median	
L_5	5th percentile	
L_{90}	90th percentile	
L_{95}	95th percentile	
L_{day}	Average sound pressure level over 1 day	
L_{DEN}	Day-Evening-Night-Level, also referred to as DENL, is the A-filtered average sound pressure level, measured over a 24 h period, with a 10 dB penalty added to the night (23:00 to 07:00h or 22:00 to 06:00h, respectively), and a 5 dB penalty added to the evening period (19:00 to 23:00h or 18:00 to 22:00h, respectively), and no penalty added to the average level in the daytime (07:00–19:00h or 06:00 to 18:00h, respectively).	
L_{eq}	Average level of sound pressure within a certain time period. If the A-filter is used for frequency-weighting, the average level is referred to as L_{Aeq}	
L_{max}	The highest sound pressure level in a given time period.	

L_{night}	The A-weighted long-term average sound level as defined in ISO 1996-2: 1987, determined over all the night periods of a year; in which: the night is eight hours (usually 23.00 – 07.00 local time).	
NO_2	Nitrogen Dioxide	(ppm)
O_3	Ozone	(ppm)
PM_1	$\leq 1\mu m$ sized particles	$(\mu g/m^3)$
PM_{10}	$\leq 10\mu m$ sized particles	$(\mu g/m^3)$
$PM_{2.5}$	$\leq 2.5\mu m$ sized particles	$(\mu g/m^3)$
°C	Degrees Celsius	

1 Introduction



1.1 Indoor environmental quality and health

On average, people in the UK spend more than 95% of their time indoors, with 66% of this time in our homes (Schweizer et al., 2007; Taylor et al., 2015). Adults with young children, children, elderly and those that are unemployed are likely to spend much longer than the average person indoors (Liddament, 2001; Schweizer et al., 2007). Furthermore, the recent COVID-19 pandemic and national lockdowns resulted in people spending more time indoors at home and also led to people using the spaces in their homes in different ways. Following the pandemic, fewer people are returning to work in offices, with more people working from home than before the pandemic (ONS, 2022). The conditions people experience and are exposed to in their homes are important for comfort, well-being, and health.

Indoor environmental quality (IEQ) is typically classified as comprising of four component parts: the thermal environment, visual environment, acoustic environment, and indoor air quality (CIBSE, 2020). Whilst spending time indoors, occupants are exposed to these different components of IEQ which in turn impacts the comfort, well-being, and physical health of the occupants.

The thermal environment can affect human health through exposure to high and low indoor temperatures. Low indoor temperatures affect the normal function of the cardiovascular and respiratory systems in humans and can result in serious harm to health including death (Marmot Review Team, 2011). In England and Wales, the 5 year moving average excess winter deaths (EWD) was 31,512 deaths for 2019/2020 (ONS, 2023). Due to climate change and a warming planet, EWD in the UK are predicted to reduce by 2% by the 2050's (Hajat et al., 2014).

On the other hand, high temperatures can cause discomfort, heat stress, heat strain, and heat stroke, which can also lead to death in humans (Andersen et al., 2013; UKHSA, 2023*a*). Exposure to high temperatures during the night can disturb sleep, which can impact occupant well-being and have health implications (AECOM, 2012*b*; Anderson et al., 2013; Royé et al., 2021). Much of the knowledge and understanding of how heat impacts health is derived from outdoor air temperatures and health, but can be translated to the indoor environment with care (AECOM, 2012*a*; Anderson et al., 2013). The indoor environment has the potential to both protect occupants from or exacerbate exposure to high temperatures. This is because the indoor environment can contain, capture, and trap sources of heat that are not present outdoors, but the insulated fabric can also reduce exposure to high outdoor temperatures. Additionally, the extent and operation of comfort cooling, passive and active ventilation can also alter indoor temperatures. Thus, occupant exposure to indoor temperature is related to the balance of gains and losses over time. 2,000 people in the UK are estimated to die each year from exposure to high indoor temperatures and this is expected to rise by 257% by 2050 because of climate change and an ageing and growing population (Hajat et al., 2014).

It has been estimated that up to 20% of the UK housing stock overheats, even during cool summers

(Zero Carbon Hub, 2016*a*; CCC, 2019). In addition to the warming climate, deaths due to overheating are expected to increase as there are more frequent heat waves (CCC, 2022), urbanisation (Mylona and Davies, 2015), urban densification, and an ageing and growing population (ONS, 2018). Finally, in the UK, current energy efficiency policies that aim to reduce carbon emissions from heating, have the potential to exacerbate indoor overheating (Hajat et al., 2014). The Committee on Climate Change (CCC, 2022) have highlighted the risks to human health and well-being associated with exposure to high temperatures as an urgent issue with "more action needed" from Government over the following five years.

Indoor air quality is a broad term, which refers to gaseous and suspended solid (particulate) pollutants that are present in the indoor air as well as biological contaminants, where human exposure to these pollutants can result in adverse health outcomes, including death. Exposure to pollutants in the indoor air can result in a range of outcomes, including irritation, respiratory diseases/illness, cardiovascular diseases/illness, neurological disorders, and cancers (CMO, 2022). There is strong evidence and a strong plausible physiological association between health and indoor air quality, but as with temperature, most of our understanding of health outcomes from exposure to air pollutants is derived from human exposure to pollutants in the outdoor air (Teichman et al., 2016; RCPL, 2016). Similar to overheating, we can translate this understanding to the indoor environment, but with caution, as the indoor environment contains its own sources of pollutants and interacts with pollutants in a different way to outdoors - buildings modify human exposure to temperatures and air pollutants. Poor indoor air quality is estimated to cause 3.8 million deaths a year globally and 99,000 deaths in Europe (WHO, 2019*a*). Two million healthy life years are lost every year to poor indoor air quality in Europe (Hänninen, 2013), where airborne solid and liquid particles ($\leq 2.5\mu m$), termed $PM_{2.5}$, were the leading risk factor (Hänninen et al., 2014). There are potentially thousands of different chemical compounds present in the indoor air at any one time, and the health impacts of a large number of chemicals are poorly understood both individually and synergistically (Knight, 27/11/2019; WHO, 2021*b*). Epidemiological research into the health impacts of exposure to different chemical and particulate pollutants found indoors is evolving fast, and as it does, our understanding of how the indoor environment can impact health also evolves. Due in part to changes in the housing stock, outdoor air quality and ventilation provision, the indoor air quality in homes has changed over recent decades and continues to change. In addition to the physical factors, socio-cultural factors such as; lifestyles and consumer products, combined with our understanding of the importance of IEQ for health has changed IEQ in homes, and this is likely to continue to change into the future. There are a number of important competing factors that could both improve (e.g., electrification of heat and transport) and worsen (e.g., densification, urbanisation, increasing use of synthetic materials) IAQ in the future, which highlights the need for continued research in this area (Ashmore and Dimitroulopoulou, 2009; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015).

After $PM_{2.5}$, environmental noise is one of the next leading risk factors for environmental burden of disease in Western Europe (Hänninen et al., 2014; Khomenko et al., 2022) and noise is also likely to be responsible for more disturbance to quality of life (CMO, 2017). The relationship between humans, noise, and health is complex and there are challenges in disentangling causes and effects, primary and modifying factors (Passchier-Vermeer and Passchier, 2000). However, there is strong evidence linking noise with a number of symptoms, which can lead to adverse health outcomes in humans. There is evidence of a causal association between exposure to environmental noise and sleep disturbance (Basner and McGuire, 2018*a*; Smith et al., 2022). Additionally, there is an established link between noise and cardiovascular disease, but the quantitative value of this risk remains unresolved (Münzel et al., 2021). Annoyance and sleep disturbance have the strongest evidence for the effects of noise on health (Stansfeld and Matheson, 2003). The health effects from annoyance and sleep disturbance contribute significantly to the burden of disease attributable to transportation noise in Europe and the UK (Peris and Fenech, 2020). Annoyance due to noise has an important and relevant behavioural subdomain, which may be associated with certain ventilation behaviours - for example, closing windows or not opening windows due to noise (Guski et al., 2017). Furthermore, there is evidence of a potential link between noise annoyance and poorer mental health; however, this is based on a small number of studies (Gong et al., 2022). Environmental noise is pervasive in England, with 356,367 noise complaints recorded by 144 local authorities in 2020/21, equivalent to 149 complaints for every 10,000 people (CIEH, 2022). In the UK, 48% of people feel that noise has spoiled their home in some way (Notley et al., 2014).

Increasing levels of urbanisation, road, and air traffic, combined with the potential future uptake of heat pumps and electric transport (drones, electric vertical take-off and landing aircraft, and flying taxis), could worsen environmental noise and result in higher morbidity and mortality in the future (Passchier-Vermeer and Passchier, 2000; Torija and Clark, 2021; Zaps and Chankov, 2022). On the other hand, some forms of electrically powered transport can be less noisy (and certainly have less air pollutants) than their fossil fuelled counterparts (POST, 2010*b*). Solutions for decarbonising heat and transport should be evaluated against the potential unintended consequences for environmental noise and its impact on well-being and health.

1.2 Ventilation, IEQ and health

Ventilation modifies IEQ and occupants exposure to IEQ, therefore, ventilation indirectly impacts the comfort, well-being, and health of building occupants.

Ventilation is the exchange of air between the inside and outside of a building, which is necessary for occupants respiration, controlling indoor air quality (remove or dilute), supplying combustion air, and providing ventilative cooling (WHO, 2009*a*; Clancy, 2011; HM Government, 2021*b*).

The introduction of the Building Regulations in 1985 in England and Wales included the first legislative requirement for ventilation in new homes (HM Government, 1985). Regulations for ventilation in new homes have been updated since then and the current Building Regulations in the UK describe a ventilation strategy for new homes comprising a combination of (1) extract ventilation from rooms where moisture or pollutants are likely to originate (typically from kitchens and bathrooms), (2) whole dwelling (background) ventilation (typically using trickle vents) to dilute, disperse, and remove moisture and pollutants not captured by extract ventilation, and (3) intermittent purge ventilation (typically using windows) to control air quality or indoor temperature during occasional activities (for example, painting, decorating, accidental release of smoke or spillage of water) (HM Government, 2021*a*).

Most homes in the UK built after the introduction of the building regulations have trickle vents and extract fans as above, however there a large amount (41%) of homes built after this date which do not have provision that meets the regulations in force at the time of construction (Van Rooyen and Sharpe, 2024). 78% of homes built before the introduction of the building regulations did not have extract and background ventilation provision (Van Rooyen and Sharpe, 2024).

Regardless of ventilation provision, occupant behaviour, including ventilation behaviour is often described as one of the most important factors influencing air exchange rates and overall IEQ in homes (Kvisgaard B, 1990; Bekö et al., 2011; Andersen et al., 2013; Few et al., 2019). However, there are many internal and external factors that influence occupant behaviour, and these factors interact in complex ways, resulting in a wide range of idiosyncratic behaviour between occupants and households (Fabi et al., 2012; Day et al., 2020).

Generally, ventilation results in higher rates of air exchange, and depending on the indoor and outdoor conditions, ventilation can either improve or worsen IEQ. Certain ventilation practices might improve one component of IEQ and at the same time also worsen another and this relationship might vary in time.Ventilation can also have other consequences for the dwelling, for example, ingress of insects and smells, compromising the security or privacy of the dwelling (AECOM, 2012*b*; NHBC, 2012; Notley et al., 2014; Sharpe et al., 2014; Gupta and Kapsali, 2016; Van Rooyen and Sharpe, 2024). The relationship between ventilation and IEQ is dynamic, as indoor and outdoor conditions vary spatially and temporally - this means that the timing of ventilation behaviours can be important for occupant exposure. Finally, a key barrier to ventilation in many situations is that it can either generate noise (mechanical ventilation) or lead to the ingress of noise (windows) and this can influence occupant ventilation behaviour (Buratti, 2002; Baborska-Narożny et al., 2017; Locher et al., 2018; MHCLG, 2019).

1.3 Ventilation and IEQ factors and complexities

This section briefly introduces some of the key internal and external factors associated with ventilation and IEQ - this is not exhaustive and there are many more factors discussed later in this thesis (Section 2.2). The interplay between these factors underline the complexity of ventilation behaviour and highlight the challenge of trying to understand this behaviour and how this then relates to ventilation practices, air exchange rates, IEQ, and ultimately occupant comfort, well-being, and health. Central to this complexity is the fact that these factors are dynamic and vary with each other, the occupants, building, and the wider social, political, and economic context.

Ventilation directly impacts air exchange rates (AER) and indoor noise levels, and AER between indoors and outdoors directly impacts indoor temperatures and IAQ. Indoor temperatures, IAQ, and noise affect comfort, well-being, and health. Therefore, there is an indirect link between ventilation and health, where ventilation modifies human exposure to IEQ (Wargocki, 2013). Indoor temperature, IAQ, noise, and ventilation are interdependent; however, much of the published research concerned with indoor temperature, IAQ, noise, and ventilation focus on a single component in isolation or two factors but does not consider all of these important factors together or in an integrated manner (Tham, 2016; ANC, 2020*a*). Additionally, research on overheating and air quality is dominated by modelling, with a dearth of empirical data from real homes in the UK (Crump, 2011; AECOM, 2012*a*; Mylona and Davies, 2015; Sundell et al., 2011).

Efforts to understand the health impacts associated with ventilation and IEQ are further complicated by a lack of understanding of the additive or synergistic health impacts of simultaneous exposure to different chemical and/or particulate pollutants, particularly at timescales which are relevant for ventilation (RCPL, 2016).

Ventilation behaviours, AER and IEQ are influenced by the ventilation provision and as mentioned previously, in UK homes, ventilation provision is strongly associated with age, with higher proportions of more recently constructed homes having purpose provided background ventilation and controlled mechanical ventilation (Van Rooyen and Sharpe, 2024). Despite modern dwellings having higher amounts of ventilation provision, there is an increasing body of evidence that recently constructed dwellings in the UK have poor levels of ventilation, a higher prevalence of overheating, and poor indoor air quality (Lomas and Porritt, 2017; Broderick et al., 2017; MHCLG, 2019; Taylor et al., 2023).

However, in the UK, most of the housing stock is old and is among the oldest in Europe, possibly the world (Piddington et al., 2020). The need to reduce energy consumption and carbon emissions from these older and less efficient homes is evident. Older homes are typically less air tight than their modern counterparts and are likely to experience greater levels of uncontrolled infiltration and exfiltration. This uncontrolled ventilation can be both beneficial and detrimental to IEQ, but it will

certainly result in a higher heat loss and energy consumption for space conditioning. Many energy efficiency measures specifically aim to reduce heat loss associated with uncontrolled air exchanges and many other thermal conductivity improvements have a secondary benefit of reducing heat loss from infiltration and exfiltration. (Hamilton et al., 2015) highlighted the potential for serious impacts on health when improving energy efficiency of homes without proper provision for ventilation. This highlights a key challenge when improving the energy efficiency of the existing housing stock, whilst ensuring a comfortable, safe, and healthy indoor environment.

From the above, it can be seen that ventilation in homes is broadly influenced by a combination of ventilation provision and the ventilation behaviours of the occupants. However, recent research suggests that the public have a poor understanding of how ventilation impacts their health and they also have not received information or advice on how to ventilate their homes (Dimitroulopoulou, 2012; Van Rooyen and Sharpe, 2024). When the lack of ventilation provision in existing homes is combined with the lack of knowledge of the importance of ventilation and how to ventilate, this could lead to low ventilation rates in UK homes. There is a growing body of evidence that many homes in the UK experience ventilation rates below the widely accepted healthy threshold but the underlying causes are not always clear (Crump et al., 2005; Aizlewood and Dimitroulopoulou, 2006; Kukadia and White, 2006; Sharpe et al., 2014; MHCLG, 2019; Few, 2021). Furthermore, what constitutes safe and healthy levels of ventilation is non-trivial and not always obvious.

1.4 Summary

To summarise the above, people spend most of their time indoors and at home, and their exposure to the indoor environment impacts their comfort, well-being, and physical health. Ventilation is an important modifier of the indoor environment and plays an important role in occupant exposure to IEQ and subsequently for occupants health. Despite this importance, there is a poor understanding of the relationship between ventilation and IEQ, and growing evidence that there is poor levels of ventilation and indoor conditions in homes in the UK. Given that IEQ and ventilation are important for health and that there is growing evidence that people are exposed to harmful indoor conditions, there is a need to better understand this relationship in order to evaluate potential solutions, with the ultimate goal of protecting the health and well-being of occupants.

In addition to its direct impact on IEQ and occupants exposure to IEQ, ventilation can impact other aspects of the household and also have implications for the wider climate. There is a need to understand these interactions and to balance these often competing positive and negative aspects of ventilation.

Historic events in the UK, such as the hearth and window taxes and the 1970's energy crisis resulted

in occupants reducing ventilation in homes in order to reduce heat loss and save energy (Glantz, 2008; Wolfson, 2013). More recently, the cost of living crisis in the UK is forcing millions of Britons to choose between 'heating or eating', potentially leading to many people sealing already poorly ventilated homes and increasing exposure to pollutants from indoor sources (Viner, 2023). This current crisis highlights the timeliness of this research, alongside other factors such as: a warming climate, poor ventilation provision in existing homes, poor knowledge of ventilation in the public, current policies that have the potential to exacerbate poor IEQ, growing and ageing population, urbanisation and densification.

The primary aim of this research is to investigate the relationship between occupants' ventilation practices/behaviours and IEQ (indoor air quality and noise) in occupied homes in the UK. The secondary aim is to develop a framework for informing ventilation advice for building occupants to reduce exposure to harmful peaks of IAQ, whilst considering other IEQ components and their impact on health.

This research used an empirical mixed methods case study approach. Quantitative and qualitative data was collected using building surveys, measurements of indoor and outdoor environmental conditions, measurements of ventilation practices, and detailed questionnaires.

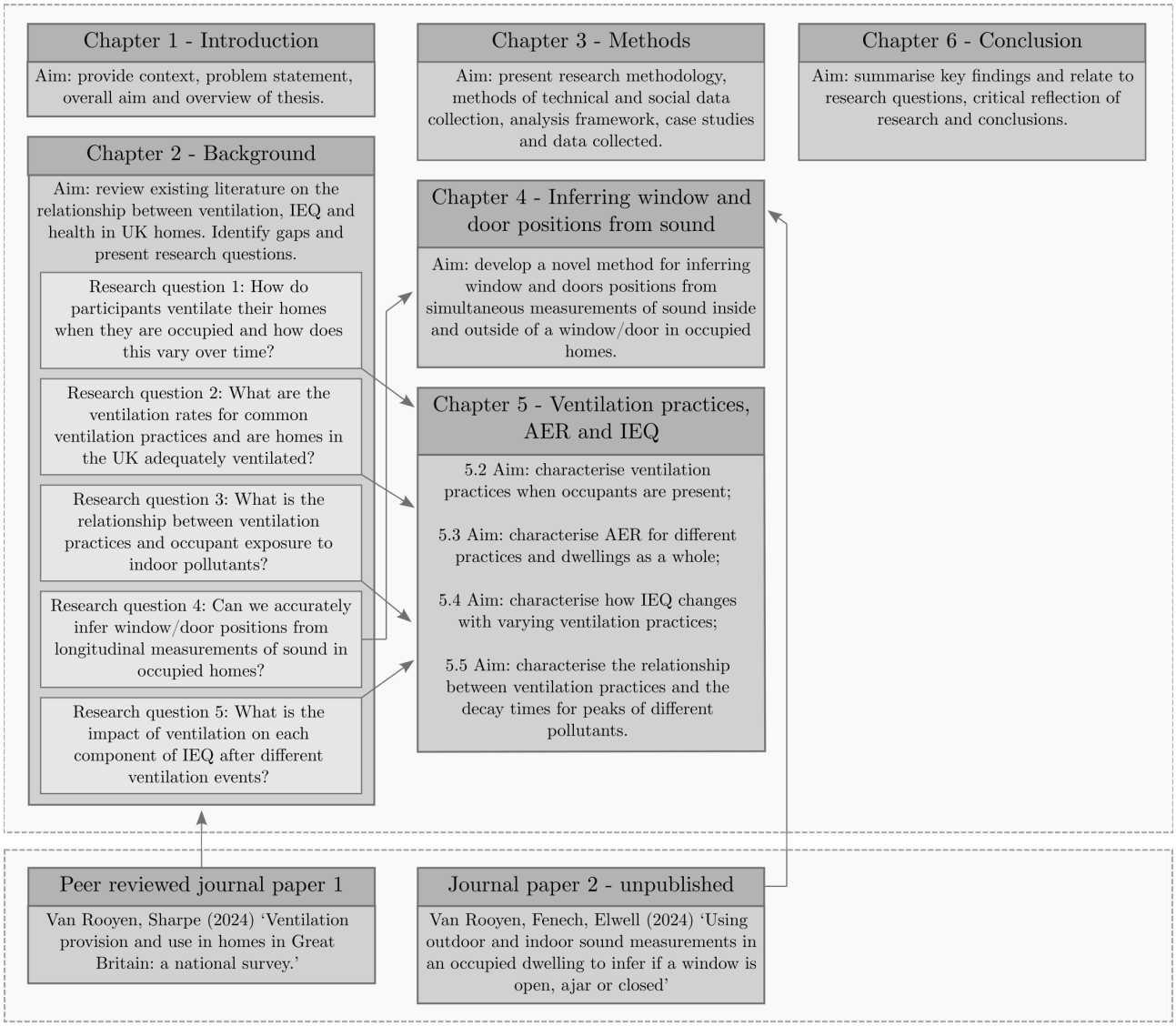


Figure 1.1: Figure showing the structure of the thesis, the relationship between the research questions, and the chapters that address them. This Figure also shows unpublished and published peer reviewed journal papers by the researcher and their relationship with chapters in this thesis.

Figure 1.1 provides a visual representation of the structure of this thesis. Chapter 2 presents a detailed perspective of the existing literature on the relationships between IEQ, ventilation, and health. In this chapter three key themes emerge, which are continued throughout this thesis: lack of ventilation provision, lacking knowledge of ventilation (impact of ventilation on health and how to ventilate), and poor ventilation rates in homes in the UK. Throughout this chapter, five important gaps in the literature are identified, and the chapter concludes by presenting research questions for each.

Chapter 3 justifies the pragmatist methodological approach taken, along with the choice of mixed methods. This chapter presents a detailed description of the analysis methods developed to address each research question and the final section of this chapter presents the case study dwellings.

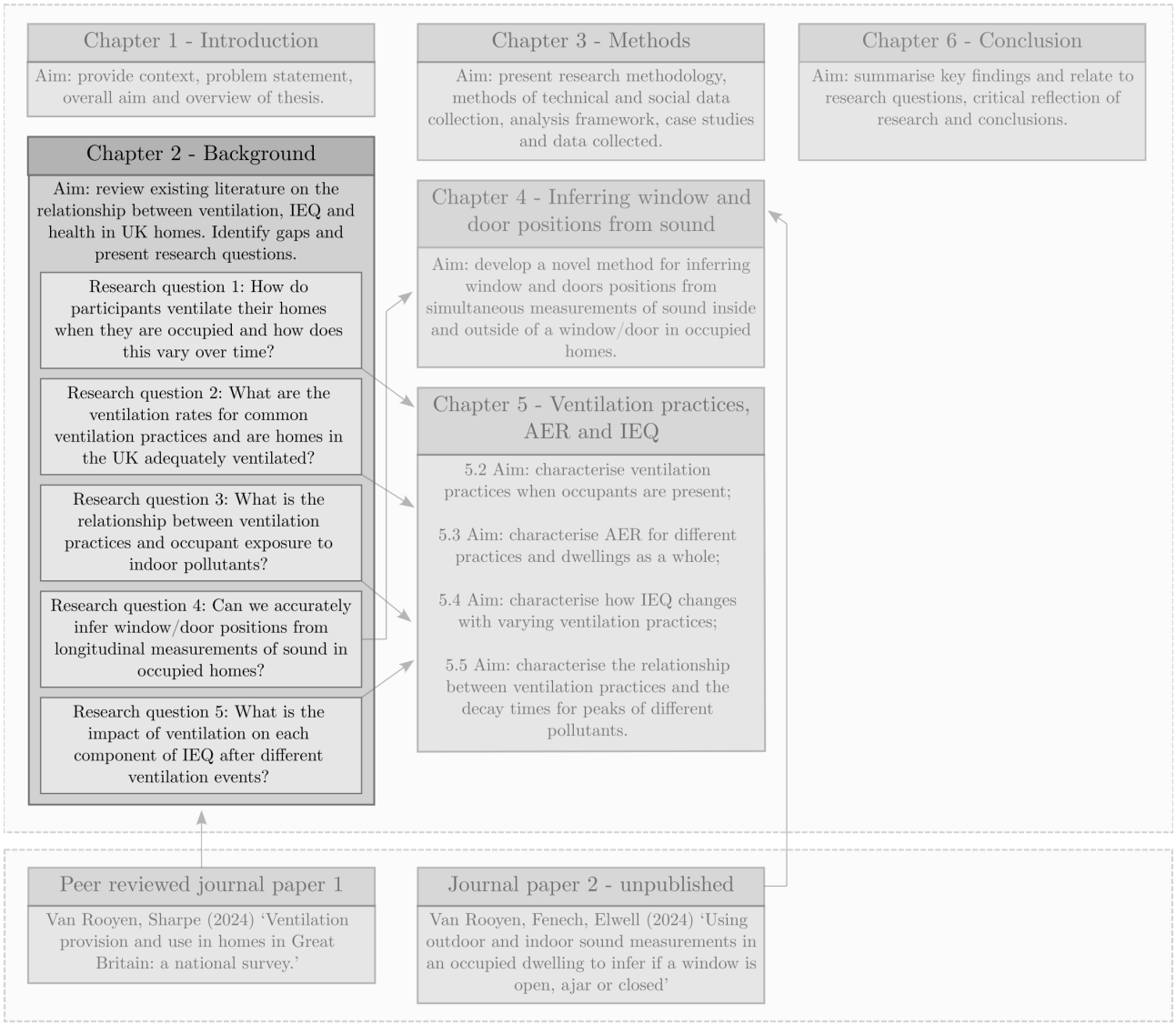
Chapter 4 presents a novel method and measurement platform that were developed to accurately infer window and door positions from simultaneous measurements of sound inside and outside of a

door/window.

Chapter 5 is closely related to three themes from the literature: lacking ventilation provision, lacking knowledge of ventilation and poor ventilation rates in many homes in the UK. The first part of this chapter characterises the ventilation practices of the seven case studies when they were occupied. The second part considers air exchange rates (AER) in each case study and the relationship between AER, ventilation practices and provision. The third section of this chapter explores the relationship between ventilation practices and the change in the different IEQ components. The fourth section presents a novel method for empirically calculating the time for peaks of indoor pollutants to decay to relevant health related thresholds. This method can be used for empirically informing ventilation advice for the public, with the aim of reducing exposure to peaks of pollutants. This chapter is concluded with a global discussion of the results in context of the three key themes that emerged from the literature.

The final chapter of this thesis (6) provides a summary of the key findings and their relationship with each of the research questions. A critical reflection of this research is discussed and the thesis ends with a summary of the conclusions.

2 | Background and literature review



The previous chapter introduced the relationships between ventilation & IEQ, and IEQ & health. This chapter explores the literature in detail, with a focus on the relationship between ventilation, IEQ, comfort, well-being, and health - illustrating the complexity of these relationships. Throughout this chapter, five gaps in knowledge are identified, which form the basis of the research in this thesis.

The first section of this chapter (2.1) describes the relationship between health and each IEQ component, then the second section (2.2) discusses the relationship between ventilation and IEQ. Together, these sections demonstrate that ventilation impacts occupants' comfort, well-being, and physical health.

Both of these sections consider how the different components of IEQ can be quantified and outline the relevant health thresholds for each. Section 2.2 explores ventilation provision in UK homes, showing that trickle vents, mechanical extract ventilation, and opening windows are the most common form of ventilation provision in UK homes. Ventilation provision is discussed in context of the policies that have shaped this provision in existing and new homes. Occupants ventilation behaviour and the many internal and external factors that influence this behaviour are discussed along with their complex interaction. Section 2.2 identifies three key themes which feature throughout this thesis: many homes with ventilation provision that does not meet current standards, poor knowledge of the importance of ventilation for health and how to ventilate, and poor ventilation rates in many homes in the UK.

The final section of this chapter (2.3) describes the aim of this research and the research questions that were developed to address the gaps in knowledge.

2.1 IEQ, exposure and health

People in England spend most of their time indoors, within their homes (Farrow et al., 1997; Schweizer et al., 2007). Whilst indoors, occupants are exposed to the indoor environment, where indoor environmental quality broadly comprises of indoor air quality (IAQ), thermal, visual, and acoustic environments (CIBSE, 2020; Khovalyg et al., 2020). The link between poor indoor environmental quality (IEQ) in housing with poor mental and physical health outcomes is long established (Marmot et al., 2020; Kulakiewicz and Wilson, 2022).

The notion that the indoor environment impacts our health is not new and can be traced back to ancient Egypt, where carvers working on stone indoors had higher incidences of respiratory illness compared with others working outside (Ashmore and Dimitroulopoulou, 2009). *'On airs, waters and places'* written by Hippocrates in the 5th Century BC, documented poor air quality as one of the most frequent causes of disease (Pappas et al., 2008; Winck et al., 2022). There were limited advancements during the Medieval era, and the general concept was that breathing was primarily for cooling the heart (Sundell, 2004). The discovery of oxygen and its role in breathing and human health brought

about a paradigm shift in the understanding of IEQ and human health (Sundell, 2004). Later, large scale air pollution disasters such as the Great Smog of London in 1952 reinforced the importance of the environment and its impact on our health. The birth of modern research into IEQ can be traced back to the 1960's and 70's, when researchers began to measure and quantify pollutants present in indoor air (Crump et al., 2005), measure and quantify temperature and thermal comfort (Mujan et al., 2019), develop theories for sound indoors (Kuttruff, 1974), and make the first evidence based links between personal exposure to IEQ and health outcomes (Ashmore and Dimitroulopoulou, 2009).

Since its inception, there has been substantial progress in our understanding of the relationship between IEQ and health - the importance of IEQ in homes for health is now well established (WHO, 1984, 2009*b*, 2010, 2018*b*, 2021*a*). Furthermore, there is good evidence for the relationship between ventilation and individual components of IEQ. However, there is a lack of evidence for the relationship between ventilation and IEQ as a whole (and health). There is no evidence that the visual component of the indoor environment is related to ventilation and health, therefore, the visual component of IEQ does not form part of this thesis.

The literature generally describes the human impacts of IEQ using three terms/domains: comfort, health, and well-being (Rohde et al., 2019). Of these terms, thermal comfort is a well-researched and established field in the literature (Ormandy and Ezratty, 2012; Mujan et al., 2019), health has generic and non-specific definitions, and there is no consensus on a definition of well-being in the literature - this lack of a clear and accepted definition leads to these terms being used interchangeably (Rohde et al., 2019). For this research, the definitions proposed by Rohde et al. (2019) for the indoor environment (IE) are used:

Comfort:

> 'IE conditions that facilitate a state of satisfaction of bodily wants in occupants, based on their individual preferences and their given activity, and that limit physical stressors causing annoyance.' (Rohde et al., 2019, p. 11)

Well-being:

> 'IE conditions that afford mental resilience and restoration, offer variation, provide controllability and advance positive stimuli to improve occupant happiness.' (Rohde et al., 2019, p. 16)

Health:

> 'IE conditions that promote physical resilience and restitution of occupants, and limit physical stressors causing infirmity, disease and years of potential life lost.' (Rohde et al., 2019, p. 12)

The relationship between comfort and health is complex and cannot be clearly determined - it is both conceivable that a person might feel comfortable in an environment which is harmful to their

health (for example, carbon monoxide is poisonous, but we cannot detect this) and a person might also feel uncomfortable in an environment which is harmful to their health (for example, the body becoming uncomfortably hot before heat stroke) (AECOM, 2012*b*; Kelly and Fussell, 2019). It is, however, important to highlight that thermal comfort and overheating are concepts that are both concerned with temperature but do not measure the same thing - comfort is a subjective perception of temperature, whereas overheating is an objective physical reaction to temperature. Ormandy and Ezratty (2012) and Andersen et al. (2013) argue that thermal comfort is inextricably related to health, and Ormandy and Ezratty (2012) reported poor thermal comfort to be significantly associated with self-reported poor health. In the context of IEQ: comfort, well-being, and health are all linked together by indoor environmental conditions and ventilation, because ventilation modifies IEQ.

Figure 2.1 illustrates the interconnectedness of these three domains with IEQ. This diagram does not include the visual component of IEQ, as this is not related to ventilation. Rohde et al. (2019) argue that well-being is a positive third dimension of IEQ and must be considered alongside and with comfort and health to create 'good IEQ'.

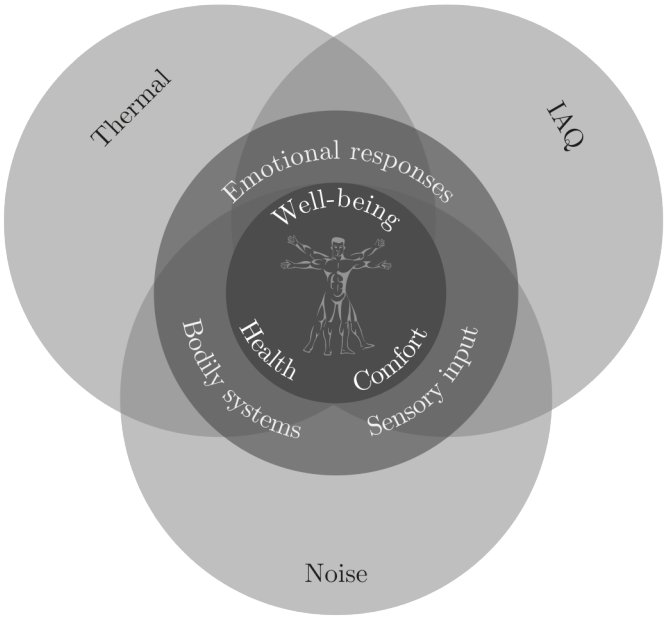


Figure 2.1: Conceptual model of IEQ (excluding visual) and comfort, health, and well-being (adapted from Rohde et al. (2019)).

The sections below explore the relationship between overheating, IAQ, and noise with comfort, health and well-being, with a focus on the relationship between each of these IEQ components and health.

2.1.1 Overheating and health in UK homes

A healthy human has a core body temperature of around 35°C, and the human body will try to maintain this temperature - this is called thermoregulation. When the human body is exposed to high ambient temperatures, the core temperature of the body rises, and the body's defence mechanisms react by widening the blood vessels, and sweating occurs in an attempt to increase heat-loss to reduce the core temperature and restore heat balance (UKHSA, 2023*a*). Heat exhaustion and dehydration can follow after extended periods of perspiration and exposure to high temperatures (AECOM, 2012*b*; Dengel et al., 2016; CIBSE, 2020). If the body is exposed to high temperatures for a prolonged period of time, heat stroke can occur, which can be fatal (Anderson et al., 2013). The progression from heatstroke to death can occur after just a few hours, and heatstroke has a high case-mortality ratio (Kovats and Hajat, 2008; Ormandy and Ezratty, 2016; CIBSE, 2020).

High indoor temperatures also indirectly impact health and well-being. High indoor temperatures can significantly impact sleep and productivity (Anderson et al., 2013; Evans, 2015). Poor sleep arising from thermal discomfort in bedrooms can result in an increased risk of atypical behaviour and accidents (AECOM, 2012*b*). High temperatures have also been associated with exacerbation of schizophrenia and dementia, accelerated absorption of insulin in people with type one diabetes, and worsened respiratory symptoms (Thompson et al., 2018; Tham et al., 2020).

The systematic review by Tham et al. (2020), found that in 90% (n=22) of studies there was a significant relationship between high temperatures indoors and negative health outcomes. However, there is limited empirical evidence on the direct relationship between indoor and outdoor temperatures and the relationship between indoor temperatures and health (AECOM, 2012*a*; Ormandy and Ezratty, 2016). Most of our current understanding of heat and health is derived from the relationship between outdoor temperatures and health, where outdoor temperature is the main predictive weather variable for temperature related morbidity and mortality (AECOM, 2012*a*; Anderson et al., 2013).

2.1.1.1 Most vulnerable groups

There is agreement in the literature that the elderly, young, and infirm are considered to be the groups that are most vulnerable to health risks associated with the effects of overheating (Kovats and Hajat, 2008; AECOM, 2012*a*; Anderson et al., 2013; Hajat et al., 2014; Vardoulakis et al., 2015; Ormandy and Ezratty, 2016; Dengel et al., 2016; Lomas and Porritt, 2017; Bundle et al., 2018; UKHSA, 2023*a*) - these groups are also likely to spend more time indoors than other groups in the population. The elderly are cited as the highest risk group because they are likely to be less sensitive to temperature and typically feel colder than non-vulnerable people, they are also less able to regulate core temperature, and they are more likely to suffer from cardio or respiratory disease, which result in more serious health outcomes from heat (Lomas and Porritt, 2017).

2.1.1.2 Scale of overheating

A survey of summertime temperatures and overheating risk in English homes (n=207) reported that even during a mild/cool summer, 21% of bedrooms exceeded overheating criteria (Beizaee et al., 2013). Similarly, the CCC (2022) reported that 20% of homes currently overheat and that high temperatures are an urgent issue for health and well-being of the public. This concern is shared by the wider public, and a survey by Wright et al. (2018) reported a growing concern among the general public about overheating and the associated health risks. This concern is further reflected in a survey by Evans (2015), which reported that overheating would influence 54% of Londoners decision when buying a home.

The finding that homes currently overheat and also overheat during cool/mild summers suggest that overheating could be much worse during hot summers and worsen further due to the warming climate. This increasing risk of overheating, coupled with the finding that elderly people are most vulnerable and the UK population is ageing, is likely to result in an increased risk for higher morbidity and mortality in the future.

2018 and 2022 were two of the hottest summers on record in England (Met Office, 2022*a*), where ambient temperatures were typical of those expected during 2050 - during the summer of 2018 Lomas et al. (2021) estimated that 19% of all bedrooms and 15% of living rooms overheated. Hajat et al. (2014) estimated that deaths due to high temperatures will rise by 257% by 2050, from a baseline of 2,000 deaths a year.

The annual healthcare costs associated with mortality and morbidity from overheating are estimated to increase from £23m (2012) and £73m (2012) to £107m and £256m in 2050 respectively (Zero Carbon Hub, 2015*b*). Furthermore, economic loss of business due to staff days lost because of indoor temperatures that exceed 26°C is estimated to increase from £0.77bn to £1.1-5.3bn by the 2050's.

2.1.1.3 Existing models of thermal comfort

Thermal comfort is a subjective condition, where an individual is satisfied with the thermal environment (Frontczak and Wargocki, 2011; Rode et al., 2019). This satisfaction is influenced by a wide range of dynamic objective environmental and subjective individual variables (Frontczak and Wargocki, 2011; Ormandy and Ezratty, 2012, 2016; Bundle et al., 2018; Mujan et al., 2019).

Research into thermal comfort began in the 1970's with Fanger's predicted mean vote (PMV) index, which is widely used in standards and regulations throughout the world (Mujan et al., 2019; Khovalyg et al., 2020). Although widely used, the PMV model is inherently imprecise given: [1] human senses are better at detecting changes in the environment, rather than absolute levels (Seppeanen and Fisk, 2004), [2] humans are all different physiologically, [3] the PMV model considers conditions with acceptability of 90% of people, and [4] there is a wide range of conditions over which people will or will not feel

comfortable (Ormandy and Ezratty, 2012; Lomas and Porritt, 2017).

In the late 1990's there was a paradigm shift away from Fanger's physical deterministic model, to the adaptive acceptance model of comfort (de Dear et al., 2013). This new model was used to describe naturally ventilated buildings and includes the idea that occupants are an integral part of the comfort system and that comfort can be achieved over a wider range of temperatures (linked to outdoor temperature), as occupants can take action to restore comfort and adapt to the conditions (Fabi et al., 2012; CIBSE, 2013). These subjective adaptive processes are classified as physiological, psychological, and behavioural (Mujan et al., 2019; Rohde et al., 2019). However, there is a lack of evidence explaining the mechanisms/logic humans use to integrate different senses to evaluate/assess comfort (Seppeanen and Fisk, 2004). We also know very little about how people act during times of overheating and thermal discomfort, including how occupants ventilation behaviour might change during periods of overheating (Anderson et al., 2013; Wright et al., 2018). However, because occupants actions to regulate their body temperature (thermoregulation) is a fundamental concept of the adaptive comfort model and we have a limited understanding of how people evaluate/assess thermal comfort or act during periods of overheating/thermal discomfort, the adaptive thermal comfort model is also limited.

The adaptive thermal comfort model is currently the most popular and most appropriate model for domestic environments. The first reason is that the PMV model is deterministic and was developed for office environments with central HVAC systems. Second, the adaptive model is based on the assumption that people could have greater opportunity to adapt at home (change clothing, activity, and ventilation easier), which is relevant for the majority of homes in the UK which are naturally ventilated (Ormandy and Ezratty, 2012; Lomas and Kane, 2013; CIBSE, 2015; Mavrogianni et al., 2016; Mujan et al., 2019). In 2017, the Chartered Institution of Building Services Engineers (CIBSE) released Technical Memorandum 59, which provides advice for evaluating overheating in homes (CIBSE, 2017). The advice contained in TM59 is derived from the British and European standard (BS EN 15251) and is based on the principle of adaptive comfort.

The adaptive comfort model is, however, limited; for example, whilst sleeping, an occupant's ability to adapt is reduced, and time spent sleeping can represent a large amount of the time people spend at home (Anderson et al., 2013; Sharpe et al., 2014; Lomas and Porritt, 2017). Additionally, whilst sleeping, ventilation rates might also be reduced due to curtains/blinds and closed internal doors. Both the PMV and adaptive comfort models are further limited, as they only focus on thermal comfort and do not consider other important IEQ factors and how these might impact thermoregulation and ventilation behaviours, comfort, and health more widely. An example of this is indoor and outdoor air quality and noise, which are known to be important factors that influence occupant ventilation behaviour, but these factors are not accounted for in either PMV or adaptive comfort models. This highlights the challenge of integrating across the different components of IEQ. In addition, neither of these models

consider the ability for populations to acclimatise or adapt to temperatures over time - particularly as higher temperatures become more frequent with climate change (Lomas and Porritt, 2017). Finally, these models are inherently based on the 'average person' and do not necessarily represent a substantial minority, including many vulnerable groups, such as elderly, young children, and people with complex health needs.

2.1.1.4 Factors influencing overheating in UK homes

This section discusses five main factors identified from the literature that have been shown to influence overheating in UK homes. The main factors identified from the literature are: dwelling type, dwelling age, spatial differences in dwellings, geographic location, and occupant behaviours.

Dwelling types

In the literature, empirical studies of overheating regularly find flats and dwellings located on top floors or directly under roofs as having the highest incidences of overheating (Lomas and Kane, 2013; Lomas and Porritt, 2017; Beizaee et al., 2013; Evans, 2015; Mavrogianni et al., 2015, 2016). Potential reasons for this are that flats generally have a lower external surface to volume ratio, external surface to floor area ratio, fewer windows per unit floor area, and less potential for cross flow ventilation relative to other dwelling types, which results in lower air infiltration rates and air exchange rates (Beizaee et al., 2013). The UK population is increasing, and this is resulting in a higher demand for flats, particularly in large urban areas (Dianati et al., 2017). These factors, combined with numerous authors suggesting that elderly people are most at risk from overheating, an ageing population, the heat island effect, and a warming climate, culminate in the 'triple jeopardy' scenario, which could significantly increase future morbidity and mortality from overheating in major cities in the UK (Evans, 2015; Taylor, Wilkinson, Davies, Armstrong, Chalabi, Mavrogianni, Symonds, Oikonomou and Bohnenstengel, 2015; Taylor et al., 2018).

There is suggestion that socio-economically deprived groups are at a higher risk of overheating (Vardoulakis et al., 2015); however, the evidence for this is not clear. Furthermore, the review by Ormandy and Ezratty (2016) reported inconsistencies between studies, with some not finding a relationship between socio-economic status (SES) and overheating mortality. Research considering this relationship is, however, limited, and more research is necessary to better understand this potential association.

The physical monitoring by Beizaee et al. (2013) (n=207) and Lomas and Kane (2013) (n=268) reported that detached dwellings were significantly cooler than other types of dwellings. However this conflicts with the results of modelling carried out by Taylor et al. (2015), Taylor et al. (2016) and mixed methods research by Wright et al. (2018) (n=8), who reported that bungalows were prone to and experience overheating. The research by Taylor et al. (2015) and Taylor et al. (2016) used only modelling, with no empirical evidence, and the research by Wright et al. (2018) collected only limited

measurements of temperature from a small sample of eight homes. In the UK, bungalows are favoured by the elderly, who are one of the highest at risk groups for the health impacts of overheating, and based on the empirical results from Lomas and Kane (2013) and Wright et al. (2018), this predisposes them to lower amounts of overheating and safer summer temperatures.

The way in which a building is serviced and the level of control that an occupant has over the systems/services that affect the indoor environment appear to play a role in thermal comfort and building overheating. Frontczak and Wargocki (2011) report that occupants in naturally ventilated buildings are more forgiving of the thermal environment than those that occupy air conditioned buildings. Fans and air movement have also been shown to be effective for reducing thermal discomfort but can cause uncomfortable draughts (Lomas and Porritt, 2017; Wright et al., 2018).

Dwelling age

The literature shows a relationship between the age of dwellings and their propensity to overheat, where more recently constructed dwellings are more prone to overheating (AECOM, 2012*a*; Evans, 2015).

The introduction of Building Regulations in 1985 (HM Government, 1985) was subsequently followed up with Part L, which represents an effort to reduce carbon emissions from buildings and requires minimum material and workmanship standards to reduce heat loss through fabric and infiltration (HM Government, 2016, 2021*b*). Compliance with these standards has tended to result in more insulated, lightweight, airtight, and mechanically ventilated buildings when compared with older homes, and this has had the unintended consequence of exacerbating overheating. These tendencies are the likely outcome of the construction industry meeting the requirements of the building regulations in the most cost effective manner. Mavrogianni et al. (2016) found a positive correlation between wall and floor insulation levels and peak temperatures in dwellings. On the other hand, dwellings with higher levels of thermal mass were found to be significantly cooler (Lomas and Kane, 2013) and reduce both peak and average temperatures (Mavrogianni et al., 2016). Furthermore, modelling of the GB housing stock by Taylor et al. (2016) reported an increased risk of overheating in homes with higher air tightness. However, the increased risk of overheating reported is likely to be the result of a combination of different factors (e.g., new lightweight highly insulated and airtight buildings) and not air tightness alone.

In addition to the above, the design of new dwellings is critical for overheating and has the potential for significant mitigation of overheating by optimising orientation, fenestration design, fabric specification, geometry, and solar shading. However, up until recently, there had been no requirement for the design of dwellings to meet any standards for mitigating overheating. In 2021, new regulations were introduced to ensure that the design of new dwellings included an assessment of overheating in an effort to mitigate overheating in new dwellings (HM Government, 2021*c*).

Spatial differences within properties

It is expected that there would be spatial variation of overheating in dwellings, owing to a number

of factors. For example, different rooms might have varying occupancy, solar gains, and ventilation flow rates. However, research into the spatial variation of these factors with overheating is limited.

A number of studies have reported that bedrooms overheat more than other spaces in dwellings, but the reasons for this are not clear (AECOM, 2012*a*; Lomas and Kane, 2013; Beizaee et al., 2013). Possible reasons include occupant gains overnight, heat rising to upper floor bedrooms, heat gains from lofts and less adaptive opportunities when sleeping.

The overheating criteria in many assessment methods have a lower temperature threshold in bedrooms than other types of rooms - overheating criteria is discussed later in Section 2.1.4.1. This makes it challenging to compare and contrast spatial differences of overheating across different room types.

Geographic location

Outdoor temperatures in the UK are generally higher in the south, and these regions regularly experience the highest summer temperatures across the UK (Met Office, 2022*b*). Following this, as expected, the literature shows a relationship between geographic location in the UK and indoor overheating, where dwellings located in the South East and in urban heat islands, such as London, have a higher risk of overheating (AECOM, 2012*a*; Beizaee et al., 2013; Zero Carbon Hub, 2015*b*; Taylor et al., 2016; Mavrogianni et al., 2016; Lomas and Porritt, 2017).

Due to the increased risk from the urban heat island and its location in the South East, London is often a focus of overheating research in the UK.

Empirical overheating research conducted between 2009 and 2010 found that 29-37% of living rooms and 31-49% of bedrooms overheated in a sample of 122 dwellings in London (Pathan et al., 2017). In another piece of research, when questioned, a much higher percentage of people (83% n=1000) living in London reported their home to be uncomfortably hot at least once during 2015, and only 13% felt they did not suffer from overheating (Evans, 2015). Overheating, however, is not limited to urban areas or the South of the UK and could be experienced anywhere in the UK. Beizaee et al. (2013) discovered incidences of overheating in homes in the East, East Midlands, and West Midlands.

It must be noted that although there is some quality evidence, the most recent research is around 5 years old, and the UK has experienced some of the hottest summers on record over the past 5 years, during which there was likely to have been significantly higher incidences of heating throughout the UK (Met Office, 2022*a*). Furthermore, with a warming climate, this is likely to continue to worsen into the future.

Occupant behaviour

Occupant behaviour is frequently cited in the literature as a key determinant of IEQ and overheating. Behaviour in the context of indoor overheating can be classified as either (1) causing (or exacerbating) overheating or (2) responding to actual or anticipated overheating (AECOM, 2012*a*). Furthermore, overheating has been shown to affect behaviour (e.g., impaired cognitive performance) (AECOM,

2012*a*).

Mavrogianni et al. (2014) suggests that occupant behaviour during the summer can be a significant determinant of building overheating, but the scientific community knows very little about how people behave or operate their homes during the summer, and what effect this behaviour has on indoor temperatures and overheating (AECOM, 2012*a*; Mavrogianni et al., 2014, 2015, 2016). The notion that occupant behaviour can significantly impact overheating risk is illustrated in research by Baborska-Narożny et al. (2017), who observed a high variation in summer temperatures between a sample of similar naturally ventilated flats located near each other, where the variation was attributed to occupant practices, particularly ventilation practices - the relationship between overheating and ventilation is discussed more in Section 2.2.5.1.

Occupant behaviour is highly variable, complex to understand, and idiosyncratic. Baborska-Narożny et al. (2017) explains that occupants react to overheating based on their knowledge and skills, and learning is most effective when triggered by senses and feedback from the senses. This learning can be strengthened by social learning and a full understanding of overheating. Ventilation behaviour is discussed in more detail in Section 2.2.2.

The lack of knowledge of how people behave in buildings means that researchers using modelling need to rely on assumptions, which are often derived from best practices or experimental inputs but not always from actual behaviour. This can result in a 'performance gap' between models and reality (Nicol, 2001; Lomas and Porritt, 2017). Mavrogianni et al. (2016) found a significant difference between the (modelled) predicted and monitored temperatures from 101 homes during the summer of 2009, where this performance gap was attributed in part to ventilation and shading habits.

2.1.1.5 Summary of overheating and health in UK homes

Buildings are modifiers of the effect of the indoor and outdoor thermal environment on health (Anderson et al., 2013). Indoor overheating is a context specific, complex, dynamic phenomenon that results from an interaction between occupants, their susceptibility to heat, their behaviours and physical characteristics of the building, its climate and surroundings (AECOM, 2012*a*; Symonds et al., 2016; Ormandy and Ezratty, 2016; Bundle et al., 2018). The literature review has highlighted that the elderly are identified as the most at risk from overheating, but there is little research on the impact of overheating on vulnerable groups and those with complex health conditions. Figure 2.2 illustrates the interaction between a range of physical and physiological factors and their relationship with ventilation and health.

A summary of the physical characteristics of the building that have been found to influence overheating are: dwelling type, age, geometry/orientation, fabric, shading, solar gains, ventilation provision, and location (AECOM, 2012*a*; Mavrogianni et al., 2012; Beizaee et al., 2013; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015; Symonds et al., 2016; Ormandy

and Ezratty, 2016; Mavrogianni et al., 2016). This list highlights that the design and construction of dwellings play an important role in the risk of overheating and in mitigating overheating. However, Building regulations require new homes to be thermally efficient and air tight, which can lead to an increased risk of overheating if the impact of these requirements on overheating are not appropriately accounted for during the design and construction. Research frequently reports that recently constructed dwellings are prone to overheating and have potentially harmful indoor environments. Taylor et al. (2018) estimated that fabric improvements, which result in a 26% reduction in energy consumption, equated to an increase of 3-4% of summer deaths. This study estimated that the provision of external shutters could reduce heat mortality by 37-64% and low absorptance surface coatings by 12-15%. This study also reported that occupant behaviour was the single largest modifier of indoor heat exposure and heat-related mortality risk, where keeping windows closed led to an increase in heat mortality in the population of 29-64%.

Occupant behaviour has a substantial influence on overheating risk through an individual's perception of the thermal environment (thermal comfort), their understanding of overheating, and their ability/willingness to engage in adaptive actions, such as changing clothing, building shading, and ventilation practices (AECOM, 2012*a*; Mavrogianni et al., 2014; Ormandy and Ezratty, 2016; Mavrogianni et al., 2016).

Building occupants frequently report that the thermal environment is the most important aspect of IEQ, and therefore indoor temperatures are an important factor for occupant behaviour (such as ventilation) in buildings (AECOM, 2012*b*,*a*; Frontczak et al., 2012). Ventilation behaviour can modify indoor temperatures, and this also alters occupants thermal comfort and their exposure to high temperatures. Therefore, an occupant's actions to maintain comfortable indoor temperatures could also reduce their exposure to high indoor temperatures and protect their health (Ormandy and Ezratty, 2016).

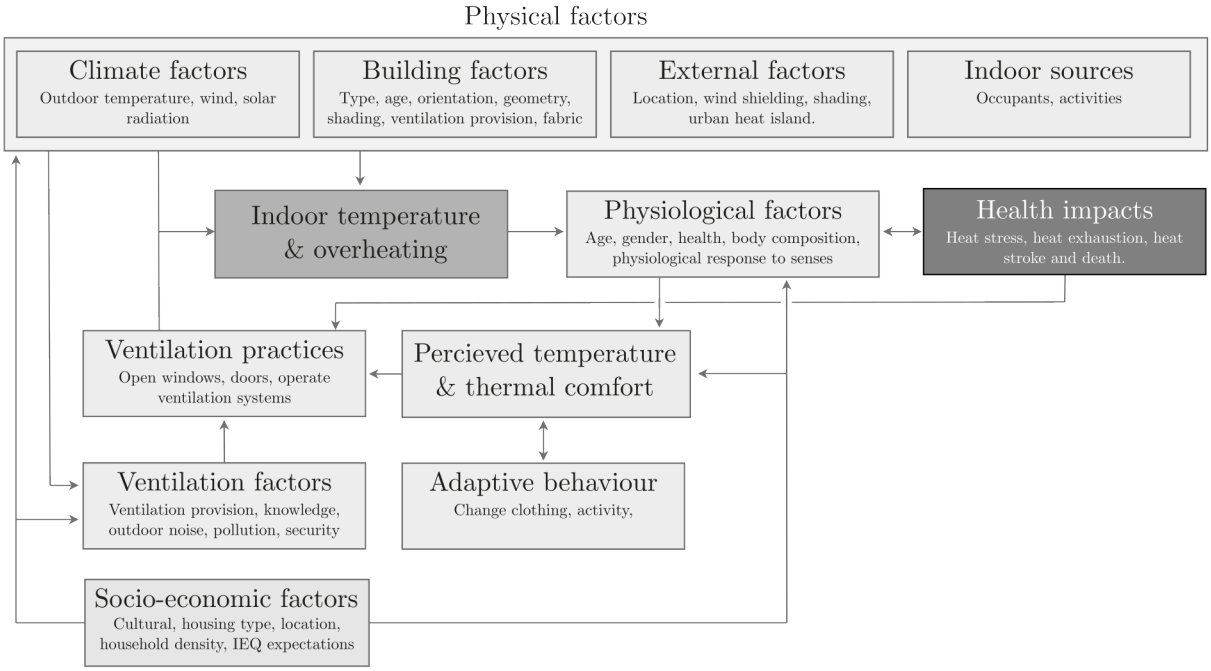


Figure 2.2: Diagram showing the relationship between a range of physical and socio-economic factors with indoor temperature, ventilation and health. This diagram also illustrates a number of possible causal relationships.

2.1.2 IAQ and health in UK homes

Indoor air quality (IAQ) is a broad term that encompasses an important complex multifactorial component of overall IEQ. 'Good' indoor air quality is 'air with no known contaminants at harmful concentrations' - this definition is directly related to the health of human occupants of buildings (Clancy, 2011). Furthermore, indoor air should also 'be perceived fresh and pleasant rather than stale, stuffy, and irritating' - this requirement is related to occupants perception of the air and impacts comfort and well-being rather than health specifically (European Commission - Institute for Health & Consumer Protection, 1992).

Humans are exposed to pollutants present in the indoor air by three mechanisms: (1) inhalation, (2) dermal absorption (absorb through the skin), and (3) ingestion (Jones, 2017). Overall exposure is dependant on both the amount of time the person is in contact with the pollutant and the concentration of the pollutant in question (Ashmore and Dimitroulopoulou, 2009). Europeans spend most of their time indoors, and because of this, it is expected that their total exposure is closely linked with indoor air quality (Ashmore and Dimitroulopoulou, 2009).

Indoor air contaminants can be from (1) penetration of outdoor pollutants, (2) an indoor source, or (3) reaction products from indoor materials (Kelly and Fussell, 2019). Air contaminants affect the human body in different ways and can also affect different people in different ways. There is a wide range of health and well-being outcomes from exposure to air pollutants, which range from odour annoyance and sick building syndrome through to acute toxication and long term cancers (European

Commission - Institute for Health & Consumer Protection, 1992; Tham, 2016). This section provides an overview of the health impacts of different pollutants.

Of the combined burden of disease from indoor and outdoor air in Europe, indoor air is responsible for an estimated 34% of the burden of disease - where cardio-vascular disease is responsible for 35%, lung cancers 26%, asthma 20%, respiratory infections 9%, ischaemic heart disease 6%, and chronic obstructive pulmonary disease (COPD) and acute toxication responsible for 3% of DALY's each (Hänninen et al., 2014). The environmental burden of disease is challenging to estimate, due in part to the wide range of data and knowledge required. This wide range can also introduce uncertainties and affect the results, but it is useful and important to make these estimates to quantify health impacts and rank the relative importance of different factors. Poor indoor air quality mostly impacts the lungs and heart (POST, 2010*a*, 2023).

Children are one of the groups that are most at risk from poor indoor air quality due to their immature lung structure and immune systems (Ashmore and Dimitroulopoulou, 2009; POST, 2010*a*; Jacobson et al., 2019). The elderly and people who have an existing illness are also at increased risk from the health effects of poor indoor air quality (POST, 2010*a*; Jacobson et al., 2019). Similar to overheating, these groups are also more likely to spend more time indoors than other groups in the population.

In many cases, there is a strong plausible physiological association between health and indoor air quality, but there is limited epidemiological evidence clearly linking exposure to an indoor pollutant with a health outcome. This is due to a large number of confounding variables such as exercise, obesity, diet, housing, and exposure to allergens (RCPL, 2016). There is an incomplete understanding of how exposure to different compounds in the indoor air affects human health, and much of the understanding is derived from the relationship between outdoor air pollution and health (Teichman et al., 2016; RCPL, 2016; WHO, 2021*a*).

There is a substantial amount of information on how many chemical compounds affect health, and guidance exists on how to manage exposure to these compounds (Health and Safety Executive, 2023). However, over recent years, synthetic materials have become more pervasive in indoor environments, and there is a lack of understanding of how many chemicals found indoors impact health. Knight (27/11/2019) reported that 80,000 chemicals are used in manufacturing, but only 300 have been tested for safety. In addition to the lack of understanding of how many individual compounds impact health, we know very little about the additive or synergistic interactions of compound mixtures on human health (European Commission - Institute for Health & Consumer Protection, 1992; RCPL, 2016; Kelly and Fussell, 2019; CIBSE, 2020).

2.1.2.1 Scale of IAQ problems

3.8 million people are estimated to die from exposure to poor indoor air quality around the world (WHO, 2019*a*). In Europe it was estimated that 550,000 deaths were due to indoor and outdoor air pollution (WHO, 2019*b*). This equates to approximately 11% of all (5.1m) deaths in the European Union (EU) in 2016 (Eurostat Press Office, 2019). In Europe, $PM_{2.5}$ is the leading environmental risk factor for the burden of disease, and it is estimated that during 2010, 25,000 deaths in England were attributed to human-made $PM_{2.5}$ and an estimated 3,500 premature deaths a year in London (Hänninen et al., 2014; Symonds et al., 2016). This compares to the UK, where it was estimated that between 26,000 and 38,000 people die each year from exposure to outdoor air pollution (CMO, 2022). As mentioned in the previous section, it is challenging to estimate the environmental burden of disease and separate out the various components, particularly as there are many confounding factors. Furthermore, there is a lack of evidence of conditions inside homes, therefore, it is difficult to make accurate estimates of the burden of disease arising from exposure to this. After $PM_{2.5}$, noise, second hand smoke and radon were the leading risk factors (Hänninen et al., 2014).

Raw et al. (2004) carried out the largest study of IAQ in homes in England. This study measured carbon monoxide, nitrogen dioxide, formaldehyde, and VOCs in 876 homes, but notably, did not measure two leading risk factors for the burden of disease - particulate matter or radon. This study found carbon monoxide and nitrogen dioxide levels were highest in dwellings with gas cookers and unflued appliances, and TVOCs were highest in new dwellings, but generally most of the dwellings had concentrations that were low for most of the time (Raw et al., 2004). Furthermore, research participants frequently report that they are satisfied with the IAQ in their homes, but as Section 2.1.2.2 will explain, this does not necessarily mean IAQ is safe or healthy (Dimitroulopoulou et al., 2005; MHCLG, 2019; Van Rooyen and Sharpe, 2024).

Part F of the Building Regulations describes performance criteria for indoor humidity, carbon monoxide, nitrogen dioxide, and formaldehyde; however, these criteria do not include particulate matter, which is the leading risk factor for burden of disease in Europe (Hänninen et al., 2014; HM Government, 2021*a*). Furthermore, there are other important components of IEQ for health identified below, which are not included in Part F. One clear issue is that concentrations of pollutants in real dwellings and occupant exposure are heavily influenced by behaviours of the occupants, which cannot be directly regulated. In this case, providing information to occupants on the health risks of exposure to certain aspects of IEQ is important - knowledge of ventilation is discussed more in Section 2.2.2.

2.1.2.2 Perceived IAQ and health

Humans use olfactory, general chemical, and thermal senses to evaluate air quality - this is termed 'perceived air quality' (European Commission - Institute for Health & Consumer Protection, 1992;

CIBSE, 2015, 2020). However, there is a lack of understanding about how humans integrate and evaluate these senses to assess air quality (Seppeanen and Fisk, 2004; CIBSE, 2015). Human senses can detect some harmful compounds, but there are many harmful compounds which humans cannot detect/sense, such as carbon monoxide or radon, which are tasteless, colourless, and odourless (Seppeanen and Fisk, 2004). This is problematic, as many international ventilation standards (CIBSE, 2015, May 2016) are based on humans perception of IAQ and not measurements of components of IAQ directly (Sundell et al., 2011; Jones, 2017). Similar to thermal comfort, perceived air quality is measured according to the amount of dissatisfied occupants (European Commission - Institute for Health & Consumer Protection, 1992), which is inherently imprecise due to the way humans sense and detect IAQ, the differences between people and the acceptability limits of the model.

The limits to human perception of IAQ is illustrated by Dimitroulopoulou et al. (2005), who found no significant relationship between occupants satisfaction with air quality and measured concentrations of air pollutants, suggesting that when people were satisfied with (their perception of) IAQ, this did not correspond with good or healthy IAQ (low levels of air pollutants). However, in situations where humans can detect harmful compounds, perceived air quality could be useful. For example, Van Dongen and Phaff (1989) and Andersen et al. (2009) found that occupants ventilated more when pollutants were perceived in the indoor air, such as tobacco smoke, moisture, mould, and during times of cooking. However, in research such as this, it is not clear if occupants ventilation behaviours were associated with the activity rather than detecting compounds.

Other key limitations of humans perception of IAQ are that (1) humans senses are better at 'first impressions' than absolute concentrations, (2) better at detecting changes than absolute levels, and (3) humans can adapt to sensory irritants in a short space of time and become less sensitive to them, and over longer periods (weeks/months) people eventually accept them as normal or harmless (European Commission - Institute for Health & Consumer Protection, 1992; Seppeanen and Fisk, 2004; CIBSE, 2015). Furthermore, occupants are unable to effectively identify sources of pollutants that might be harmful to their health, for example, pleasantly scented candles and air fresheners.

2.1.2.3 Which aspects of IAQ are the most important?

As outlined above, there are thousands of compounds present in the indoor air, and this section considers which compounds are identified as the most important for health in the literature.

A summary of the most prevalent and important indoor air pollutants from the literature are shown in Table 2.1. This table highlights that there is a large body of evidence across a wide variety of authors for many of the pollutants which are most prevalent and important for health in the indoor air and less evidence for a smaller number of pollutants. This table also shows that the literature does not always report the same pollutants as being important for health, so this table identifies common pollutants in the literature, but is not a definitive list. Guideline values for the different pollutants are presented in

Section 2.1.4.2.

Table 2.1: Summary of the most common and important pollutants of the indoor air referenced in the literature.

Pollutant	Sources
Formaldehyde	Tham (2016); RCPL (2016); CMO (2017); Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi (2019); CIBSE (2020).
Particulate matter	Hänninen et al. (2014); Tham (2016); RCPL (2016); WHO (2019*a*); CIBSE (2015, 2020).
Tobacco smoke	Tham (2016); RCPL (2016)
Nitrogen dioxide	HM Government (2013); CIBSE (2015); Tham (2016); RCPL (2016); WHO (2019*a*)
Carbon monoxide	HM Government (2013); Sharpe et al. (2014); CIBSE (2015); Tham (2016); RCPL (2016); WHO (2019*a*)
Woodsmoke	Tham (2016)
Biological agents	Tham (2016); RCPL (2016)
VOCs	HM Government (2013); Sharpe et al. (2014); Tham (2016); RCPL (2016); CMO (2017); Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi (2019)
Radon	Sharpe et al. (2014); Tham (2016); RCPL (2016)
Ozone	Sharpe et al. (2014); CIBSE (2015); RCPL (2016); WHO (2019*a*)
Sulphur dioxide	Sharpe et al. (2014); CIBSE (2015); WHO (2019*a*)
Carbon dioxide	Sharpe et al. (2014)
Nitrogen	Sharpe et al. (2014)
Bacteria and viruses	RCPL (2016)
PAH's	RCPL (2016)
Pollen	RCPL (2016)
Phthalates	RCPL (2016)
Polychlorinated biphenyls	RCPL (2016)
Insecticides	RCPL (2016)
Methane	RCPL (2016)
Lead	RCPL (2016)
Mineral dust and fibres	RCPL (2016)

Following on from the above table, the remaining detail in this section of the literature review will focus on indoor air pollutants, which are most widely recognised as being both prevalent and important for health, these are listed below. Note that this list is not ordered.

1. Moisture, humidity and biological agents, including mould (2.1.2.4)
2. Particulate matter (2.1.2.5)
3. Tobacco smoke (2.1.2.6)
4. Nitrogen dioxide (2.1.2.7)
5. Carbon monoxide (2.1.2.7)
6. VOCs (2.1.2.8)
7. Radon (2.1.2.9)

8. Ozone (2.1.2.10)
9. Carbon dioxide (2.1.2.11)

2.1.2.4 Humidity and biological agents

Moisture can be generated within a building or enter a building via a number of different routes, such as water leaks, cleaning, washing, cooking, occupant's breathing, and ventilation. The WHO (2009*a*); Dimitroulopoulou (2012) and BRE (2019) report that indoor humidity is strongly influenced by outdoor humidity. A large review of research in Europe, Canada, and America by the WHO (2009*a*) found at least 20% of dwellings had one or more signs of dampness. 22% of respondents from a nationally representative sample in the UK reported dampness or mould in their homes (Van Rooyen and Sharpe, 2024). Humidity indoors can have direct and indirect impacts on human comfort and health.

Low levels of humidity can directly impact health and have been linked with eye, throat, and sinus irritation, reduced nasal mucous transport and ciliary activity, and a higher risk of respiratory infections (Arundel et al., 1986; Tham, 2016; CIBSE, 2020). High levels of humidity can also directly impact health, and high humidity when combined with high temperatures can result in discomfort and a reduced potential for evaporative cooling, which can lead to overheating (Arundel et al., 1986; CIBSE, 2020). Dampness in buildings has also been linked with tiredness and headaches, but the underlying mechanisms are not known (Tham, 2016).

The main indirect health effects of moisture and humidity indoors are due to exposure to microbial agents, microscopic organisms or VOC emissions from materials.

Humidity and moisture indoors directly influence the rate of growth of Legionella, dust mites, fungi, bacteria, and mould (Arundel et al., 1986; WHO, 2009*a*; Brown et al., 2015). The presence of microbial growth indoors has been linked with increased prevalence of respiratory symptoms, allergies, asthma, and perturbation of the immunological system (WHO, 2009*a*; Ormandy and Ezratty, 2012; Dimitroulopoulou, 2012; CIBSE, 2015; Clark et al., 2023; DHSC et al., 2023). Bacteria such as e coli, mycoplasma pneumoniae (causes pneumonia), streptococcus, serratia marcescens (causes respiratory infections in patients in hospital) are shown to be less effective and survive for shorter amounts of time in mid humidities (Arundel et al., 1986). Despite the long established relationship between mould and human health, there are continued cases of mortality due to exposure. The recent tragic death of 2 year old Awaab Ishak in the UK was due to mould exposure, which was attributed to the lack of ventilation (Kearsley, 2022).

Humidity and moisture indoors is also responsible for the physical and chemical degradation of materials, which can result in the emission of harmful chemical compounds into the air (European Commission - Institute for Health & Consumer Protection, 1992; WHO, 2009*a*; CIBSE, 2015). Arundel et al. (1986) report that humidity indoors is directly proportional to the rate of off-gassing of formaldehyde, the rate at which salts and acids form from sulphur and nitrogen dioxide and also

the rate at which ozone forms indoors.

Humidity and moisture indoors is also linked with the survival of viral pathogens in the indoor environment (Arundel et al., 1986; WHO, 2009*a*). Infection rates and the survival of influenza, measles, herpesvirus varicella (chickenpox), adenoviruses (acute respiratory), and Coxsackie viruses (rashes and fevers) have all been linked with humidity (Arundel et al., 1986). Domestic pets and pests are sources of allergens indoors (Vardoulakis et al., 2015; Tham, 2016).

The literature describes a range of different thresholds for RH. The extensive literature review by Arundel et al. (1986) into moisture, humidity, and health summarises by stating that most of the adverse health outcomes are minimised by maintaining indoor levels between 40% and 60%. This agrees with CIBSE (2020), who recommend that RH remains in the range of 40% to 60% in dwellings.

HM Government (2013) recommend that winter RH levels are maintained below 65%, 75%, and 85% for moving average periods of 1 month, 1 week, and 1 day respectively. These guidelines are pragmatic, as its challenging to manage RH with natural ventilation alone. European Commission - Institute for Health & Consumer Protection (1992) state that few health related problems occur when RH is between 30% and 70%.

Mould germinates and grows optimally with sufficient moisture and temperature. A practical guideline of 80% surface RH is recommended by CIBSE (2015) for the UK climate.

2.1.2.5 Particulate matter

Solid or liquid material that is suspended in the air is referred to as particulate matter (Brunekreef and Holgate, 2002). Particulate matter can have varying sizes, where its size and weight, in part, determine how long it is suspended. PM is most often classified according to its size and is normally classified according to three groups of sizes PM_1 ($\leq 1\mu m$) sized particles, $PM_{2.5}$ ($\leq 2.5\mu m$) sized particles, and PM_{10} ($\leq 10\mu m$) sized particles. PM can arise from a wide variety of natural and anthropogenic sources, such as construction activities, vehicles, combustion (cookers, open fires, candles), fibrous particulates, vacuum, tobacco, aerosols, smoke etc. (Géhin et al., 2008; POST, 2010*a*; Sharpe et al., 2014; CIBSE, 2020). Research has identified cooking, candles, and smoking as the main sources of PM indoors (Dimitroulopoulou et al., 2006; Géhin et al., 2008; Taylor et al., 2015; Verniers et al., 2023).

Indoor concentrations of PM are often reported to be higher than outdoors, even during periods when outdoor concentrations are elevated (Taylor et al., 2015). Outdoor concentrations of PM are also observed to have diurnal variations, and lower levels are observed during warm weather, which is attributed to lower emissions from heating systems and higher dispersion.

Humans can be exposed to PM through inhalation, dermal absorption, or ingestion, and there is strong evidence of adverse health effects even at very low levels (CIBSE, 2020; CMO, 2022). The health effects of exposure to PM are wide, but the most common are to the cardiovascular and respiratory systems (WHO, 2006; Vardoulakis et al., 2015; Broderick et al., 2017; BRE, 2019). Exposure to PM has

also been linked to anxiety and hypertensive conditions (BRE, 2019). PM can comprise of or contain harmful carcinogenic or toxic compounds (Vardoulakis et al., 2015).

Research into the exposure-health relationship for particulate matter is ongoing and due to a lack of evidence, there are currently no published air quality guideline values for PM_1 (WHO, 2021*a*). In 2021, The WHO (2021*a*) published recommended limits for concentrations of $PM_{2.5}$ and PM_{10} - the 24 hour and annual average air quality guideline concentrations for $PM_{2.5}$ are $15\mu g.m^{-3}$ and $5\mu g.m^{-3}$ respectively, and $45\mu g.m^{-3}$ and $15\mu g.m^{-3}$ for PM_{10}.

2.1.2.6 Environmental tobacco smoke

Second hand tobacco smoke can contain more than 7,000 chemicals, and epidemiological evidence shows a strong relationship between exposure to environmental tobacco smoke with both acute and chronic cardiovascular and respiratory health conditions, including cancers (European Commission - Institute for Health & Consumer Protection, 1992; Vardoulakis et al., 2015; Tham, 2016; RCPL, 2016). Smoking indoors is also linked with significantly higher levels of PM (2.5 times), acetaldehyde, and BTEX (Brown et al., 2015).

2.1.2.7 Products of combustion

Carbon monoxide (CO) is generated from the incomplete combustion of gas, coal or wood, and common indoor sources are unflued heating appliances, environmental tobacco smoke, cooking, and from outdoor sources such as nearby roads and/or adjoining garages (European Commission - Institute for Health & Consumer Protection, 1992). Exposure to high concentrations of CO can be fatal, where exposure to lower concentrations causes headaches, dizziness, nausea, reduces the maximum exercise ability in healthy humans, increases symptoms of ischaemic heart disease, and is significantly associated with Parkinson's and cardiovascular disease (WHO, 2010; BRE, 2019; Chen et al., 2022; CMO, 2022). There were approximately 20 deaths in England and Wales from accidental CO poisoning in 2021 (DBT, DESNZ, DSIT, DLUHC, HSE, HSENI, Ofgen, UKHSA, DHSC, PHW, Welsh Government, Sottish Government, HPS, HO, MAIB, 2022).

Nitrogen dioxide (NO_2) is a toxic gas that is generated when burning fossil fuels at high temperatures. Exposure to NO_2 can cause respiratory health issues such as bronchoconstriction, increased bronchial reactivity, airway inflammation, and decreases in immune defence, which can lead to higher susceptibility of respiratory infections (WHO, 2010). The main health effects of exposure to NO_2 are damage to the cells in the respiratory tract, development of chronic obstructive pulmonary disease (COPD) in adults, and cancer (Kornartit et al., 2010; BRE, 2019; Chen et al., 2022). People with asthma and females are at higher risk of exposure to NO_2 (Vardoulakis et al., 2015).

Outdoor sources of CO and NO_2 have been measured to be higher during winter and autumn, and in areas with increased urbanisation, with the highest concentrations recorded in central urban locations

(Raw et al., 2004).

Research often reports that indoor concentrations of CO and NO_2 are below WHO guideline values (Coward et al., 2001; Dimitroulopoulou et al., 2005; Ashmore and Dimitroulopoulou, 2009; Kornartit et al., 2010; Vardoulakis et al., 2015), and related to occupant activity, highly variable and found to mainly contribute to short-term exposures rather than long-term exposures (Coward et al., 2001; Ashmore and Dimitroulopoulou, 2009). The season, ventilation (presence of fans and window opening), location (urban/rural), outdoor concentrations, cooking fuel, dwelling type and age, and indoor smoking are the main determinants of indoor CO and NO_2 in UK dwellings (Dimitroulopoulou et al., 2005; Ashmore and Dimitroulopoulou, 2009; Kornartit et al., 2010). Most exceedances in the literature were observed during the winter and in kitchens with gas cookers (Raw et al., 2004; Crump et al., 2005; Dimitroulopoulou et al., 2005; Kornartit et al., 2010; Vardoulakis et al., 2015).

The WHO (2021*a*) recommend that the 15 minute, 1 hour, and 8 hour mean concentrations of CO do not exceed 100mg.m^{-3}, 35mg.m^{-3}, and 10mg.m^{-3} respectively. HM Government (2013) includes these same thresholds.

The WHO (2021*a*) recommend that the 1 hour and annual mean concentrations of NO_2 do not exceed 200mg.m^{-3} and 40mg.m^{-3} respectively. HM Government (2013) recommend that the 1 hour and 'long-term average' concentrations of NO_2 do not exceed 288mg.m^{-3} and 40mg.m^{-3} respectively.

2.1.2.8 Volatile organic compounds

Organic chemical compounds that have a low boiling point are referred to as volatile organic compounds (VOCs). VOCs will evaporate (or 'off gas') when exposed to temperatures above their boiling point and enter the surrounding air, where humans can be exposed to the VOCs. The health effects of exposure to different VOCs depend on the chemical composition, duration, and concentration of the exposure. VOCs can cause a wide range of health issues, including acute or subacute inflammation of the skin or mucous membranes, sensory irritation, headaches, dizziness, nausea, allergic reactions, and some VOCs are carcinogenic (European Commission - Institute for Health & Consumer Protection, 1992; Vardoulakis et al., 2015).

It is estimated that there are over a million different types of VOCs, and approximately 80,000 synthetic chemicals are used in manufacturing in the US, where we have health data on only 15% of these chemicals (Knight, 27/11/2019). A large amount of manufactured goods such as furnishings, cleaning products, painting and decorating products, consumer products, and air fresheners are found indoors, and these products can release VOCs into the indoor air (Crump et al., 2005; Sharpe et al., 2014; Jones, 2017; Vardoulakis et al., 2015). A review by Ashmore and Dimitroulopoulou (2009) found that consumer products (cosmetics and air fresheners), tobacco smoke, and building materials are the main sources of VOCs in indoor air in Europe. Building materials were reported to be responsible for up to 40% of indoor VOCs by Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi (2019). Coward

et al. (2001) and Crump et al. (2005) found painting and decorating to be a dominant determinant of overall levels of VOCs indoors. The rate of emission of VOCs from materials are influenced by temperature, vapour pressure gradients, and ventilation rates.

Measured concentrations of VOCs are typically higher indoors than outdoors (European Commission - Institute for Health & Consumer Protection, 1992; Tham, 2016). Arif and Shah (2007) found indoor concentrations of VOCs to be between 2 and 5 times higher than outdoors and can be up to 10 times higher (CIBSE, 2015).

Hernandez et al. (2020) categorises VOCs as either persistent, receding or irregular in their nature. It is common to find VOCs to recede over time. For example, when a dwelling has been newly constructed, the new materials, decorations, fixtures, and furnishings off gas the most, and as time passes, the VOC emissions will recede/reduce (Coward et al., 2001). Coward et al. (2001) notes that measured total VOCs (TVOCs) in the indoor environment have reduced in bedrooms between 1996 and 2001, which could be a result of the improved knowledge of how VOCs affect health. Additionally, certain environmental assessment methods (such as BREEAM) now include low VOC materials in their assessment methodology.

The INDEX project identified high priority compounds based on health impacts, these included benzene, naphthalene, formaldehyde, toluene, xylenes, styrene, limonene, and alpha-pinene (Kotzias et al., 2005). Many of these compounds cannot be detected by humans, but some are also accompanied with an odour. The health impacts of these compounds vary, but are typically associated with sensory irritation (eyes and smells), respiratory symptoms, and in some cases, cancer (European Commission - Institute for Health & Consumer Protection, 1992; WHO, 2010; BRE, 2019). Recent research has also shown diminished cognitive performance with exposure to VOCs from essential oils (Du et al., 2021).

Total volatile organic compounds (TVOC) is a 'simplified metric' (HM Government, 2021*b*) and provides a measure of the total concentration of VOCs present in the air. High concentrations of TVOCs have been associated with new homes and homes where painting has recently been carried out (Dimitroulopoulou et al., 2005; Crump et al., 2005; Mujan et al., 2019). Although, with respect to painting, there has been an increased use of low VOC paints, which highlights the need to re-evaluate indoor VOC concentrations as the sources change over time (Jiménez-López and Hincapié-Llanos, 2022). TVOCs as a measurement do not reveal anything about the nature of the individual compounds, their concentrations, or potential health impacts (Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi, 2019) - this severely limits the usefulness of TVOC when researching IEQ and its relationship with health. Despite this important limitation, TVOC is often used as a standard and proxy for indoor air quality and ventilation rates (Hollick and Sangiovanni, 2000; Teichman et al., 2016; Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi, 2019; HM Government, 2021*b*). The reason for the widespread use of TVOC is likely due to the ease of measurement.

In the UK, Approved Document Part F (HM Government, 2021*b*) recommends that the 8 hour

mean TVOC concentration should remain below 300μg.m^{-3}, which is lower than the Japanese Ministry of Health Labour and Welfare (<400μg.m^{-3}), the Finnish Society of Indoor Air Quality and Climate (<600μg.m^{-3}), and the National Health and Medical Research Council in Australia (500μg.m^{-3}) (Coward et al., 2001).

Crump et al. (2005) measured TVOC concentrations in 37 homes built after 1995, and found that 3 of the 37 dwellings exceeded the thresholds in the regulations in winter and 9 of the 37 in summer. However, more recent measurements of TVOC by McKay and Ross (2010) and MHCLG (2019) found higher incidences of exceedances in new homes. McKay and Ross (2010) measured TVOC in 22 new homes built to the 2006 Building Regulations and found that in more than half, the TVOC concentrations exceeded the guidance value in the regulations. Similarly, MHCLG (2019) measured TVOC in 10 homes constructed to the 2010 Building Regulations and found that 6 out of 10 UK dwellings had TVOC concentrations that exceeded the thresholds in the regulations.

2.1.2.9 Radon

Radon is a naturally occurring radioactive gas, which is emitted from rocks and soil (Vardoulakis et al., 2015). Radon can infiltrate the indoor air through the floor of a building and be inhaled by building occupants (European Commission - Institute for Health & Consumer Protection, 1992), which can cause lung cancer, and there is suggestive evidence that it can also be linked with leukaemia and cancers of the extrathoracic airways (WHO, 2010). All exposures are relevant for protecting health. Concentrations of radon vary with geographical location and geological conditions in the UK. Building Regulations require protective measures to prevent radon entering new and extended buildings.

Large scale monitoring of radon in UK homes (n=595,700) found 12% of homes to have radon levels at or above the action level (PHE, 2017). Recent monitoring by MHCLG (2019) found radon concentrations in all participants homes to be below recognised thresholds.

2.1.2.10 Ozone

Ozone (O_3) is a gaseous pollutant which is typically not directly emitted but instead is created through complex reactions between chemicals and light from solar radiation. Because of this, outdoor (and indoor) ozone concentrations are higher during periods of high solar radiation and heat waves (WHO, 2006; AECOM, 2012*a*; WHO, 2013). Human exposure most typically occurs by inhalation and can cause sensory irritation, respiratory symptoms, increases in respiratory hospital admissions, and all-cause mortality (WHO, 2006; Vardoulakis et al., 2015; Tham, 2016). Ozone is a highly reactive compound and is easily destroyed by indoor surfaces, filtered by the building fabric, or destroyed in reaction with other chemicals in the indoor air, so indoor concentrations are generally substantially lower than outdoor concentrations (Vardoulakis et al., 2015; CMO, 2017). Ozone is scavenged by nitric oxide emitted by vehicles, and therefore concentrations of ozone are typically lower in the city centres

than in the suburbs (Brunekreef and Holgate, 2002). Vardoulakis et al. (2015) reports that the main source of indoor ozone is infiltration from outdoors, where ventilation could be an important vector for transporting ozone indoors. The most common chemicals that react to form ozone are nitrogen dioxide, methane, and VOCs. Indoor sources of ozone are rare but can be created from reactions of formaldehyde, acetaldehyde, and other organic acids or emitted from printers, photocopiers, and other electronic devices (WHO, 2006, 2013).

The WHO (2021*b*) recommends that the 8-hour average concentration of O_3 should remain below $100\mu g.m^{-3}$ and the 'peak-season' average remain below $60\mu g.m^{-3}$.

2.1.2.11 Carbon dioxide

Carbon dioxide (CO_2) is a colourless and odourless gas that is exhaled by humans and is a product of combustion (Zhang et al., 2017). The metabolic rate of emission of CO_2 is dependant on the size and physical activity of the person(s) (Persily, 1997). CO_2 is often emitted at the same time as other nuisance human bio effluents and is correlated with poor levels of perceived air quality and body odour acceptability (Persily, 1997).

There is a "general acceptance that CO_2 keeps 'bad company', and that levels above 1,000ppm are indicative of poor ventilation rate" (European Commission - Institute for Health & Consumer Protection, 1992; Persily, 1997; Sharpe et al., 2014; Jones, 2017). However, in the absence of other sources of CO_2, metabolic CO_2 alone can give an indication of human body odour acceptability and bio-effluents, but not concentrations of other harmful compounds, and so, CO_2 is not an effective indicator of 'healthy' indoor air quality (Persily, 1997, 2022). Despite this, CO_2 is widely used as a proxy for indoor air quality and ventilation rates (Persily, 1997; Sharpe et al., 2014; Jones, 2017).

Exposure to high concentrations of CO_2 ($\geq$ 5,000ppm) are known to be toxic, however, there is mixed evidence for health impacts of exposures at low concentrations (Zhang et al., 2017; Jacobson et al., 2019).

Research by Zhang et al. (2017) reported that exposure to pure CO_2 (at 3,000ppm) did not cause a change in perceived IAQ, health, or cognitive performance, but when CO_2 rises along with other bio-effluents, perceived air quality reduced significantly, increased intensities of headaches were reported, fatigue and sleepiness increased and cognitive performance reduced. This suggests that bio-effluents alone or in combination with CO_2 are important for reported health and well-being symptoms in other studies and not (purely) CO_2 alone.

The recent review of CO_2 on health by Lowther et al. (2021) concluded that due to previous research not sufficiently controlling for confounding factors and numerous conflicting results in the literature, it is not possible to say with confidence if there are any health impacts of exposure to low concentrations.

The comfort, health, and well-being impacts of exposure to varying concentrations of CO_2 are not well understood, and Jacobson et al. (2019) calls for more research into the health effects of CO_2

exposure.

1,000ppm is a frequently used threshold for ventilation rates (Sharpe et al., 2014; CIBSE, 2015; Winck et al., 2022), and the review paper by Wargocki (2013) reported that CO_2 concentrations below 900ppm "seem to protect against health risks". The European Commission - Institute for Health & Consumer Protection (1992) recommend that CO_2 concentrations remain below 3,500ppm for health. Persily (2022) recently published a method for calculating a 'space-specific' CO_2 threshold concentration as a metric for ventilation. This metric is calculated using only metabolic CO_2 in a specific space, given its expected ventilation rate, occupancy and their CO_2 generation, and time after space was occupied. This new metric is more specific than the aforementioned, generic CO_2 concentration from the literature, but is subject to limitations associated with time to reach a steady state and occupant assumptions (movements, activities and CO_2 generation). The occupant assumptions can give rise to substantial uncertainties, which are discussed more in Section 2.2.3.

It is common to observe high concentrations of CO_2 in bedrooms, with concentrations often exceeding 2,500ppm (Seppanen, 1987). These high concentrations are attributed to the fact that doors and windows are often closed in bedrooms during the night time (Gupta and Kapsali, 2016; Jacobson et al., 2019). Howieson et al. (2014) recorded CO_2 concentrations in the bedrooms of 20 newly built dwellings, with an occupied mean peak of 2,317ppm and an occupied time-weighted average of 1,834ppm. A recent study by MHCLG (2019) found concentrations of CO_2 in bedrooms of 30% (16 of 54) of homes to exceed their derived threshold of 1830ppm. The authors calculated a threshold derived from the steady-state equilibrium of two occupants with an assumed metabolic production rate, an assumed air flow rate, and a fixed outdoor concentration. This study, however, was conducted over a winter period, where ventilation practices are likely to have been affected by the colder weather - later in this chapter (Section 2.2.2) a strong association is found in the literature between ventilation behaviour and season.

2.1.2.12 Summary of IAQ and health in UK homes

Indoor air quality is a complex, dynamic aspect of IEQ with potentially thousands of component parts, of which there is limited understanding of their impact on health both individually and as combinations.

Occupant behaviour can have a significant impact on IAQ by influencing the type and concentration of pollutants emitted indoors and air exchange rates between indoors and outdoors. Source control and ventilation behaviour are cited in the literature as the most important factors for IAQ. The relationship between ventilation and IAQ is discussed later in this chapter (2.2.5.2).

Indoor air quality is influenced by numerous factors, which are summarised below:

1. physical and chemical properties of pollutants - size, deposition, chemical composition;
2. materials (building fabric, furniture), site geology and location (urban/rural) - which absorb or emit compounds into the indoor/outdoor air;

3. equipment or occupant processes that emit compounds into the indoor/outdoor air;
4. internal temperature and humidity - impact the rate of emission or movement of pollutants;
5. ventilation and wind exposure - both controlled intentional ventilation and uncontrolled infiltration of air between indoors and outdoors and different rooms;
6. occupant movement and activities - generate pollutants (smoking, cooking, cleaning chemicals) or resuspend PM;
7. presence and number of humans - bioeffluents, respiratory gases, respiratory contamination, and other pollutant-producing activities associated with higher quantities of occupants;
8. temporal - daily/seasonal differences in outdoor pollution and outdoor environment;
9. outdoor air quality - concentration of pollutants in outdoor air;

(European Commission - Institute for Health & Consumer Protection, 1992; Crump et al., 2005; Brown et al., 2015; Vardoulakis et al., 2015; Tham, 2016; Taylor et al., 2016; Broderick et al., 2017; CMO, 2017; CIBSE, 2020)

Figure 2.3 illustrates IAQ as a multifactorial, complex, and dynamic phenomenon with its potential health outcomes.

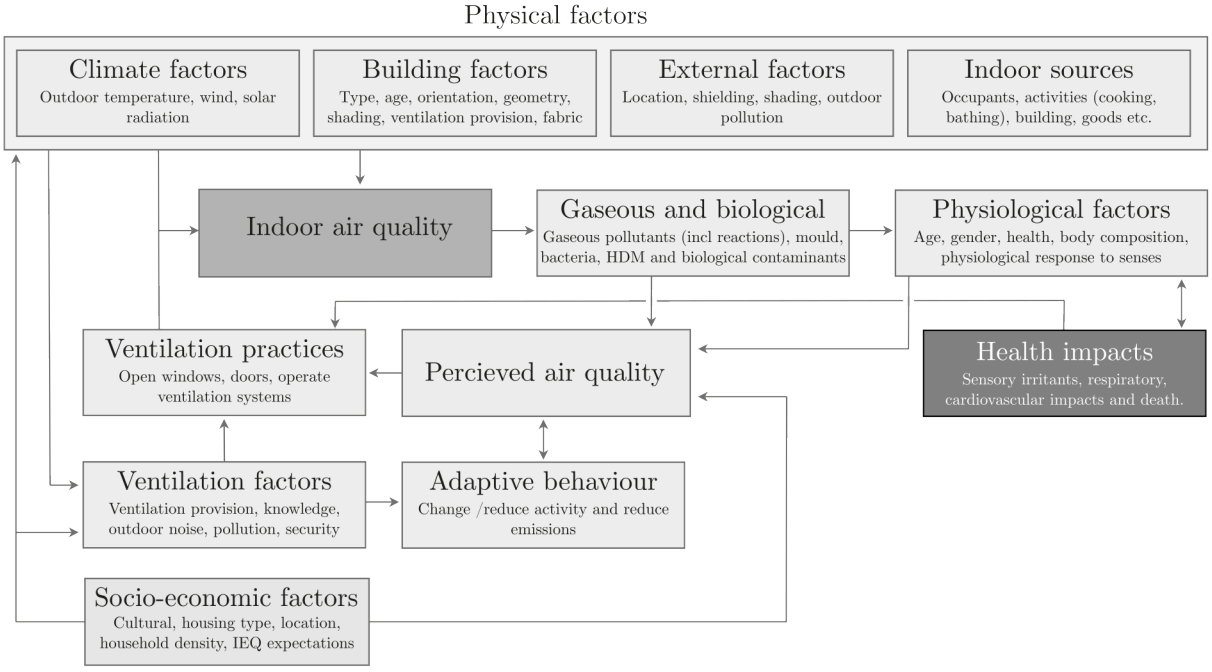


Figure 2.3: Diagram showing the relationship between a range of physical and socio-economic factors with indoor air quality, ventilation, and health. This diagram also illustrates a number of possible causal relationships.

2.1.3 Noise and health in UK homes

Traffic noise is estimated to be the second main cause of environmental burden of disease in Europe, and it is argued that it is responsible for more disturbance to quality of life (Hänninen et al., 2014; CMO, 2017). In the UK, noise is the single biggest issue of complaint to local authorities (CMO, 2017),

and road traffic noise is the biggest cause of outdoor environmental noise pollution, estimated to disturb 40% of the population in the UK (Mitchell, 2009; Jephcote et al., 2023). It is estimated that 4.5% of the public are exposed to high levels of noise from rail traffic and 4.8% aircraft noise (Jephcote et al., 2023).

Indoors, the main cause of noise is road traffic and neighbours, with indoor noise levels highest during summer when windows are open most often (Buratti, 2002). In the 2012 National Noise Attitude Survey, 83% of respondents reported hearing noise from road traffic, 83% from neighbours or people nearby, 72% from aircraft, and 48% from construction, demolition, renovation, or road works (Notley et al., 2014). 48% of people felt their home life is spoilt to some extent by noise (Notley et al., 2014). 21% of people reported that they had been awoken or kept awake by outside noise during the last year, 17% by noise from neighbours (Notley et al., 2014).

Sounds can be perceived on a simple scale as either positive or negative, where this perception can be different for different people and context specific: for example, music in a nightclub is music for the patrons, but noise to local residents (Passchier-Vermeer and Passchier, 2000). Noise is defined here as an unwanted, unpleasant, or disturbing sound which can have a negative effect on a person's sense of well-being and also affect a person's physical health (Basner et al., 2014; ANC, 2020*a*). However, sounds indoors can also be positive and have a positive effect on a person's mood and sense of well-being, it can be joyful and relaxing (CIBSE, 2020).

Most of the respondents to a large scale survey (n=1,878) in Britain reported that noise was fairly important (46%) for health, 36% very important, 14% not very important, 2% not at all important, and 1% didn't know (Van Rooyen and Sharpe, 2024). This suggests that most British people feel that noise is important for their health.

Many of the health impacts of noise were hypothesised or known as far back as the 1960s, where these are broadly characterised as auditory and non-auditory, and the effects can be physiological and psychological (Basner et al., 2014; CIBSE, 2020). However, the relationship between humans, noise, and health is complex, and the main challenges lie with untangling causes and effects, primary and modifying factors - many of the observed health impacts are non specific and could be due to a number of reasons (Passchier-Vermeer and Passchier, 2000).

2.1.3.1 Auditory health impacts

Auditory health impacts include hearing impairment (tinnitus and permanent hearing loss), which typically results from exposure to high levels of sound energy (Passchier-Vermeer and Passchier, 2000; Stansfeld and Matheson, 2003; Basner et al., 2014). Noise induced hearing loss is most prevalent in occupational settings but more recently by social noise exposure from headphones and loud music (Basner et al., 2014). Hearing loss can impair a person's ability to communicate effectively.

2.1.3.2 Non-auditory health impacts

In addition to the auditory health impacts above, there are numerous non-auditory health impacts from exposure to noise. When a person is exposed to noise and loud sounds, this can stimulate the autonomous neurological and endocrine systems, which can raise heart rate, blood pressure, breathing rate, and muscle tension. These symptoms can disturb sleeping, result in stress responses, and impact cognitive performance (WHO, 2018*a*). Noise exposure can also lead to long-term physiological health impacts such as hypertension, cardiovascular disease, and ischaemic heart disease, which can all ultimately result in myocardial infarction and strokes (Basner et al., 2014; CIBSE, 2020). Road and aircraft noise has been associated with an increased risk of hypertension, cardiovascular risk, and hospital admissions, an increased risk of stroke, and even mortality (CMO, 2017).

Sleep and annoyance were the main cause of disability adjusted life years (DALYs) attributed to environmental noise in Europe (Basner et al., 2014) and the UK (Jephcote et al., 2023). Relatively soft noise levels (as low as 33dB LAmax) can induce reactions (autonomic, motor, and cortical arousals) during sleep and disturb sleep (Basner et al., 2014). Sleep is a biological necessity, and exposure to noise can increase blood pressure, increase heart rate, arousals, and body movement, sleep stage changes and awakenings (Passchier-Vermeer and Passchier, 2000; Stansfeld and Matheson, 2003; WHO, 2009*a*). These symptoms can cause impaired moods, insomnia, fatigue and reduced performance which can lead to accidents (Stansfeld and Matheson, 2003; WHO, 2009*a*; Basner et al., 2014).

Due to the impact of noise on sleep and the importance of sleep for health, the WHO (2009*a*) published the night noise guideline (NNG), which recommended that $L_{night,outside}$ should be less than 40 dB to protect public health. This same publication described that when night noise levels exceed 55dB, cardiovascular health effects become a major public health concern.

People can 'habituate' to night-time noise, that is to say, the probability that noise events will cause physiologic reactions lessens over time; however, habituation is incomplete (Basner and McGuire, 2018*b*), and not all studies find habituation (Stansfeld and Matheson, 2003). Basner and McGuire (2018*b*) summarised other research that found arousals of the vegetative nervous system to habituate less to noise than cortical arousals, which gives plausibility for the association between noise exposure and cardiovascular disease. However, there is a lack of knowledge about the differences in people's ability to habituate and the factors that influence this (Basner and McGuire, 2018*b*).

Annoyance is dependant on the source of noise, its perception, and other non-acoustic factors. For example, the review paper by Passchier-Vermeer and Passchier (2000) identified noise from rail to be less annoying than air or road noise. This agrees with the EEA Technical report by Nugent (2010), which identified that noise with a higher content of low frequencies results in higher amounts of annoyance.

Noise can impair communication, mask speech, reduce social processing of social cues, reduce helping behaviour, increase aggression, and be distracting (Passchier-Vermeer and Passchier, 2000; Stansfeld

and Matheson, 2003). Stansfeld and Matheson (2003) report that noise exposure is correlated with psychological symptoms but not with a defined psychiatric disorder.

2.1.3.3 Inequality and most vulnerable

The effects of noise are not equitably distributed, with some people disproportionately affected due to their income, age, or disability (Mitchell, 2009). The evidence is, however, complex and challenging to disentangle, as there are many potential confounding factors, such as housing quality, ability to cope, co-exposure to other physical and social stressors. One example is that sources of noise vary with location in the UK - London, South East, and North West UK were reported to have the highest number of DALY's from road traffic noise and most (63%) DALYs from aircraft noise were in London (Jephcote et al., 2023). The literature identifies children, the elderly, pregnant women, shift workers, and people with pre-existing conditions to be most at risk from noise induced health issues (Passchier-Vermeer and Passchier, 2000; Stansfeld and Matheson, 2003; WHO, 2009*a*; van Kamp and Davies, 2013; Basner et al., 2014).

Children are particularly vulnerable to the cognitive and cardiovascular effects of noise (Stansfeld and Matheson, 2003; van Kamp and Davies, 2013; Basner et al., 2014), as they are still developing physically and cognitively and are less likely to have the capacity to understand and anticipate stressors or to have well-developed coping strategies (Stansfeld and Matheson, 2003).

2.1.3.4 Summary of noise, ventilation and health

Noise can have both direct and indirect implications for physical health and mental well-being, where these are varied and serious. Noise is shown to be widespread and affect a large proportion of the population, where the health impacts of noise exposure could increase with the trend of a growing population, urbanisation, and densification. Children, the elderly, pregnant, shift workers, and people with pre-existing conditions are considered as the groups most at risk from the effects of noise on health.

Figure 2.4 illustrates noise as a multifactorial, complex, and dynamic phenomenon with its potential health outcomes.

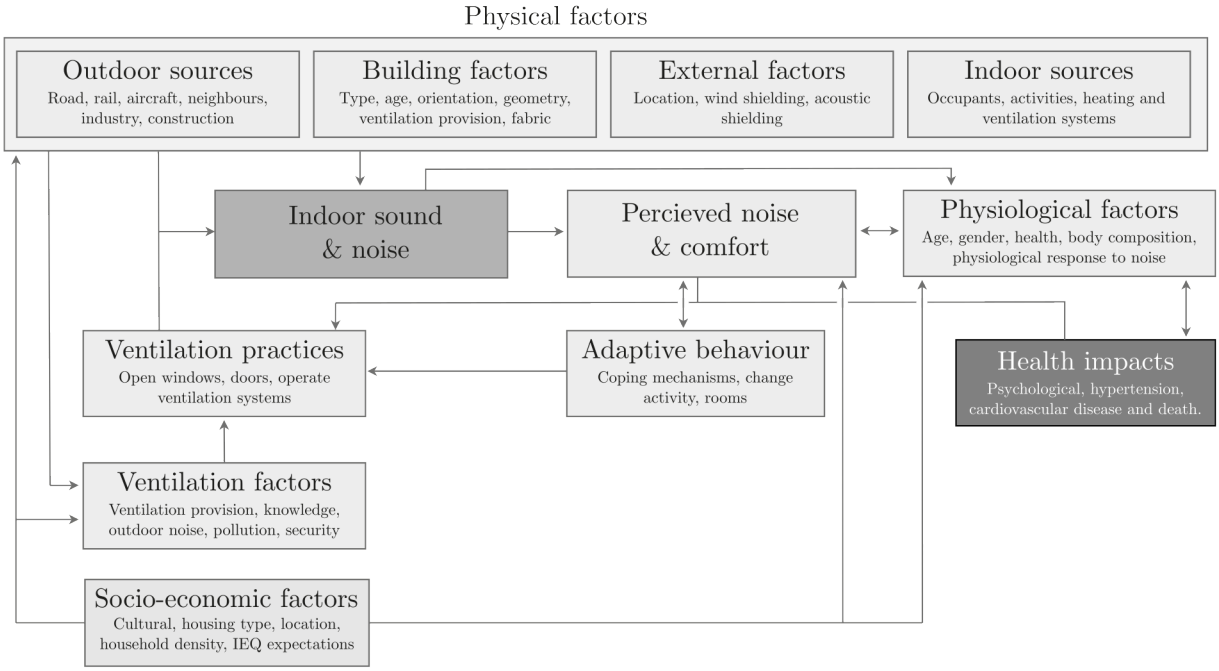


Figure 2.4: Diagram showing the relationship between a range of physical and socio-economic factors with noise, ventilation, and health.

2.1.4 Quantifying IEQ and health

Above, sections 2.1.1, 2.1.2 and 2.1.3 all outline the links between overheating, IAQ, and noise with health. Scientific enquiries into these component parts of IEQ can be quantified using a range of methods, including theoretical modelling, physical measurements, controlled trials, lab experiments, or by questioning occupants (Lomas and Porritt, 2017). Ideally, research on IEQ would use a combination of methods in order to bring a nuanced understanding of IEQ from different perspectives and disciplines. Few (2021) highlighted the importance of multidisciplinary research (physics and social science), where using only a single approach would have severely limited the understanding of ventilation in its context.

The World Health Organization has published numerous guidelines for IEQ, which are frequently cited throughout the literature and employed in policies and regulations around the world. These guidelines are characterised by a high standard of scientific rigour, international consensus, and they are not influenced by commercial interests: the BRE (2019) recommended that these take precedence. Using these guidelines, it is possible to assess individual components of IEQ; however, understanding their combined effect on health, their interactions, and relationship with ventilation is much more challenging. Currently there is no internationally accepted and agreed metric/indices for quantifying the numerous components of IAQ and IEQ together as a whole/composite (Broderick et al., 2017; Cony Renaud-Salis et al., 2019). Therefore, typically each component of IEQ is measured and assessed individually. Furthermore, there is a lack of consensus of health-related thresholds for many individual compounds/pollutants; these are discussed below (Teichman et al., 2016; Broderick et al., 2017; Toyinbo et al., 2022; Dimitroulopoulou et al., 2023).

Critically, with regards to IEQ and health research, there is a lack of understanding of the synergistic or additive health impacts of simultaneous exposure to combinations of different harmful components, particularly for short-term exposures that are associated with ventilation and are common in indoor environments (Stansfeld and Matheson, 2003; WHO, 2021*a*). The literature shows that many homes have a high risk of overheating, high indoor noise levels, and poor indoor air quality, yet here is no research concerning how these different aspects of IEQ could potentially combine to create a cumulative health impact that is greater (or less) than the sum of the individual exposures to IEQ. Therefore, the following sections detail a range of common guidelines for overheating, IAQ, and noise individually.

2.1.4.1 Overheating guidelines

'*At present there is no robust, defensible and universally accepted definition of overheating either for use in the assessment of proposed dwellings, for example, by modelling, or for as-built evaluation.*' (Lomas and Porritt, 2017, p.6) (NHBC, 2012; Anderson et al., 2013; Mylona and Davies, 2015; Zero Carbon Hub, 2015*b*; Gupta and Kapsali, 2016; Taylor et al., 2016). One of the main reasons for the lack of a single unified/accepted definition of overheating is due to the lack of epidemiological evidence to support an indoor temperature threshold for health (AECOM, 2012*a*; Lomas and Porritt, 2017; Tham et al., 2020). Additionally, many studies regarding indoor overheating and health suffer from low sample sizes, convenience sampling, and inadequate control of confounding variables (Tham et al., 2020). This presents a challenge around the definition of the metric/guideline for overheating.

There is a wide range of static and adaptive overheating guidelines and metrics based on comfort and health in the literature, with temperatures ranging from 26°C to 32 °C (Tham et al., 2020). The disparate thresholds are summarised in Table 2.2 on page 69.

2.1.4.2 IAQ guidelines

Table 2.1 (54) from Section 2.1.2.3 summarised the most prevalent and important indoor air pollutants, and Table 2.3 (page 70) below provides a summary of indoor air quality guidelines for these pollutants. As mentioned above (2.1.4), the guidelines published by the WHO are subject to a high standard of scientific rigour and have international consensus; therefore, these guidelines take precedence. Guideline values from the Building Regulations in England are also presented due to their regulatory status.

2.1.4.3 Noise guidelines

The CIBSE (2020) and HM Government (2013) recommend that internationally recognised and widely adopted health-based guidelines from the WHO are used for noise assessments. The WHO (2018*a*) have published guidelines for external noise, based on recent evidence, however the guidelines from 1999 remain relevant for indoor noise.

Table 2.2: Summary of overheating definitions, metrics and guidelines.

Reference	Adaptive/Static	Health/Comfort	Definition/Metric	Source
SAP	Static	Comfort	SAP calculated indoor temperatures > 23.5°C result in a high likelihood of overheating	BRE (2014)
CIBSE A	Static	Comfort	Bedroom temperatures > 24°C impact on sleeping	CIBSE (2015, 2017)
CIBSE A	Static	Comfort	Temperatures should not exceed > 26°C in bedrooms	CIBSE (2015, 2017)
CIBSE A 2006	Static	Comfort	Operative temperature in living room should not exceed 28°C for more than 1% of annual occupied hours	CIBSE (2006)
CIBSE A 2006	Static	Comfort	Operative temperature in bedroom should not exceed 26°C for more than 1% of annual occupied hours	CIBSE (2006)
CIBSE A 2015	Static	Comfort	Operative temperature should not exceed 30°C in free-running conditions	CIBSE (2015)
WHO	Static	Comfort & health	Temperatures above 24°C cause discomfort and harm to at risk groups	Ormandy and Ezratty (2012); Dengel et al. (2016)
Passivhaus	Static	Not clear	Indoor temperature should not exceed 25°C for more than 876 hours per year	(PassiveHaus Trust, 2016)
PHE	Static	Health	Excess deaths apparent when temperatures exceed 24.5°C	PHE (2018)
PHE	Static	Health	Cool rooms (temperature $<$26°C) are provided in hospital and care/nursing homes for at risk occupants	PHE (2018)
ZCH	Static	Health	Temperatures above 25°C detrimental to health and sleep	Zero Carbon Hub (2015*a*)
DCLG	Static	Health	Mortality increases when temperatures exceed 25°C	DCLG (2006)
Anderson	Static	Health	Temperature differences between days that is greater than 3K affects health	Anderson et al. (2013)
Tham	Static	Health	Temperatures above 26°C are detrimental to health	Tham et al. (2020)
TM59	Adaptive	Comfort	[1] $\Delta T \geq 1$K during May to September $\leq 3\%$ of occupied hours and [2] in bedrooms $\leq$33 hours $>$26°C	CIBSE (2017)
Lomas	Static	NA	Mean night time temperature between 26°C and 29°C	(Lomas and Li, 2023)

Table 2.3: Summary of guidelines for IAQ

Pollutant	Short term		Long term		Source
	Concentration	Averaging time (hours)	Concentration	Averaging time (years)	
Benzene	No safe level				WHO (2010)
Carbon dioxide	≤1000ppm good IAQ, 1000-1500ppm acceptable IAQ, ≥1500ppm poor IAQ				Lowther et al. (2021)
Carbon monoxide	100 $mg.m^{-3}$	0.25	-	-	WHO (2021*a*)
	35 $mg.m^{-3}$	1	-	-	WHO (2021*a*)
	10 $mg.m^{-3}$	8	-	-	WHO (2021*a*)
Nitrogen dioxide (NO_2)	200 $\mu g.m^{-3}$	1	10 $\mu g.m^{-3}$	1	WHO (2021*a*)
	288 $\mu g.m^{-3}$	8	40 $\mu g.m^{-3}$	1	HM Government (2013)
Ozone	100 $\mu g.m^{-3}$	8	-	-	WHO (2006)
Particles (PM_1)	Insufficient data for recommendations				WHO (2021*a*)
Particles ($PM_{2.5}$)	15 $\mu g.m^{-3}$	24	5 $\mu g.m^{-3}$	1	WHO (2021*a*)
Particles (PM_{10})	45 $\mu g.m^{-3}$	24	15 $\mu g.m^{-3}$	1	WHO (2021*a*)
Polycyclic aromatic hydrocarbons	No safe level				WHO (2010)
Radon	UK target level = 100 $Bq.m^{-3}$ UK action level = 200 $Bq.m^{-3}$				UKHSA (2023*b*)
Relative humidity	Relative humidity between 40 and 60%				Arundel et al. (1986)
Relative humidity	Relative humidity between 40 and 60%				CIBSE (2020)
Relative humidity	Winter averages: 1 day (<85%), 1 week (<75%), 1 month (<65%)				HM Government (2021*a*)
Tetrachloroethylene			0.25 $mg.m^{-3}$	1	WHO (2010)
Trichloroethylene	No safe level				WHO (2010)
TVOC	300 $\mu g.m^{-3}$	8			HM Government (2013)
TVOC	400 $\mu g.m^{-3}$	8			Japanese Ministry of Health Labour and Welfare Coward et al. (2001)
TVOC	600 $\mu g.m^{-3}$	8			Finnish Society of Indoor Air Quality and Climate Coward et al. (2001)
TVOC	500 $\mu g.m^{-3}$	8			National Health and Medical Research Council in Australia Coward et al. (2001)
Toluene	Uncertain evidence				WHO (2010)

Section 2.1.3.2 (page 65) identified sleep disturbance as one of the main causes of DALYs attributed to environmental noise in Europe and the UK (Basner et al., 2014; Jephcote et al., 2023), therefore, guidelines are focused on sleep disturbance.

Table 2.4 provides a summary of the WHO (1999) and most recent WHO night noise guidelines (NNG) (WHO, 2009*a*).

Table 2.4: Summary of noise guidelines. Night time is defined as 2300-0700. See nomenclature for definitions (page 27).

Day/Night	Location/Source	Recommendation	Source
Day (16hrs)	Inside dwelling (excl bedrooms)	< 35 dB_{LAeq}	WHO (1999)
Night	Inside bedroom	< 35 dB_{LAeq}	WHO (1999)
Night	Inside bedroom	< 45 dB_{LAmax}	WHO (1999)
Night	Outside bedroom	< 45 dB_{LAeq}	WHO (1999)
Night	Outside bedroom	< 60 dB_{LAmax}	WHO (1999)
Night (NNG)	Outside / environmental	< 40 $L_{night,outside}$	WHO (2009*a*)

2.2 Ventilation, AER, IEQ, exposure, and health

Section 2.1 above, demonstrated links between human exposure to indoor overheating, air quality, and noise with health. This section discusses the relationship between ventilation and IEQ and shows that ventilation modifies IEQ, which in turn modifies occupant exposure and the effect of the indoor environment on health (Wargocki et al., 2002; Anderson et al., 2013); this is conceptualised in Figure 2.5. This section begins by providing context on ventilation provision in UK homes, followed by discussing behaviours and air exchange rates relevant to the UK. The final sections discuss how these behaviours and air exchange rates (AER) modify IEQ, exposure, and health.

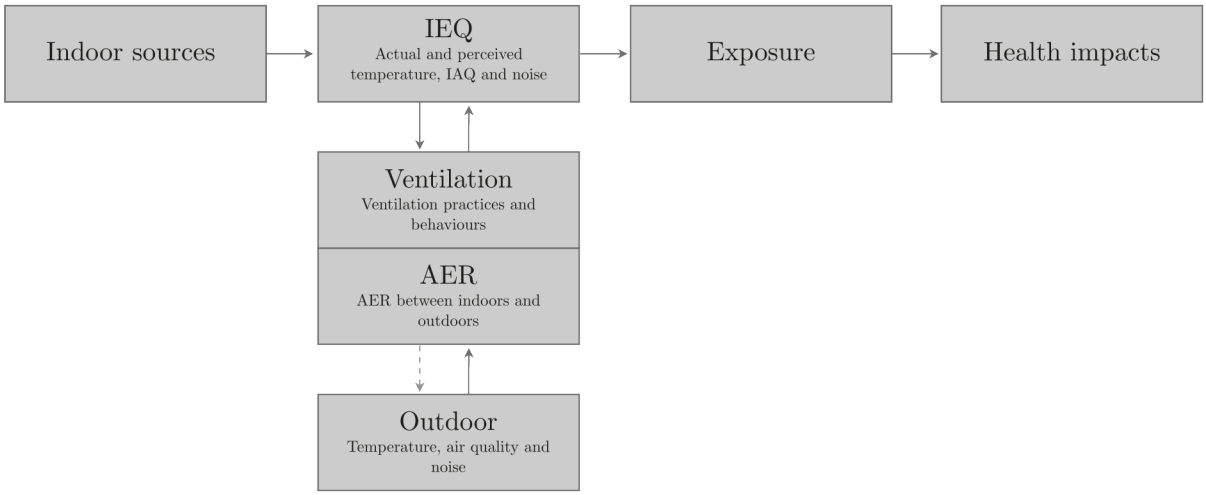


Figure 2.5: Conceptual diagram of the relationship between ventilation, AER, IEQ, exposure, and health.

2.2.1 Ventilation provision in UK homes

Ventilation is the exchange of air between the inside and outside of a building, which is necessary for a number of reasons (WHO, 2009*a*; Clancy, 2011; HM Government, 2021*b*):

1. Provide oxygen for occupants to breathe;
2. Remove and/or dilute indoor pollutants (including room pressurisation) - control indoor air quality;
3. Provide air for combustion appliances;
4. Distribute conditioned air for space heating and cooling;
5. Cool by allowing natural air movement between indoors and outdoors - controlling overheating;

Ventilation in buildings can be characterised as either intentional/planned or unintentional/unplanned, and ventilation rates arise from a combination of both intentional and unintentional ventilation. Infiltration is a form of unintentional ventilation which occurs from uncontrolled air exchange between inside and outside of a building through holes and leakage paths in the building fabric. The rate of air infiltration is directly related to the pressure difference between inside and outside the dwelling and the air tightness (leakiness/air permeability) of a dwelling, where higher air tightness and lower pressure differences result in lower rates of air infiltration. Intentional or purpose provided ventilation is the planned controllable air exchange between inside and outside of a building by either natural or mechanical/forced means (HM Government, 2021*b*). Although there is planned/designed provision for intentional ventilation, it is not always operated as intended - this is discussed in the next section of

this chapter.

2.2.1.1 History of energy efficiency and ventilation regulations in new UK homes

Standards for ventilation in UK homes can be traced back to 1631, when King Charles I concluded that IAQ was linked with health and ordered that windows should be higher than their width and ceilings at least 10 feet high (Matson and Sherman, 2004). The Great London Fire (1666) destroyed many dwellings and made way for larger homes with improved ventilation, large windows, fireplaces, and chimneys. Soon after this, the chimney and window taxes led to many people blocking up windows in order to avoid paying taxes, potentially worsening IAQ and health of occupants (Glantz, 2008). The more recent energy crisis of the 1970s placed a greater emphasis on energy saving in buildings and resulted in reduced ventilation in existing and new homes.

National standards for ventilation and conserving fuel and power in new buildings were first introduced in the UK in the 1985 Building Regulations (HM Government, 1985). Part L of the Building Regulations requires that dwellings are constructed to minimum standards of thermal efficiency and air tightness to minimise unintentional and uncontrolled infiltration and thus minimise unplanned heat-loss and carbon emissions arising from dwellings in the UK (HM Government, 2021*c*). These requirements have increased over time, resulting in improved standards of thermal efficiency and air tightness in modern buildings. Part F of the Building Regulations required the provision of intentional ventilation for the occupants and to prevent condensation in roof voids (HM Government, 1985). These regulations were updated in 1991 which then required background ventilation and mechanical extract in kitchens and bathrooms (HM Government, 1992). Over a short period of time (less than 40 years), since their first introduction, building standards have evolved substantially, and there are now requirements for new homes to achieve stringent standards for air tightness and energy efficient fabric, combined with ventilation provision of increasing sophistication. There is a growing body of evidence that recently constructed air tight homes and refurbished homes with improved air tightness can experience poor levels of ventilation and harmful indoor environmental quality (Dimitroulopoulou et al., 2005; Dimitroulopoulou, 2012; Guyot et al., 2018; MHCLG, 2019; Ortiz et al., 2020). The correct operation of ventilation systems is critical to ensure safe and healthy indoor conditions; however, the next section of this chapter highlights a widespread lack of understanding in the UK public of how to operate these ventilation systems and the importance of ventilation for health.

As previously mentioned, these regulations have had a marked impact on ventilation provision in homes in the UK. Only 22% of dwellings constructed before 1991 had extract ventilation in bathrooms and kitchens, and background ventilation provision, and in homes constructed after 1991 this rose to 59% (Van Rooyen and Sharpe, 2024).

Part L aims to reduce energy consumption, in part, by preventing the uncontrolled exchange of air between indoors and outdoors, and Part F aims to provide a safe and healthy indoor environment by

providing effective means of exchanging air between indoors and outdoors to manage IAQ. Although these regulations acknowledge each other, the previous sentence describes a potential conflict in the way they deal with ventilation. The unintended consequences of improving the energy efficiency of dwellings to the detriment of ventilation rates and IAQ was described almost 40 years ago by Seppanen (1987) and again in a more recent modelling study by Hamilton et al. (2015). Despite the apparent co-evolution of Part L and Part F of the Building Regulations, there is a growing body of evidence that recently constructed dwellings suffer from poor levels of ventilation, overheating, and poor indoor air quality (see Sections 2.1.1.4 and 2.2.4).

The 2021 Approved Document Part F1 provides guidance on how new buildings comply with Part F of the Building Regulations and describes requirements for three forms of ventilation (HM Government, 2021*b*):

1. Extract ventilation - intermittent or continuous mechanical extract ventilation to kitchens, utility rooms, bathrooms, and sanitary accommodation;
2. Whole dwelling (background) ventilation - continuous supply fans or background ventilators (trickle vents) to habitable rooms, including undercut internal doors;
3. Purge ventilation - openings (windows or doors) or mechanical extract ventilation to provide purge ventilation to each habitable room.

2.2.1.2 Energy efficiency and ventilation regulations in existing UK homes

In existing UK homes, there is a wide variation in the type and configuration of ventilation systems, but background ventilation (trickle vents) with natural purge ventilation (windows or doors) and intermittent mechanical extract ventilation (MEV) are the most common types of ventilation systems (McKay and Ross, 2010; Dimitroulopoulou, 2012; Litiu, 2012; Van Rooyen and Sharpe, 2024). Trickle vents are intended to provide whole-dwelling background ventilation (constant low-rate ventilation for managing indoor air quality), intermittent extract fans provide local powered extract ventilation to kitchens and bathrooms (to control odour, moisture generation and pollutants from cooking) and purge ventilation by opening windows to control air quality or indoor temperature during occasional activities (painting, decorating, accidental release of smoke or spillage of water) (HM Government, 2021*b*).

The UK building stock is the oldest in Europe and possibly the world (Piddington et al., 2020), and the need to upgrade this stock to reduce energy consumption and carbon emissions is evident. Older buildings typically have liberal ventilation rates owing to leaky building fabric, and upgrade works typically involve improvements to the air tightness of the building fabric, reducing adventitious ventilation and thus energy loss for space conditioning. However, these improvements result in a reduction of the effective overall ventilation rates, and this increases the need for intentional and controlled ventilation provision to maintain a safe indoor environment, particularly for reducing exposure to sources of indoor pollutants. There are building regulations for refurbishment of existing

buildings, however, their application and enforcement remains a somewhat grey area, particularly when improvements are completed incrementally over time. For example, a common upgrade in the UK has been to replace older glazing with double glazing and installing draught proofing, which do not necessarily support good ventilation rates and are often installed with the specific intention of reducing unintentional ventilation. The regulations for upgrades require that intentional ventilation is replaced on a 'like-for-like' basis, not for making improvements to the ventilation at the same time as other upgrades, to ensure that overall ventilation remains suitable after improvements/upgrades. Furthermore, standards for energy retrofit such as PAS2035 (BSI, 2019*a*) are clear about the need for ventilation during retrofit/upgrades, but these remain guidance and not legislation.

In other industries (e.g., product safety), standards and regulations are applied retrospectively, but this is very rarely the case in buildings in the UK. Current standards for ventilation and energy efficiency in new buildings are not retrospectively applied to existing buildings. Thus, the issue of how to improve the energy efficiency and ventilation provision in existing homes remains.

In both new and existing homes, occupants operation of their ventilation provision is critical for ensuring these systems perform as intended. The following section of this chapter explores the ventilation behaviour and practices of the occupants.

2.2.2 Ventilation behaviour / practices

Ortiz et al. (2020) describes humans as "sentient and cognizant beings, with needs, attitudes and emotions, combined with tools offered by their environment, they are active makers and changers of comfort (and health), depending on their needs" (Ortiz et al., 2020, p. 6).

The literature concerning ventilation behaviour is extensive and contains reports of this behaviour being influenced and shaped by many factors that interact in complex ways - these factors can be broadly categorised as internal or external (Fabi et al., 2012). Internal factors come from within the occupant and include biological (age, body composition, physiological response to IEQ), socio-economic and psychosocial (preference, attitudes, cultural background, social norms for temperature or clothing) factors (Fabi et al., 2012; Day et al., 2020). External factors include building (equipment, appliances, time of day), technological innovation, policy context, cultural, or social practices (Day et al., 2020). Ventilation behaviour is a complex response to the needs of the occupant, which are shaped and influenced by these internal and external factors (Fabi et al., 2012). This was illustrated through a recent paper by Kim and Park (2023), who were unable to characterise ventilation behaviour using a single environmental parameter and argue that ventilation is the response to the complex interaction of environmental, non-environmental, and other unknown/unmeasured factors. The internal and external factors from the literature are summarised in Figure 2.6 and discussed in more detail below.

The preceding paragraphs highlight the complex nature of the term 'behaviour', and this underpins the challenge of creating an appropriate definition for this term. There are a number of similar

definitions of occupant behaviour in the literature that are specifically concerned with IEQ and ventilation (Schweiker, 2010; Polinder et al., 2013). Typically, these relate to conscious and unconscious actions to control/adapt to IEQ based on perceptions of IEQ and/or external/internal stimuli. However, these definitions are incomplete and restricted, as they do not encompass environmental education and other social sciences factors (e.g., health-focused ventilation, and habitual ventilation practices) (Fabi et al., 2012).

Therefore, a hybrid definition is suggested by combining the definitions proposed by Schweiker (2010) and Polinder et al. (2013), and the review paper by Fabi et al. (2012). The following definition is suggested: occupant behaviour is the conscious or unconscious actions or reactions of a building occupant to control or adapt to IEQ. These actions are based on a combination of internal and external factors, including the occupant's perception of IEQ, their sum of past experiences, their environmental education, external and internal stimuli.

Bekö et al. (2011) carried out measurements of AER in 500 Danish children's bedrooms, alongside dwelling inspections, questionnaires and interviews with their parents. They reported that occupant behaviour was a far stronger predictor of ventilation rate ($r^2 = 0.30$) than building characteristics ($r^2 = 0.09$) alone. This study and many others highlight that occupants' ventilation behaviour is one of the most important determinants of IEQ and air exchange rates (Crump et al., 2005; Bekö et al., 2011; Andersen et al., 2013; Gupta and Kapsali, 2016). However, there is a lack of understanding of ventilation behaviour and occupant drivers/barriers (Fabi et al., 2012; AECOM, 2012*b*). Furthermore, the observed behaviour is described as highly variable both within individual case studies and across different case studies (Van Dongen and Phaff, 1989; Kukadia and White, 2006; Andersen et al., 2009, 2013; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015; Kim and Park, 2023). The wide range of internal and external factors and their complex interaction could explain the high variation in observed ventilation behaviours. Further research is required to understand ventilation behaviour - occupant barriers/drivers and to characterise ventilation behaviours (Fabi et al., 2012; Few, 2021).

The challenges associated with understanding occupant behaviour and the range of issues are illustrated through the use of windows and a theoretical framework proposed by Day et al. (2020). Operating windows and doors is one of the most simple and prevalent tools available to occupants for controlling the indoor environment in their homes. The actuator and interface are integrated, providing a high degree of perceived control and instant sensory feedback (temperature, noise, airflow) (Day et al., 2020), reinforcing occupants' 'trigger and feedback' learning (tacit knowledge and sensory learning) which is strengthened by cognitive apprehension and social learning (Baborska-Narożny et al., 2017). However, there is disagreement in the literature about which factors are most important for this seemingly simple behaviour - Andersen et al. (2009) found that Danish occupants ventilation behaviour was largely based on occupants knowledge and education about how IEQ impacts health and

not based on sensory learning or past experience. The literature often reports that occupants prefer to have control of ventilation and IEQ, where this is perceived to provide sensory feedback and improved thermal comfort, however, this is likely to be very context specific - see internal and external factors in figure 2.6 (Frontczak and Wargocki, 2011; Frontczak et al., 2012; Luo et al., 2016; Larsen et al., 2020; Day et al., 2020).

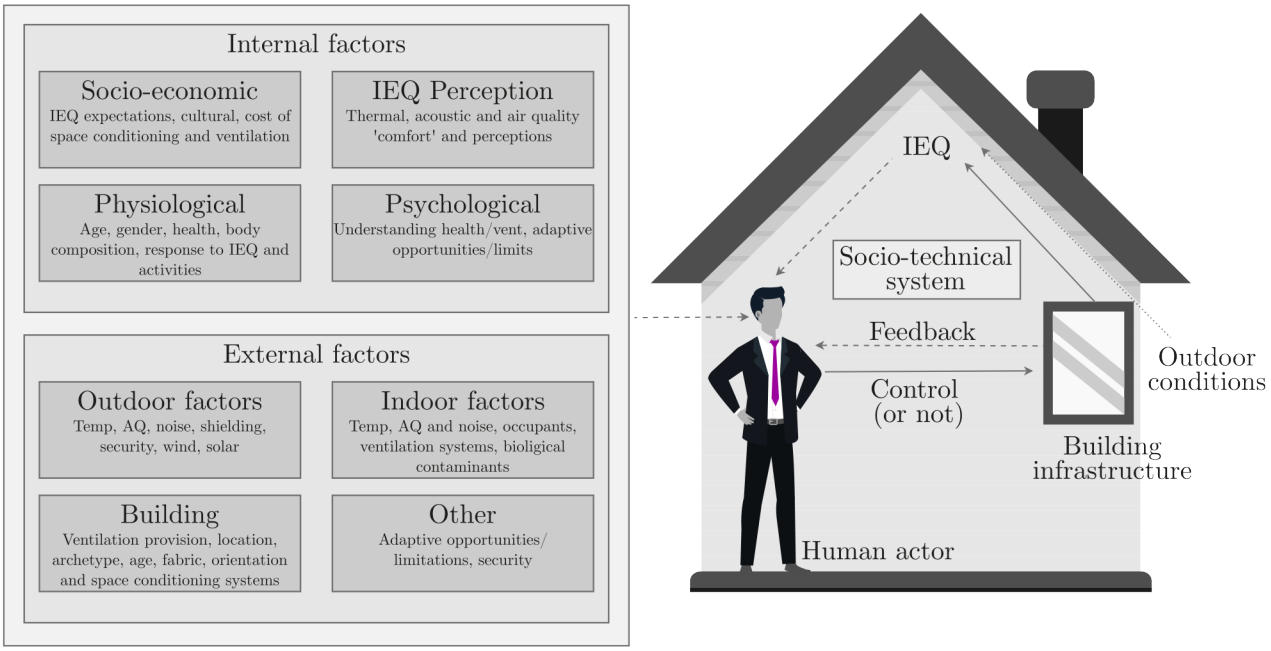


Figure 2.6: Diagram showing a conceptual diagram of the relationships between a range of internal and external factors with ventilation.

2.2.2.1 Overview of factors influencing ventilation behaviour

The research described in this thesis is focused on ventilation in UK homes and therefore, the context of the factors described above on ventilation in the UK are important and were used to shape a recent questionnaire, which was issued to 1,861 adults in Britain (Van Rooyen and Sharpe, 2024). This survey reported a range of different drivers and barriers for opening windows, trickle vents, and operating mechanical ventilation systems. The two main respondents' reasons for opening windows were fresh air and indoor temperatures, which aligns with other research (Brundrett, 1977; Andersen et al., 2009; Roetzel et al., 2010; Jones et al., 2017; Mavrogianni et al., 2016; Van Rooyen and Sharpe, 2024). Despite the many barriers referenced in the literature, most participants in recent research by the MHCLG (2019) and Van Rooyen and Sharpe (2024) (32%) reported they had no barriers to opening windows. After this, the main barriers were security (19%), pests/insects (10%), heat loss (9%), and noise (8%) (Van Rooyen and Sharpe, 2024). Similarly, both Mavrogianni et al. (2016) (n=89) and Wright et al. (2018) (n=8) reported that security were top barriers for opening windows, followed by noise, outdoor temperatures, air pollution, and pests.

2.2.2.2 Influence of occupant knowledge on ventilation behaviour

Research suggests that there is a lack of understanding among participants on how to operate and maintain ventilation systems and how ventilation can impact health and well-being, however, the results are mixed and the differences in research design make direct comparisons challenging. Occupant interviews in a study of 29 different buildings by Aizlewood and Dimitroulopoulou (2006) reported widespread misunderstanding of ventilation systems. Baborska-Narożny et al. (2017) found a lack of understanding among occupants of how the installed ventilation systems impacted overheating. Furthermore, a recent study of 80 recently constructed homes in England by MHCLG (2019) found that around half of homes had turned off mechanical ventilation systems due to noise and misunderstanding of how to operate their ventilation systems. Interestingly, in this same research, when asked about trickle vents, 86% reported to understand the purpose and operation of trickle vents, which is similar to the 75% of 645 Danish respondents, who claimed to know how to operate their ventilation systems optimally (Frontczak et al., 2012). The understanding of trickle vents reported by MHCLG (2019) is contrasted by research by Dimitroulopoulou et al. (2005) and Baborska-Narożny et al. (2017), who both found many participants unaware of the purpose of trickle vents and occupants did not know how to use them, resulting in them not being used. A large scale survey of 1,861 British respondents reported that 77% had never seen/heard/received information on how to use their ventilation provision (Van Rooyen and Sharpe, 2024).

The review by Dimitroulopoulou (2012) summarised that occupants believe that ventilation is important but do not have a good understanding of the ventilation systems in their homes and concluded that poor use and knowledge are key issues for under ventilation of dwellings.

2.2.2.3 Influence of season on ventilation behaviour

A large amount of literature describes indoor and outdoor temperature and season to have a significant impact on window opening behaviour and the probability of window opening and closing (Andersen et al., 2009; Roetzel et al., 2010; Fabi et al., 2012; Andersen et al., 2013; Jones et al., 2017; Sun and Wallace, 2020; Liu et al., 2022). Windows and doors to the outside are reported to be open more frequently, for longer, and in greater numbers during warmer outdoor temperatures and during the summer season. However, not all studies find statistically significant relationships, and the authors often report results using different measurements (frequency, duration, number of windows), which makes it challenging to compare and contrast the results (Frontczak et al., 2012). Although outdoor temperatures are higher in summer, season and outdoor temperature are not necessarily the same, and there is a need to better understand if season/time of year, or temperature is more important. Finally, much of the research is derived from questionnaires, which can be subject to recall bias and errors in reporting, and there is a need for empirically derived evidence of ventilation behaviours in UK homes

(Fox, 2008; Bone et al., 2010; AECOM, 2012*b*; Andersen et al., 2013; Zero Carbon Hub, 2015*a*).

2.2.2.4 Influence of other factors on ventilation behaviour

The literature relates many other factors with ventilation behaviours, including: room type, occupant age (mixed results), activities (cleaning, occupancy, sleeping, and cooking), household/family size, time of day, outdoor air quality, wind speed (mixed results), rain, condensation, smoke/odours/stuffiness, and daylight (Brundrett, 1977; Dubrul, 1988; Van Dongen and Phaff, 1989; Grey and Raw, 1990; Berry, Brown, Coward, Crump, Gavin, Grimes, Higham, Hull, Hunter, Lea, Llewellyn and Raw, 1996; Andersen et al., 2009; Roetzel et al., 2010; Bekö et al., 2011; AECOM, 2012*a*; Fabi et al., 2012; Frontczak et al., 2012; NHBC, 2012; Sharpe et al., 2014; Howieson et al., 2014; Mavrogianni et al., 2016; CMO, 2017; Jones et al., 2017; MHCLG, 2019; Day et al., 2020; Few, 2021).

2.2.2.5 Summary and research gap 1

Despite the extensive body of research concerning ventilation behaviours and practices, Fox (2008); Bone et al. (2010); AECOM (2012*b*); Andersen et al. (2013); Zero Carbon Hub (2015*a*); Borsboom et al. (2016), and Nazaroff (2021) highlight the lack of longitudinal empirical evidence on occupant ventilation behaviours in occupied homes under real-life conditions.

Research gap 1
There is a lack of empirical evidence of how occupants ventilate their homes when they are occupied and how this varies over time.

In addition to the gap above, the literature frequently describes many occupants to have a lack of knowledge of ventilation. This lack of knowledge specifically refers to (1) the importance of ventilation for health and (2) how to ventilate their homes.

2.2.3 Quantifying ventilation and ventilation guidelines

2.2.3.1 Ventilation guidelines

A minimum AER of 0.4h^{-1} was identified in 1987 by Seppanen (1987). The review of ventilation in European dwellings by Dimitroulopoulou (2012) reported that 0.5h^{-1} is a frequently used air change rate in national standards/regulations for health, but higher rates (0.8h^{-1}) might be required to control house dust mite (HDM) growth. This agrees with the report by ODPM (2006), which states that AER$>0.5\text{h}^{-1}$ is required to prevent mould growth and AER$>0.8\text{h}^{-1}$ to limit the growth of HDM populations. Sharpe et al. (2015) and Sundell et al. (2011) reported AER below 0.5h^{-1} was associated with poor respiratory health and higher risks of negative health outcomes. A multidisciplinary review

of 105 papers by Wargocki et al. (2002) found AER above $0.5h^{-1}$ reduced house dust mite infestations, and later in 2013, Wargocki (2013) summarised that health risks are likely to occur when AER are below $0.4h^{-1}$ in existing dwellings.

The AER of the stock of homes in the UK is poorly characterised (discussed in 2.2.4), however, below it is argued that ventilation needs are highly context-specific and variable across different homes - thereby questioning the relevance of a single (average or otherwise) AER for all homes.

In an occupied home, ventilation rates should ideally vary dynamically, according to occupants' needs, activities, indoor, and outdoor conditions, pollutants, and noise, in order to provide a comfortable, safe, and healthy indoor environment that does not consume more energy than is necessary (European Commission - Institute for Health & Consumer Protection, 1992; Wargocki, 2013). These factors will all be highly variable across different homes, and so, defining a single AER for a large group of homes is not likely to adequately capture the needs of all.

However, even when considering each individual home, it is challenging to fully define a 'healthy ventilation rate' because (1) it is not possible to identify and quantify the spatial and temporal variation of all sources of harmful pollutants indoors, (2) there is insufficient data on safe guideline values for all pollutants (e.g., PM_1), and (3) there is insufficient data on safe threshold values for combinations/cocktails of pollutants (Seppeanen and Fisk, 2004). This is further complicated when considering all IEQ components that are known to impact health, as there is a lack of understanding of the relationship between exposure to all IEQ components, health, and ventilation, particularly at short timescales that are relevant for ventilation - these have been discussed in the previous section (2.1) and the subsections above.

The next two subsections below consider how ventilation rates can be quantified using theoretical modelling (2.2.3.2) and empirical measurements (2.2.3.3). The subsection following this focusses on a discussion of the most common empirical measurement technique (2.2.3.4).

2.2.3.2 Quantifying ventilation using modelling

Modelling typically involves using building physics software to predict ventilation, IEQ, and energy consumption in buildings: EnergyPlus is widely used in research in the UK (Mavrogianni et al., 2012, 2014; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015; Taylor et al., 2016, 2018). These models use inputs for building geometry, indoor sources of heat/pollutants, outdoor environmental data, and simplified rules to model ventilation/window operation to calculate theoretical air exchange rates, which can be used for a range of calculations, including estimating indoor air quality or overheating risk. However, without clear evidence of how homes are used, it is not possible to accurately model occupant behaviours, and in these situations, modellers use assumptions. These assumptions of behaviour are often modelled using simplified rules (e.g., open windows when indoor temperature exceeds a certain threshold), which do not fully account for the many factors discussed

above or their interactions. These assumptions and simplifications can introduce uncertainty and propagate performance gaps (Beizaee et al., 2013; Lomas and Kane, 2013). There is a need to conduct empirical research to derive insights that can support modelling and reduce uncertainty.

2.2.3.3 Quantifying ventilation using measurements

Ventilation rates can also be estimated using direct or indirect measurements (Clancy, 2011). Direct methods involve using a device to measure air flow or velocity directly. Rotating vane anemometers and airflow capture hoods can be used to measure air velocity and air flow rates in mechanical ventilation systems such as extract fans and kitchen canopies (McKay and Ross, 2010). These devices can measure the velocity of air across the face area of specific devices, but are less suitable for measuring ventilation rates for whole spaces over longitudinal campaigns. Measurements of air permeability use a 'blower door' fan to positively pressurise (normally 50Pa) a building and measure the amount of air flow required to maintain the pressure (Dimitroulopoulou et al., 2005; Kukadia and White, 2006; Hartless and Standen, 2013). Air permeability measurements using the blower door are typically conducted under conditions where all windows, doors, and background ventilation devices are closed - so these methods are not suitable for estimating background or natural ventilation rates when these devices are open. Direct air flow rates are typically expressed as a volumetric flow in litres per second or cubic metres per second.

2.2.3.4 Quantifying ventilation using measurements - tracer gas technique

The most widely used indirect method of quantifying building air exchange rates is using tracer gases, which have been used since the early twentieth century (Cui et al., 2015; Persily, 2016; Men et al., 2020). Air exchange rates are expressed as air changes per hour, which is the amount of times that the total volume of a building or space is replaced with outdoor air every hour. Tracer gases are used to tag or label air in order that its variation over time and space can be quantified, and from this, ventilation rates can be estimated (Nazaroff, 2021). Common tracer gases are SF_6 (Dimitroulopoulou et al., 2005; Aizlewood and Dimitroulopoulou, 2006; Clancy, 2011), butane (Hartless and Standen, 2013), CO_2 (Claude-Alain and Foradini, 2002; Few and Elwell, 2019; Men et al., 2020), and perflourocarbon tracers (PFTs) (Dimitroulopoulou et al., 2005; Kukadia and White, 2006). SF_6 and PFTs are harmful to the environment. SF_6 also uses bulky, complex, and expensive equipment which is poorly suited for measuring ventilation in occupied homes (Men et al., 2020; Nazaroff, 2021). By contrast, passive PFT tubes are cheap, can be mailed, are easy to use, and can be deployed in occupied homes (Nazaroff, 2021). CO_2 is a popular tracer gas for indirect measurements of AER, as sensors are small, cheap, and pervasive. Additionally, CO_2 has a density similar to air and can be sourced from occupants respiration, which is safe and free. The use of CO_2, however, has limitations discussed below, where SF_6 offers an advantage over CO_2, as this can be used when occupants are present in the space.

Tracer gas techniques are categorised as (1) passive tracer, (2) decay, (3) constant injection, (4)

constant concentration, and (5) tracer build up.

Passive tracer techniques are typically used with PFTs, where a source emits PFTs at a known rate and a diffusion tube absorbs this over time - this allows the average AER to be estimated over the duration of exposure, which is typically a couple of weeks (Nazaroff, 2021). An important limitation of PFT's, which is often violated in other research, is that this technique is limited to environments with a constant AER (Sherman, 1990; Liddament, 1996). Where there are large short-term variations in AER, for example, from opening windows, the PFT method does not provide an accurate assessment of the average AER and should be avoided (Sherman, 1990; Nazaroff, 2021). Ventilation operation is expected to have a significant impact on AER, and understanding the temporal variation of AER is important because, when measuring ventilation from a health perspective, we are interested in the conditions that the occupants experience, which are not constant and vary substantially over time (Few, 2021). Due to the time averaged nature of PFT techniques, they are unsuitable for identifying the variation of ventilation performance of a building or the conditions experienced by the occupants (Persily, 2016).

The decay technique considers the concentration of decay of a gas from an elevated level back to the background concentration, after the source of the gas is removed. The tracer gas technique requires homogeneity of an isolated environment (single zone) and perfectly mixed conditions to ensure accurate estimations of AER (Sherman, 1990; Men et al., 2020; Few, 2021). The decay technique allows measurements over much shorter periods of time when compared with passive tracer techniques, and metabolic carbon dioxide from occupant respiration can be used with the decay method. However, occupants and other sources of CO_2 need to be accounted for, which limits the use of the CO_2 decay method to periods when occupants and other sources are not present and leave the zone under investigation. Various researchers have attempted to identify periods when occupants are present in buildings for this purpose, however this is not trivial. Guo and Lewis (2007) have suggested that the difficulty associated with determining occupancy is a key reason that the use of metabolic CO_2 as a tracer gas is not more widely used. A recent example of a method for accurately determining occupancy with a high temporal resolution is presented by Few and Elwell (2019) and Few (2021) - this method is used in conjunction with the CO_2 decay method to estimate short-timescale AER in occupied homes.

Constant injection techniques involve maintaining a constant rate of injection of a tracer gas, until the concentration reaches equilibrium (ASTMI International, 2011). When used with metabolic CO_2, equilibrium can be difficult to achieve (Mumovic et al., 2009), and assumptions/uncertainties around source locations and generation rates of CO_2 can introduce substantial uncertainties (Sharpe et al., 2014, 2015; Persily, 2016; Few, 2021). Tracer build-up techniques estimate AER from the build-up of a gas over time with a known rate of injection and have been used with metabolic CO_2, but this can suffer from the same uncertainties as the constant injection techniques. Constant concentration techniques vary the rate of injection to maintain a constant concentration, where the AER can be calculated from the rate of injection, and this method can measure short temporal variations in AER but uses complex

equipment, which is also disruptive and not suitable for occupied homes (ASTMI International, 2011).

There are no universally agreed measurement standards or reporting protocols for ventilation research, and it is clear from the discussion above that there are pros and cons to the different approaches (ODPM, 2006). The lack of standards result in differences in measurement methods, calculations and reporting, which in turn make comparisons between different research challenging, and in many cases, impossible. There is a need to develop reliable approaches and standardise methods for ventilation measurement and reporting (ODPM, 2006; Persily, 2016). This standardisation should encompass model uncertainty (JCGM, 2008) along with the fundamental assumptions and limitations of the methods. In order to standardise, there is a need for consensus on the objectives and key drivers for such measurement, which is challenging. For example, investigations concerning energy might only require the average AER over a period of time, whereas investigations concerning health are likely to require data on the temporal variation of AER with a high temporal resolution.

2.2.4 Ventilation performance in UK homes

Before focusing on UK homes, from an international perspective, Nazaroff (2021) conducted a review and meta-analysis of AER from 40 studies with measurements from approximately 10,000 homes in Northern American and Northern Europe. Nazaroff (2021) reported that the resulting distribution was be log-normal, having a geometric mean of $0.5h^{-1}$ and a geometric standard deviation of $2h^{-1}$. The variation of geometric mean within individual studies was typically within the range of 0.1-$1h^{-1}$. Interestingly, Nazaroff (2021) reported that housing type and ventilation provision were not strong predictors of AER. The remainder of this section considers research on the current state of ventilation in UK homes.

In the UK, there is no nationally representative study of AER. Limited data exists for research that has used smaller purposive samples for studying specific homes and typically for a specific reason. As such, AER are not fully characterised for the UK housing stock and there is an incomplete understanding of how AER vary within and across different aspects of the housing stock (e.g., archetype, age etc.).

Aizlewood and Dimitroulopoulou (2006) carried out measurements of two week mean ventilation rates in 8 flats using PFTs and found that 4 of the 8 dwellings had AER less than 0.5 h^{-1}. A study of 37 dwellings built after 1995 found a clear seasonal difference in ventilation performance with 68% of dwellings calculated to have an AER less than $0.5h^{-1}$ in winter and 30% in summer (Crump et al., 2005). A study of 5 dwellings built before 1995 found only one with a whole house ventilation rate greater than $0.5h^{-1}$, showing that older homes can have poor levels of ventilation (Kukadia and White, 2006). More recently, a study of 10 dwellings found most (9 out of the 10) dwellings with average AER below 0.5 h^{-1} (MHCLG, 2019). Section 2.2.2 identified season and outdoor temperature as important factors for ventilation, however, these factors have received limited study in research of ventilation in occupied homes in the UK. Much of the existing research collected measurements from campaigns with

a limited duration, typically focussed on a single season, often summer or winter, with very limited data collected during spring and autumn.

Table 2.5 provides a summary of the limited published AER measurements carried out in the UK and highlights that many dwellings do not meet the AER threshold of $0.5h^{-1}$. The available evidence of AER in UK homes suggests that many homes in the UK have inadequate rates of ventilation.

Table 2.5: Summary of empirical ventilation rate measurements in the UK

Study	Dwellings		Descriptive stats				Units	Comments
	$> 0.5h^{-1}$	$< 0.5h^{-1}$	Mean	SD	Min	Max		
Aizlewood and Dimitroulopoulou (2006)	4	4	0.47	0.31	0.13	0.98	h^{-1}	
Crump et al. (2005)	12	25	0.44	0.11	0.19	0.68	h^{-1}	Winter
Crump et al. (2005)	26	11	0.62	0.23	0.19	1.06	h^{-1}	Summer
MHCLG (2019)	1	9	0.33	0.14	0.19	0.61	h^{-1}	
Kukadia and White (2006)	1	4	0.4	0.1	0.29	0.55	h^{-1}	

Similar to the study by Bekö et al. (2011) described in Section 2.2.2, Wallace et al. (2002); Howard-Reed et al. (2002) and Kukadia and White (2006) found occupant behaviour (opening windows) to have a greater effect on AER compared with other factors.

Opening windows in the building regulations is considered necessary for occasional ventilation (see Section 2.2.1), but that is the case for homes which have provision for background ventilation. However, Van Rooyen and Sharpe (2024) found that 49% of 1,861 homes in Britain had no trickle vents in their home, and only 29% had them on all windows - the lack of background ventilation provision makes opening windows ever more important for providing both background and occasional ventilation.

In addition to windows, the use of trickle vents have also been shown to have a significant impact on AER (Dimitroulopoulou et al., 2005). The Building Regulations state that background ventilators are intended to remain open; however, research often reports that trickle vents are often closed (McKay and Ross, 2010; Sharpe et al., 2014; MHCLG, 2019), which is problematic, as this undermines their intended function of providing background ventilation. As expected, the literature shows a positive correlation between window opening and AER (Dick J.B and Thomas D.A, 1951; Roulet and Scartezzini, 1987; Hill et al., 2001; Howard-Reed et al., 2002; Crump et al., 2005; Fan et al., 2022). Section 2.2.2 found that occupants open windows more frequently in summer than winter, and so, AER are higher in summer than winter and exceed the $0.5h^{-1}$ threshold in most homes during the summer, but not during the winter (Crump et al., 2005). It is important to highlight that AER alone do not tell us if the IEQ in these homes was unhealthy or unsafe, so more evidence is required to understand if the AER correlate with conditions that meet the occupants needs and also provide a safe and healthy IEQ.

2.2.4.1 Summary and research gap 2

Much of the evidence on AER in UK homes is conducted over short timescales and Howard-Reed et al. (2002) explained that the relationship between ventilation practices/behaviour and AER is poorly understood. Additionally, Few and Elwell (2019); Few (2021); Nazaroff (2021) describe the lack of understanding of the variation of AER in occupied homes, and Royal College of Paediatrics and Child Health (2020) call for more empirical evidence of ventilation rates in buildings of different ages and designs.

Research gap 2

There is a lack of empirical evidence of air exchange rates in occupied homes in the UK and how this varies with ventilation configuration and season.

2.2.5 Ventilation modifies IEQ and exposure

2.2.5.1 Ventilation modifies indoor temperatures and exposure to overheating

The UK generally experiences mild summers, where indoor temperatures are frequently higher than the outdoor temperatures (indoor outdoor ratio > 1) (Mavrogianni et al., 2016). UK homes are mostly naturally ventilated, and theory states that when the IOR of temperature is greater than 1 and a window is open, airflow between indoors and outdoors will increase and the indoor temperature will reduce as a result (Lyberg, 1997; Butcher, 2005). This is particularly the case during the evening, where outdoor temperatures can be lower than indoor temperatures, and opening windows and doors to outside presents an important opportunity for reducing indoor temperatures and overheating risk - this is termed 'night time cooling' (Mavrogianni et al., 2014; Wright et al., 2018). Conversely, when indoor temperatures are lower than outdoor temperatures, opening windows can cause or exacerbate overheating indoors. Outdoor temperatures in the UK are continuously increasing due to climate change and heatwaves are occurring more frequently, and this is predicted to worsen into the future (Met Office, 2019, 2022*b*). The increasing outdoor temperature and more frequent occurrences of heatwaves are problematic, as ventilation during these times can increase indoor temperatures and the risk of occupants overheating.

Modelling by Taylor et al. (2015) demonstrated that trickle vent use resulted in higher AER, which reduced indoor temperatures and overheating risk. Additionally, this modelling demonstrated that higher levels of airtightness (lower AER) increased overheating risk. Furthermore, the modelling by Mavrogianni et al. (2014) found a significantly higher occurrence of high indoor temperatures when windows did not open in summer.

Gupta and Kapsali (2016) monitored six low carbon social houses and found that when the windows

in bedrooms were opened throughout the day in summer, this resulted in lower indoor temperatures. Furthermore, monitoring of 101 dwellings in London by Mavrogianni et al. (2016) reported a negative correlation between window area and indoor temperature (apart from West facing windows), which attributed to increased AER; however, the cause was not determined. It is not clear why West facing dwellings were different, where we might expect dwellings with glazing facing towards the South to experience higher heat gains and an increased risk of higher indoor temperatures. This research reported mixed results for summertime performance and living room window opening behaviour and a clear increase of bedroom temperatures with the number of open windows during the night time. In this case, the authors highlight the challenges with determining the cause and effect of overheating and ventilation, where it was not clear if the relationship was because of occupants' response to high indoor temperatures or because the higher outdoor temperatures reduced ventilative cooling. This research did not measure outdoor temperatures or the opening and closing of windows and doors to outside. Capturing window and door events and outdoor temperature data would allow for these factors to be accounted for and the potential causes and effects better understood.

Baborska-Narożny et al. (2017) studied indoor temperatures in 18 refurbished flats in a tower block in North England. The flats all had the same fabric and layouts but experienced a wide range of different temperatures. The authors reported that those participants who opened windows when the outdoor temperature was lower than the indoor temperature and mitigated solar gains, experienced lower indoor temperatures, and reduced risk of overheating. Furthermore, the lack of knowledge of how to avoid overheating was identified as a key factor in those flats with the highest temperatures.

As previously discussed, occupants can react to increasing temperatures by opening windows in an attempt to reduce indoor temperatures, seeking thermal comfort; however, noise and security are common barriers to opening windows (Mavrogianni et al., 2016; Lomas and Porritt, 2017; Wright et al., 2018), and so there is the potential conflict between occupant's desire to open windows to reduce indoor temperatures and the undesirable noise or security risk associated with opening windows. Outdoor temperatures, air quality and noise are highly variable with location in the UK. These factors are also likely to not be equitably distributed, with those who are socially economically deprived potentially living in urban locations with poor air quality, high levels of environmental noise, and an increased security risk associated with leaving windows and doors open for ventilation.

The preceding paragraphs illustrate the interlinked relationship between overheating/thermal comfort, indoor and outdoor air quality, ventilation behaviours, indoor and outdoor noise levels; however, this relationship is poorly understood. Furthermore, there is a lack of empirical evidence of actual overheating in homes in the UK, particularly where this evidence includes measurements of AER, IAQ, noise and how this relates to ventilation.

2.2.5.2 Ventilation modifies indoor air quality and exposure to pollutants

Generally, where the indoor concentrations of pollutants exceed the outdoor concentrations (IOR > 1) AER from ventilation results in the direct removal and dilution of these pollutants, resulting in lower indoor concentrations; this relationship is summarised in Table 2.6. However, the increased air movement can also result in the resuspension or movement of particulate matter into the occupied zone (Sun et al., 2022). The relationships between individual and combinations of IAQ components and ventilation are understood in principle, but there is a lack of empirical evidence demonstrating them in practice, where these relationships have not been fully characterised (Sundell et al., 2011).

The relationship between ventilation and the different components of IAQ is complex to characterise. There are many components of IAQ that all have different indoor and outdoor sources and sinks that vary temporally and spatially, and when combined with the complex geometry of a real home with time-varying ventilation and air movement, this makes the relationship between ventilation and IAQ very complex to characterise. Finally, it is challenging to accurately measure AER (see Section 2.2.3) and then to relate this to IAQ in a meaningful way (Seppeanen and Fisk, 2004).

Humidity and biological agents

The review by Dimitroulopoulou (2012) and Wargocki (2013) reported a negative correlation between ventilation rates and indoor humidity, and Wargocki (2013) reported the lower indoor humidity would likely result in lower numbers of house dust mites. The extensive literature review by ODPM (2006) reported a "general consensus that a link exists between ventilation rates in dwellings and respiratory hazards (for example, HDM)" (ODPM, 2006, p 4) and between respiratory hazards and respiratory problems.

A large survey of French dwellings found increased incidences of fungal contamination in dwellings where windows were opened less frequently (Brown et al., 2015). Tham (2016) found strong evidence to demonstrate that higher levels of ventilation correlated with a reduction in the transmission/spread of infectious diseases and a reduction in symptoms of sick building syndrome in work places. Research shows that low levels of ventilation can result in high levels of humidity, increased fungal contamination, higher transmission of infectious diseases, and an increase in symptoms of sick building syndrome. However, the relationship between ventilation and humidity is likely to be dependant on a number of dynamic factors, including indoor and outdoor sources (influenced by occupant presence and activities), ventilation rates, and air movement paths.

Particulate matter

There is very limited evidence on the relationship between PM and ventilation in the literature. Modelling by Taylor et al. (2015) reported a significant increase in indoor concentrations of $PM_{2.5}$ from outdoor sources with an increasing frequency of opening windows during the summer to mitigate overheating, but indoor concentrations of PM from indoor sources were reduced. Empirical research in

Copenhagen reported that opening windows reduces exposure to peaks of PM during occupant activities that produce PM, but increases exposure when there are no active indoor sources of PM (Spilak et al., 2014). However, Spilak et al. (2014) does not describe the relationship between AER and PM in detail in the paper.

Products of combustion

Coward et al. (2001) and Raw et al. (2004) reported that indoor sources of CO and NO_2 from gas cookers to be the main determinants of indoor concentrations in homes, and this varied with season, which was attributed to higher rates of ventilation in summer. Dimitroulopoulou et al. (2005) found ventilation to be a significant factor for CO in living rooms and NO_2 in living rooms and kitchens; however, the significance depended on season and type of ventilation. For dwellings located in areas with elevated outdoor concentrations of NO_2, higher indoor concentrations of NO_2 were observed in kitchens where the windows were opened more frequently and in living rooms when trickle vents were open.

TVOC

McKay and Ross (2010) and Broderick et al. (2017) both found dwellings with higher air tightness, had lower background AER, and higher TVOC concentrations. The relationship between TVOCs and ventilation is likely to be complicated by the fact that ventilation could increase indoor temperatures, which can cause materials to off-gas VOCs, thus the relationship between ventilation rates and contaminant levels can be non-linear (Godish and Spengler, 1996). However, this relationship is potentially complicated by the relationship between the rate of off-gassing and temperature. Hernandez et al. (2020) found TVOC concentrations three times higher in rooms relying on only infiltration (0.1^{-1}) compared with rooms with mechanical ventilation providing background ventilation (2.4^{-1}), demonstrating the importance of a constant source of background ventilation to control VOCs over time.

CO_2

Sharpe et al. (2014) and Gupta and Kapsali (2016) both found that during the summer season, when windows were opened more frequently, indoor concentrations of CO_2 were lower than in winter. Furthermore, Howieson et al. (2014) reported much higher indoor concentrations of CO_2 in dwellings that kept windows closed when compared with dwellings that opened windows frequently. During the winter, Sharpe et al. (2014) reported lower mean CO_2 concentrations in dwellings with MVHR (n=5, 858ppm) than in those with trickle vents (n=21, 1292ppm). The lower mean concentrations could be due to the continuous forced ventilation rates from the MVHR, contrasted by the variable ventilation rates from passive vents.

Combinations of pollutants

The recent research by Fan et al. (2022) investigated the impact of window position in 40 urban (n=8), suburban (n=31), and rural (n=1) Danish bedrooms during the winter and found significantly

higher AER (1.21h^{-1} vs 0.34h^{-1}), significantly lower CO_2 (904ppm vs 2310ppm), significantly lower TVOC (156PPB vs 206PPB), significantly lower PM_{10} (26μg.m^{-3} vs 47μg.m^{-3}), significantly lower temperature (22.4°C vs 23.2 °C), and significantly lower RH (48% vs 53%) when windows were open relative to closed. Concentrations of PM_1 (1.7μg.m^{-3} vs 1.8μg.m^{-3}) and $PM_{2.5}$ (3.9μg.m^{-3} vs 5.4μg.m^{-3}) were lower when windows were open relative to closed, but the difference was not significant. Most pollutants known to affect health were lower when windows were open, but concentrations of NO_2 were higher when windows were open relative to closed (10.4PPB vs 3.5PPB), which might be due to the ingress of these pollutants, as most of the sample were urban and suburban homes. This research, however, did not include measurements of indoor or outdoor noise, as this was assumed to be low and perceived by participants as low. These results show that window opening can have a significant impact on a range of IAQ variables; however, these results are likely to be highly context-specific and, we might expect them to vary in different contexts (location, ventilation provision, indoor and outdoor sources, etc.).

Verniers et al. (2023) carried out controlled experiments in a test house in Belgium, measuring VOC, PM_1, $PM_{2.5}$, PM_4, and PM_{10} concentrations for cooking, candle use, and vacuuming under different ventilation conditions. Ventilation conditions included all ventilation off, all windows open, MEV, MVHR, and cooker hood operation; however, no measurements of ventilation rate were taken as part of the research, only rates inferred from fan datasheets. As expected, during and after cooking, the cooker hood operation captured PM and VOCs at its source in the kitchen and adjacent spaces more than other ventilation conditions. The results show that PM_1 was the most dominant pollutant for all activities and that the decay of peaks took the longest when all ventilation was off, followed by MEV/MVHR and when all windows were open, the shortest decay times were observed. However, decay times were not described in the paper. Particulate matter from cooking was found to infiltrate adjacent rooms, but VOCs were less so. Window ventilation was reported to control the spread of VOCs from candles, more than MEV or MVHR. The experimental conditions, however, are not representative of practices in UK homes, where the experiments kept all internal doors closed and for the window ventilation experiments all windows were opened - both of these conflict with the reported practices in British homes (Van Rooyen and Sharpe, 2024). A key limitation of this research is the lack of measurements of ventilation rates for the different ventilation conditions - this makes it challenging to compare and contrast the various ventilation conditions, which are all expected to have different ventilation rates. In addition to this, other key IEQ components (CO, NO_2) were not quantified or considered, which limits the insights. Finally, the VOC sensors used can be subject to substantial uncertainty, which is not explored.

Empirical research has shown that dwellings experience regular indoor peaks of pollutants associated with occupant activities, such as cooking (Wang et al., 2022). The peaks and their decay substantially contribute towards occupant exposure (WHO, 2021*a*). The limited evidence described above shows, as expected, that ventilation can reduce the peak concentrations associated with indoor pollutants and

the decay of pollutants over time. Despite the link between ventilation and exposure to peaks, there is a lack of empirical evidence on the relationship between ventilation and short-term exposure to peaks of indoor pollutants.

Furthermore, typically, research concerned with the relationship between IAQ and ventilation describes this relationship using mid- and long-term time averaged exposures to individual pollutants - this is problematic as mid- and long-term average concentrations of a pollutant do not adequately characterise the short-term exposures at specific times (ventilation events/practices) due to the time-varying nature of the pollutants.

Additionally, the long term averages are not relevant for estimating exposure from most longitudinal empirical research, as the literature does not differentiate between occupied and unoccupied periods. Crump (2011); Seals and Krasner (2020) and NICE (2020) call for evidence on the exposures to indoor pollutants in real occupied dwellings, and Seals and Krasner (2020) describe the specific need for understanding peak exposures from gas cooker use.

Research gap 3

There is a lack of empirical evidence of the relationship between ventilation practices and exposure to harmful concentrations of indoor pollutants in occupied homes in the UK.

Table 2.6: Summary of relationship between ventilation and IAQ in other research

Source	Research type	Relationship
Brown et al. (2015)	Monitoring (n = 567) in France.	More often windows open = lower pollutants (4 airborne aldehydes and 16 VOCs) but higher PM.
Coward et al. (2001)	Monitoring (n = 876) in UK.	Higher ventilation in summer = lower NO_2 but higher TVOC.
Vardoulakis et al. (2015)	Literature review.	High air tightness = low AER = higher pollutants.
Tham (2016)	Literature review.	Low ventilation = higher building related illness.
Taylor et al. (2016)	Modelling.	Low AER = higher indoor concentrations of pollutants.
Taylor et al. (2016)	Modelling.	High outdoor pollution (London) + low AER = lower indoor concentrations of pollutants.
Dimitroulopoulou et al. (2005)	Monitoring (n = 37) in UK.	Low AER = higher pollutant concentrations (CO, NO_2, aldehyde and TVOC).
Dimitroulopoulou et al. (2006)	Modelling.	High outdoor pollution (London): low AER = lower NO_2, higher CO and higher PM_{10}
Dimitroulopoulou (2012)	Literature review.	High AER = low humidity.
McKay and Ross (2010)	Monitoring (n = 22)	Higher AER = lower pollutants (RH, TVOCs and HCHO)
MHCLG (2019)	Monitoring (n = 80/54/10 higher detailed monitoring)	Low AER (not achieving ADF2010) = higher pollutants.
Broderick et al. (2017)	Monitoring (n = 15) pre and post retrofit in UK.	Higher air tightness = lower AER = higher pollutants ($PM_{2.5}$, CO_2, CO, formaldehyde, TVOC)
Gupta and Kapsali (2016)	Monitoring (n = 6)	Windows opened more in summer = lower CO_2
Sharpe et al. (2014)	Monitoring (n = 26)	Windows opened more in summer = lower CO_2
Howieson et al. (2014)	Monitoring (n = 20)	Windows closed = higher CO_2
Aizlewood and Dimitroulopoulou (2006)	Monitoring (n = 8)	Higher AER = lower RH, lower TVOC but mixed results for fungi, bacteria and PM_{10}. Higher AER = higher NO_2 (high concentrations outside).

2.2.5.3 Ventilation modifies sound levels and exposure to noise

Indoor noise levels and ventilation are linked in three ways: (1) ventilation equipment itself can generate noise, (2) ventilation allows outdoor sources of sound/noise to ingress the indoor environment, or (3) sound/noise can affect occupants decisions to ventilate.

Noise generated by mechanical ventilation equipment can be a barrier to occupants operating ventilation systems. Research have reported varying amounts of occupants affected by noise from

ventilation equipment in different ways. This is expected, as different installations will produce different sound (frequency and amplitude), be dampened by the fabric in different amounts, and be perceived by occupants in different ways. For example, Baborska-Narożny et al. (2017) found that 23% of participants ventilation systems (MEV in kitchens and bathrooms) were turned off due to noise, but Zero Carbon Hub (2016*a*) found "nearly all" (MEV and MVHR) were turned off due to noise. Similarly, the MHCLG (2019) highlighted concerns raised by participants about noise; some participants did not operate mechanical ventilation systems (MEV) due to the noise they produced. 13% of participants in a large scale survey (n=1,861) of ventilation use in Britain responded that noise from their mechanical ventilation was one barrier to operating it, but only 7% reported it was the single most important barrier (Van Rooyen and Sharpe, 2024).

Buratti (2002) and Locher et al. (2018) carried out controlled experiments of noise in a laboratory and in Swiss dwellings, and both found that the indoor to outdoor sound difference decreased with the amount that a window was opened. For dwellings, this means that when a window or door is opened to outside, the more the window or door is opened, the higher the noise ingress from outdoors to indoors. This noise ingress can affect occupants decisions to ventilate and is a common barrier to occupants opening windows in pursuit of reducing indoor temperatures or improving indoor air quality (NHBC, 2012; PassiveHaus Trust, 2016; CIBSE, 2017).

Andersen et al. (2009) found perceived outdoor noise levels to be a significant predictor of when a window was open in a sample of 933 participants. They also found participants who perceived outdoor noise as high and indoor air quality as low had less windows open than in dwellings where the noise levels were considered quiet - this could suggest that those participants valued indoor noise levels over indoor air quality. Eze et al. (2017) and Bekö et al. (2011) observed lower numbers of open windows in rooms located on noisier roads than quiet roads. Similarly, Howieson et al. (2014) and the MHCLG (2019) found it common that trickle vents were blocked or closed to reduce noise entering inside, particularly in dwellings near roads with traffic noise. Similarly, Sharpe et al. (2014); Evans (2015) and Mavrogianni et al. (2016) all reported that noise was a common reason for participants keeping windows closed. In a large survey of 2,747 people in the UK, 14% reported they would keep their windows closed due to sleep disturbance from noise, and noise was the fourth most frequently reported reason for keeping windows closed, after keeping warm, saving energy, and security (Notley et al., 2014). However, despite the evidence presented here, when a broadly representative sample in Britain (n=1,861) was asked about the single most important barriers to operating their ventilation, most responded that there was no barrier (MEV = 45%, trickle vents = 57% & windows = 32%) (Van Rooyen and Sharpe, 2024). Noise was the most important barrier for only 7% (from ventilation system), 3% (trickle vents - outdoor noise), and 8% (windows - outdoor noise) of respondents (Van Rooyen and Sharpe, 2024).

Locher et al. (2018) reported that outdoor noise levels, window position, room type, room volume,

and building age were the most important factors for indoor noise levels when windows were open in naturally ventilated dwellings. When windows were closed, window frame material, the number of windows, and presence of window gaskets were the most important factors. Other important factors are the angle of sound incidence, orientation of the window, window size, and window opening angle.

Environmental noise can be a barrier to opening windows, which can have implications for indoor air quality and/or indoor overheating, which can affect occupant health and well-being (Lomas and Porritt, 2017). However, we do not know what sound levels people might be willing to accept in the short term to overcome overheating or IAQ events and the potential long-term effects of the compromise that is reached (ANC, 2020*a*).

2.2.5.4 Window angle and IEQ

Window opening angle is an important factor for noise ingress (Locher et al., 2018) and air exchange rates (Howard-Reed et al., 2002; Roetzel et al., 2010); however, there is no published research considering the relationship between the angle windows are opened and the corresponding impact on AER and IEQ. One reason for this, is likely to be the lack of suitable methods for measuring intermediate (or ajar) positions of external windows and doors for longitudinal monitoring campaigns in occupied homes (Liu et al., 2022). The available methods are discussed and evaluated below.

There are two broad categories of methods for recording the status of windows/doors: (1) using people or (2) using equipment/technology.

Researchers or research participants can record window positions at different times of the day, however, this is time and labour intensive and can suffer from low temporal resolution. For example, Fox (2008) visually inspected 120 dwellings a number of times every day, over a year and recorded window positions, where each set of observations took up to two hours. Similarly, other research has used photographs taken at different times of the day to record window positions (Liu et al., 2022). Despite the significant researcher commitment in the previous research, the resulting temporal resolution of the observations were limited by the number (and timing) of observational trips made each day and were not able to determine exactly when a window was opened or closed. Research participants can record each interaction with windows and doors using a diary; however, Kukadia and White (2006) found that participant diaries of window interactions suffered from a lack of completeness and accuracy, as it was not always convenient for participants to record all interactions with windows.

From a technological perspective, electronic reed switch event loggers have been widely used in research since the late 1980s (e.g., Dubrul (1988); Sharpe et al. (2014); Balvedi et al. (2018); Wright et al. (2018)). These devices work by recording the time that a window/door opens/closes and can provide data over long periods of time with a low labour cost (installation, change of batteries, data download at regular intervals) and with ease of use. However, Dubrul (1988) noted that these devices were expensive and not always found to be acceptable to participants. Additionally, a key limitation of

event loggers is that they are not designed to detect how wide a window or door is open (Dubrul, 1988; Few and Elwell, 2019) - they record an event when the magnet is close enough to the internal reed switch. This issue is particularly relevant for noise ingress and energy use, as the event sensor might detect that the window is closed, where it could be open a small amount, giving a misleading measurement. Similarly, event sensors cannot distinguish an ajar from a fully open position. Whether a window is ajar or fully open has a significant impact on noise ingress, air exchange rates, and consequently on overall IEQ and energy consumption. For top and bottom hung windows, electronic accelerometer loggers (see for e.g., Andersen et al. (2013)) can use the degree of tilt to infer how far the window has been opened. However, these can only be used for that specific type of window.

Research gap 4

There is a limited number of methods for accurately measuring positions of windows and doors (particularly intermediate positions) that are suitable for longitudinal monitoring campaigns in occupied homes.

2.2.5.5 Ventilation modifies IEQ, exposure and health

A number of review papers have been published, showing an association between ventilation and comfort, well-being, health, and performance related outcomes in homes and office environments (Wargocki et al., 2002; Sundell, 2004; Li et al., 2007; Sundell et al., 2011; Tham, 2016). In addition to these reviews, there is a growing body of evidence showing a strong positive relationship between ventilation rates and sleep quality (Mishra et al., 2018; Yan et al., 2022; Fan et al., 2022, 2023). Table 2.7 below provides a summary of key review papers that have found an association between ventilation and health.

Table 2.7: Summary of review papers on the relationship between ventilation and health outcomes.

Source	Comments	Reported relationships
Wargocki et al. (2002)	105 papers multidisciplinary review by expert EUROVEN panel	Ventilation strongly associated with comfort (perceived air quality), sick building syndrome symptoms, inflammation, infections, asthma, allergy, short-term sick leave, and productivity (performance of office work)
Sundell (2004)		Low ventilation associated with SBS, allergies, and airway infections
Li et al. (2007)	40 papers	Ventilation strongly associated with transmission/spread of infectious diseases
Sundell et al. (2011)	27 papers	Ventilation associated with multiple health endpoints. Higher ventilation rates associated with reduced SBS. Lower ventilation rates associated with inflammation, respiratory infections, asthma, and sick leave. AER$>0.5h^{-1}$ associated with lower allergic reactions in children

There is strong biological plausibility for the relationship between ventilation and health, and Table 2.7 illustrates the evidence for this; however, the evidence is limited, and there is a lack of evidence demonstrating causality for this relationship (ODPM, 2006; Sundell et al., 2011). Furthermore, there is likely to be a highly complex relationship between health, ventilation, and other causal factors. Further complicating this relationship is the lack of understanding of the additive or synergistic health impacts of simultaneous exposure to the different components of IEQ at timescales that are relevant for ventilation (RCPL, 2016).

The preceding sections in this chapter illustrate an indirect link between ventilation and health. Sections 2.1.1, 2.1.2, and 2.1.3 show that overheating, IAQ, and noise all impact comfort, well-being, and health, and Sections 2.2.5.1, 2.2.5.2, and 2.2.5.3 show that ventilation modifies indoor temperatures, IAQ, and noise. Therefore, ventilation influences IEQ and occupant exposure to indoor temperatures, IAQ, and noise, and as a result, ventilation modifies how the indoor environment affects occupant comfort, well-being, and health (Anderson et al., 2013). Figure 2.7 conceptualises this relationship and shows ventilation as modifying the relationship between occupants (comfort, well-being, and health) and IEQ (overheating, IAQ, and noise).

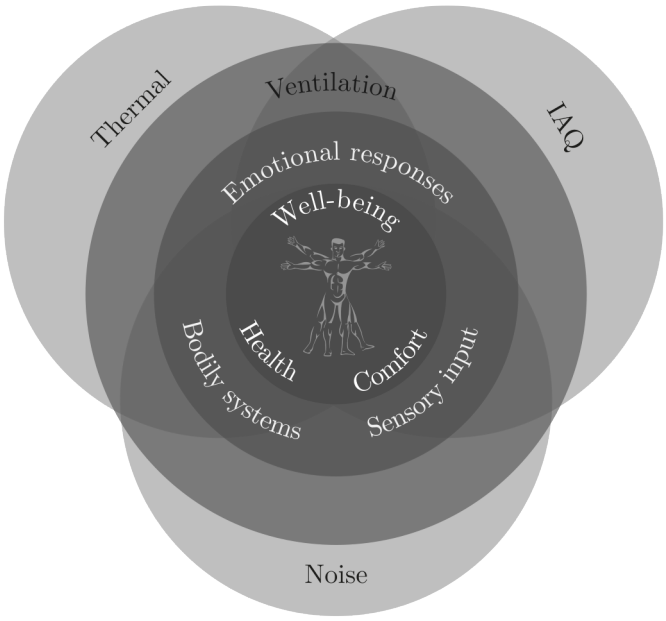


Figure 2.7: Conceptual model of IEQ, ventilation, and health, illustrating the three domains of IEQ and ventilation as a modifier of IEQ on health (adapted from Rohde et al. (2019)).

In addition to this, Figure 2.7 illustrates this interdependent relationship between ventilation, overheating, IAQ, and noise, which is described throughout Sections 2.2.5.1, 2.2.5.2, and 2.2.5.3. Despite these clear interdependences, most research considers the individual components in isolation and does not consider their dependences, synergistic effects, or interactions (Crump, 2011; Sundell et al., 2011; Fabi et al., 2012; Mavrogianni et al., 2015). Tham (2016) describes the substantial challenges associated with addressing IAQ holistically. In addition to this, there is a lack of understanding of how ventilation events, specifically the transition of state of ventilation devices, impact and change each component of IEQ at timescales that are relevant for ventilation (Fabi et al., 2012; AECOM, 2012*b*; Borsboom et al., 2016).

Research gap 5

There is a lack of empirical evidence of the relationship between ventilation practices and the component parts of IEQ when measured together in occupied homes in the UK.

Based on the literature review, Figure 2.8 illustrates the key internal and external factors associated with ventilation, IEQ, and health. This diagram attempts to outline the many relationships and complex interactions between the factors. This diagram highlights numerous potential causal paths for these factors on occupant comfort, well-being, and health. Despite the large number of variables and paths, this diagram is a simplification, and many variables represent numerous sub-variables, each with their own respective relationships. For example, ventilation provisions can be sub divided into trickle vents,

windows and mechanical ventilation, each with their own unique relationships with infiltration and AER. This diagram underlines the complex nature of research into the relationship between ventilation, IEQ, and health, particularly when trying to determine causality where there are many confounding variables.

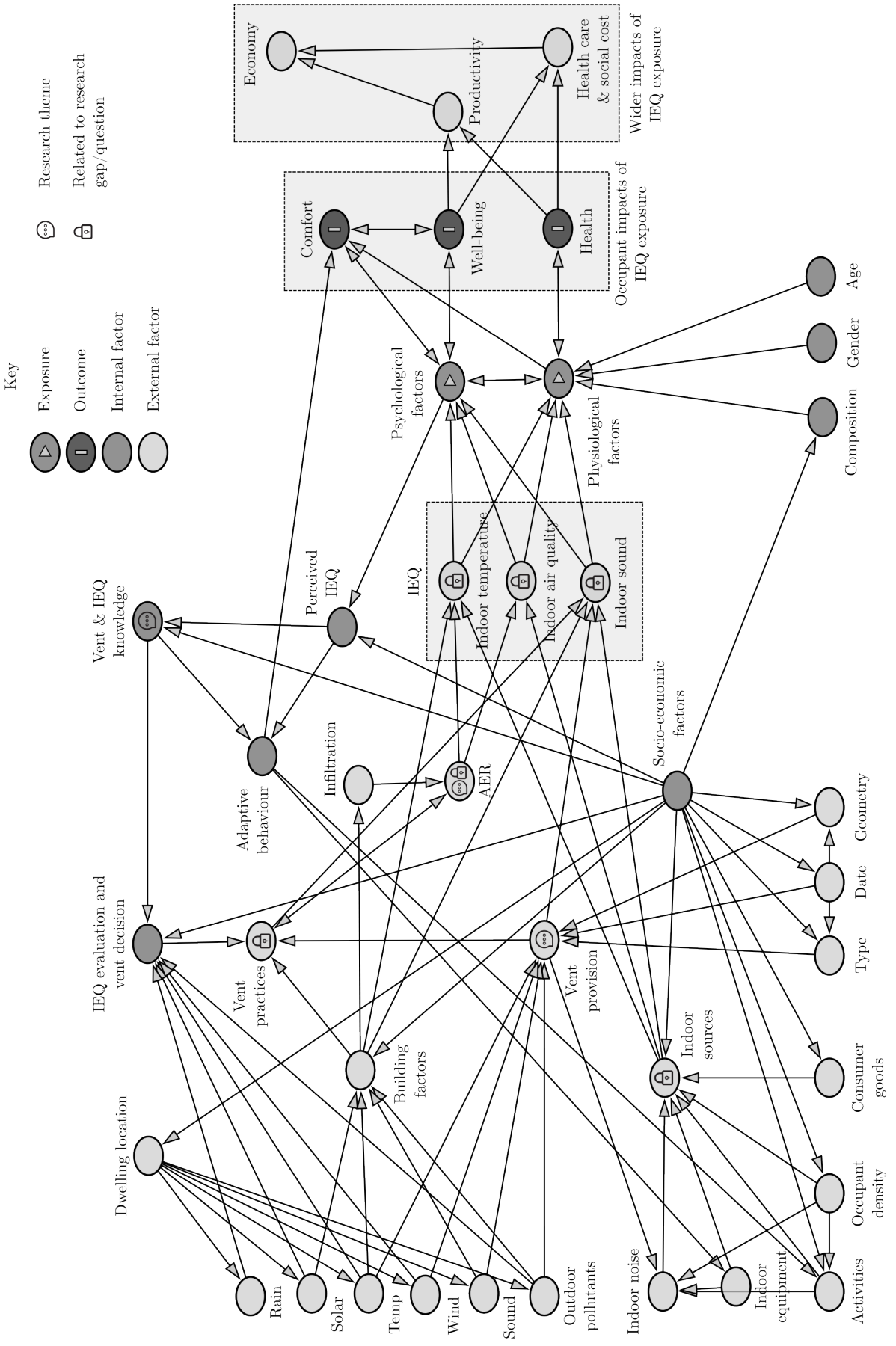


Figure 2.8: Conceptual causal diagram of internal and external factors associated with the relationships between ventilation, IEQ, and health from the literature. Diagram also shows the three key research themes and research gaps.

2.3 Summary, aim, and research questions

The first section of this literature review 'IEQ, exposure, and health' (2.1) illustrated the current understanding and limits of knowledge around the relationship between overheating, indoor air quality, and noise with health. IEQ is shown to have an impact on occupant comfort, well-being, and physical health.

The second section 'Ventilation, AER, IEQ, exposure, and health' (2.2) illustrated the relationship between ventilation and IEQ as well as the indirect relationships between ventilation and occupant comfort, well-being, and physical health. Ventilation practices alter AER and indoor noise, which both directly modify IEQ and occupant exposure to IEQ. Occupants' exposure to IEQ impacts comfort, well-being and physical health. Ventilation therefore directly and indirectly modifies IEQ and occupant comfort. Following on from this, ventilation indirectly modifies occupant well-being and health. These relationships, together with the fact that people in the UK and Europe spend the majority of their time indoors, highlights the importance of research to better understand this relationship in order to develop and evaluate strategies for reducing exposure and protecting the health of occupants.

The sub section on 'Ventilation provision in UK homes' (2.2.1) explored ventilation policy, provision, behaviour, and performance in homes in the UK and Europe. This section included a discussion of how policy to conserve fuel and power and ventilation have changed over a short space of time. There is an increasing body of evidence that recently constructed, insulated, and airtight dwellings have low ventilation rates, increased levels of overheating, and poor IAQ. Despite the improvements in standards for new dwellings, improving the energy efficiency of the existing stock remains a substantial future challenge for the UK. Furthermore, most of the existing stock does not have ventilation provision that meet current standards, which requires careful consideration during energy efficiency upgrades/retrofits. There is a need to better understand the relationship between ventilation, IEQ, and health, so that policy for improving the energy efficiency of existing homes can be aligned with this.

The UK public generally have poor knowledge on the importance of ventilation for health and how to use their ventilation, and when combined with a lack of ventilation provision in most homes, can lead to poor levels of ventilation in homes. There is a growing body of evidence that many UK homes have poor ventilation rates, and this might increase the risk of occupants' exposure to harmful IEQ.

There is a lack of empirical evidence of ventilation practices and AER in occupied homes and a lacking understanding of the relationship between ventilation, AER, and IEQ. The evidence and understanding is particularly limited when considering all components of IEQ together and with ventilation.

The most common form of ventilation in the UK is background ventilation (using trickle ventilators) combined with intermittent mechanical extract ventilation (bathrooms and kitchens) and openable

windows to provide purge ventilation. Occupants' behaviour in dwellings is described as one of the most important factors for ventilation performance and air exchange rates. However, there are many different and complex internal and external factors influencing this behaviour, and this behaviour is poorly characterised. The vast variation in dwellings, ventilation provision, and occupant's behaviour make researching ventilation very challenging.

The first aim of this research is to investigate the relationship between ventilation (practices and AER) and IEQ in occupied homes in the UK, with a focus on exposure to components of the indoor environment that impact health, specifically overheating, indoor air quality, and noise. The second aim of this research is to develop a framework for informing ventilation advice to reduce exposure to (health relevant) peaks of indoor air pollutants. This research therefore aims to develop a detailed understanding of how occupants ventilate their homes, how those practices are related to AER and IEQ, understanding how ventilation is related to exposure to peaks of harmful components of IEQ, and to develop a framework for informing ventilation advice with the overall aim of reducing harm associated with exposure to harmful peaks of pollutants.

Throughout the literature review, five key gaps in knowledge were identified (see pages 79, 85, 90, 94, and 96),and five research questions have been developed to address each of the research questions. The gaps and the corresponding research questions are summarised below:

Research gap 1: There is a lack of empirical evidence of how occupants ventilate their homes when they are occupied and how this varies over time.
Research question 1: How do participants ventilate their homes when they are occupied and how does this vary over time?

Research gap 2: There is a lack of empirical evidence of air exchange rates in occupied homes in the UK and how this varies with ventilation configuration and season.
Research question 2: What are the ventilation rates for common ventilation configurations/practices and are homes in the UK adequately ventilated?

Research gap 3: There is a lack of empirical evidence of the relationship between ventilation practices and exposure to high concentrations of of indoor pollutants in occupied homes in the UK.
Research question 3: What is the relationship between ventilation practices and occupant exposure to indoor pollutants?

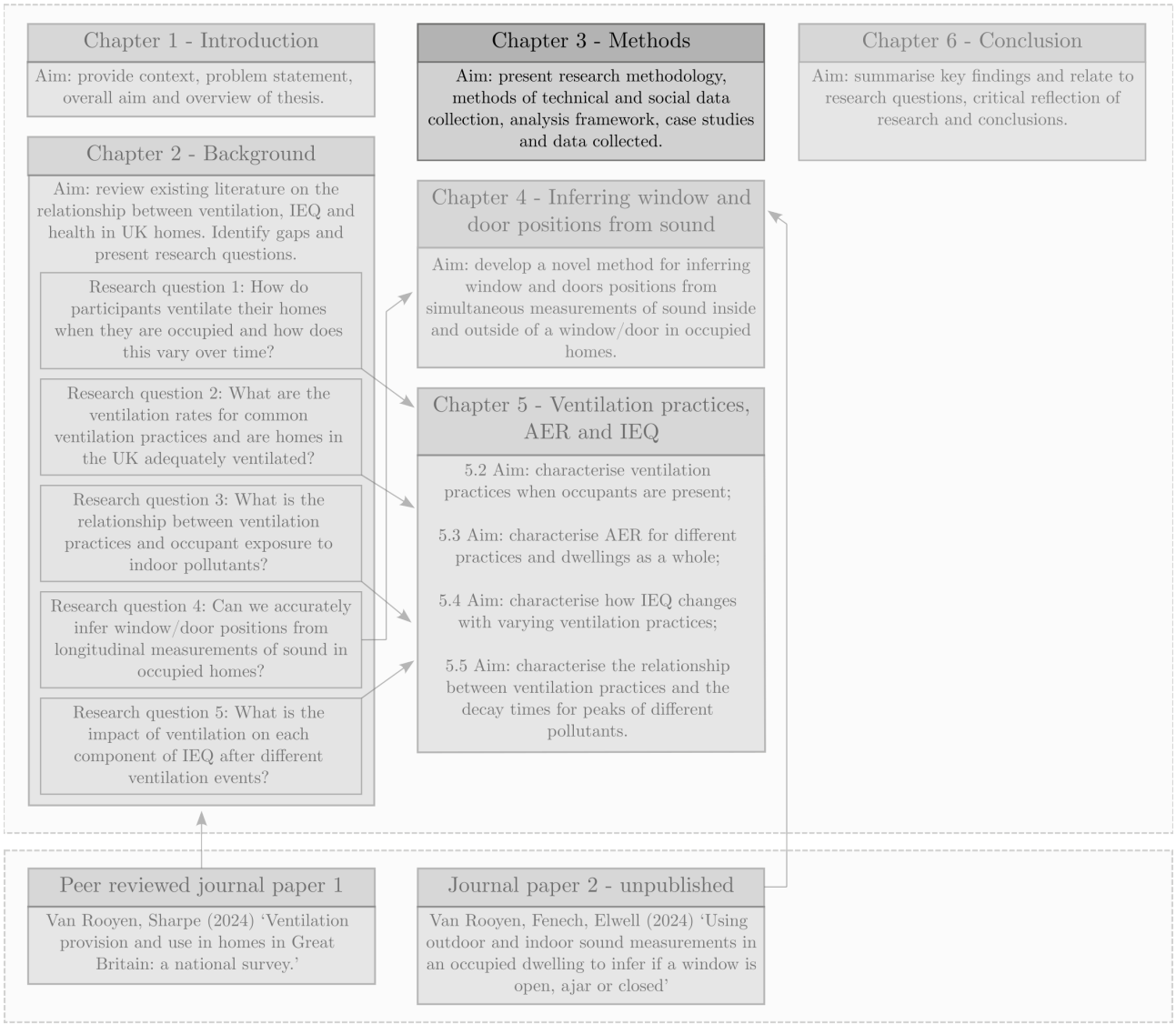
Research gap 4: There are a limited number of methods for accurately measuring positions of windows and doors (particularly intermediate positions) that are suitable for longitudinal monitoring campaigns in occupied homes.

Research question 4: Can we accurately infer window and door positions from longitudinal measurements of sound in occupied homes?

Research gap 5: There is a lack of empirical evidence of the relationship between ventilation practices and the component parts of IEQ when measured together in occupied homes in the UK.
Research question 5: What is the impact of ventilation on each component of IEQ after different ventilation events?

To summarise, this chapter has presented the theoretical, research, and regulatory context for this thesis, key themes and gaps in knowledge were identified, and five research questions were developed, which respond to these gaps in knowledge. The next chapter presents the methodology and methods that were selected to answer these research questions.

3 | Research methodology and methods



The previous chapter presented the context for this research and described ventilation, influenced by occupant and physical factors, as a key modifier of IEQ, exposure, and health. As UK homes are mostly naturally ventilated, ventilation arises from an interaction between human actors (occupants) with the building infrastructure (fans, windows) and physical/environmental conditions (wind, temperature). The research questions (Section 2.3) are primarily technical in nature, however, as ventilation is a enacted by building occupants, there is a need to investigate the social and behavioural components of this interaction in order to bring about a nuanced understanding of ventilation in homes.

The first section of this Chapter (3.1) introduces the concept of buildings as socio-technical systems and argues that a pragmatic mixed methods multi case study approach is appropriate for investigating the relationship between ventilation and IEQ in homes. This pragmatist approach incorporates both the technical and social components described above.

The second section of this chapter (3.2) details the methods and method development and contains a number of sub sections. The first three sub sections (3.2.1, 3.2.2 & 3.2.3) provide details on the methods and equipment used for technical and social measurements, along with justifications for measurements and the equipment/methods used.

Section 3.2.4 presents the 'analysis framework' and provides detailed descriptions of the development of the analysis methods used to answer each of the research questions. Research ethics are discussed in Section 3.2.5. The final section (3.2.6) of this chapter describes participant recruitment, descriptions of the case study dwellings, equipment installation, an overview of the data collected, and a discussion of the impact of the COVID pandemic on the project.

3.1 Research methodology

This section describes the methodological approach taken in this research. To facilitate this description, we conceptualise buildings as 'complex socio-technical systems' (Lowe et al., 2018), comprising of building infrastructure, human actors, and their associated behaviours. When considering ventilation and IEQ as part of this system, this socio-technical system needs to include indoor and outdoor environmental conditions, ventilation practices/behaviour, and IEQ (Lewis et al., 2023). Figure 3.1 presents a simplified version of the complex causal diagram (2.8) from the previous chapter, where variables are grouped to facilitate the discussion below.

The aim of this research is to understand the physical relationship between ventilation and IEQ, where this physical relationship is a result of the interaction between ventilation practices, the building infrastructure and environmental conditions. However, ventilation practices are a result of occupants' interactions with building infrastructure (ventilation systems), and so, researching only the physical relationship would limit the understanding of ventilation in its real life context as part of the complex

socio-technical system. Therefore, in order to bring context and a nuanced perspective to researching the relationship between ventilation and IEQ, it is important to include this social component with the technical component (Love and Cooper, 2015; Lowe et al., 2018; Few, 2021).

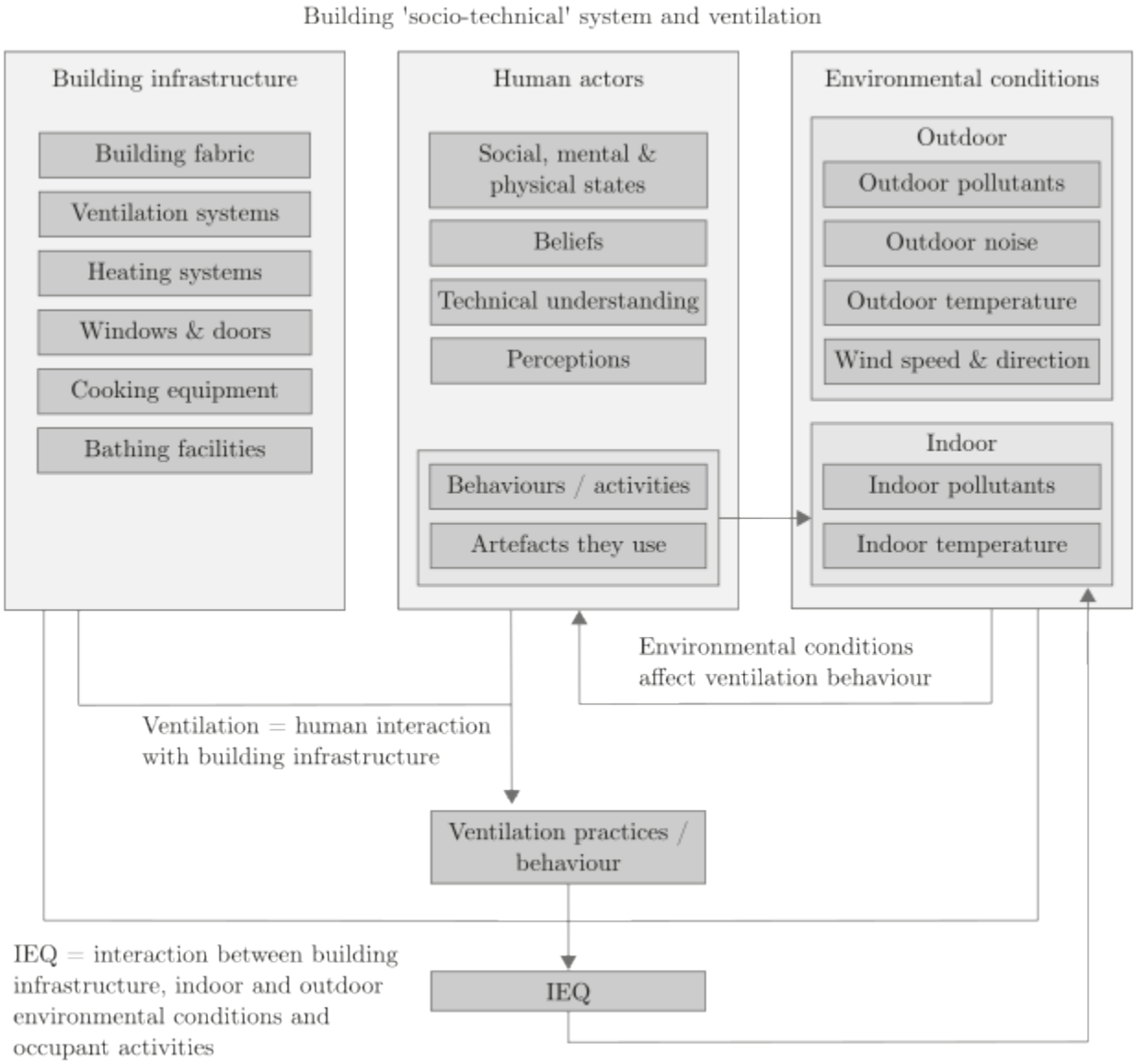


Figure 3.1: Diagram showing the building infrastructure and human actors as part of a complex socio-technical system, along with outdoor environmental conditions and their relationship with ventilation and IEQ.

In order to respond to the aim and research questions, this research adopts the view that reality is objective, independent of the observer (ontology), and that knowledge is real, objective, and obtainable by measurement and statistics (epistemology - reductionism) (Robson, 2011). Thus, the philosophical approach taken to answer the technical research questions is a positivist one (Robson, 2011). The approach taken to understand the relationship between different social factors and ventilation practices takes the view that reality is subjective, dependent on the observer (ontology), and that knowledge is dependent on beliefs, values, and lived experience (epistemology - constructivism). Therefore, the

philosophical approach taken for considering the relationship between social factors and ventilation practices/behaviours is an interpretivist one.

The ontological and epistemological approaches for the physical and social components of this research are two opposing and mutually exclusive philosophical paradigms, and therefore this research uses an overarching pragmatist philosophical approach, drawing from both the positivist and interpretivist paradigms. Additionally, a pragmatist approach is appropriate, as there are no unified/holistic socio-technical theories, models, or frameworks that enable a systematic, integrated analysis for interpreting the quantitative physical measurements of IEQ & ventilation with the qualitative social data. This lack of theory means that this research used inductive reasoning to develop a new understanding of this relationship.

Saunders et al. (2016) research onion concept is used to illustrate and describe the methodological approach taken in this research, and Figure 3.2 shows the positivist onion (main philosophical stance) on the left, with the interpretivist onion (minor/supporting philosophical stance) on the right, with both onions contained within an overarching pragmatist framework.

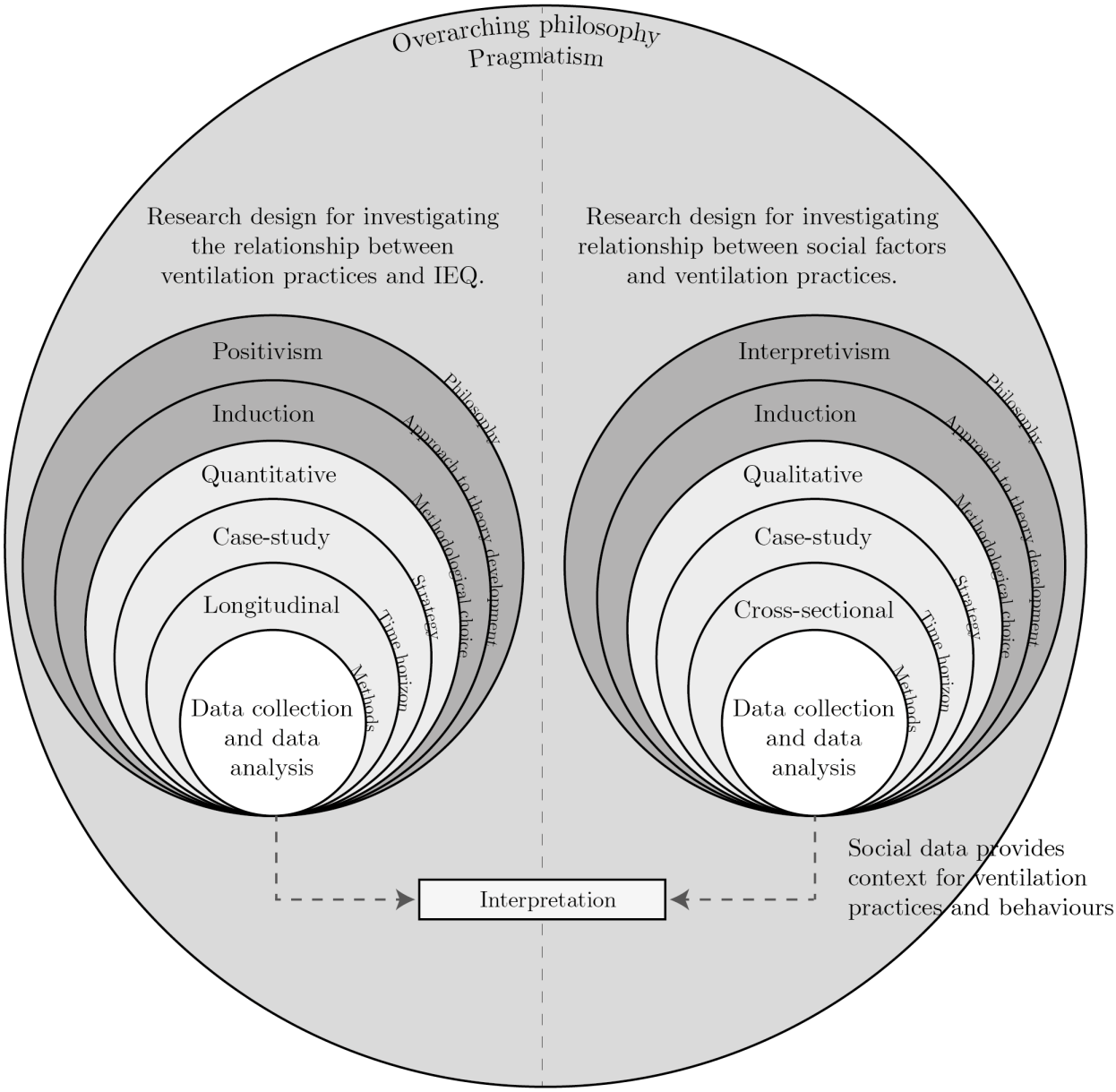


Figure 3.2: Overall research methodology showing the two different research onions (methodologies) and their interaction.

In order to answer the research questions, it was necessary to collect physical measurements of IEQ and record ventilation practices so that the relationship could be quantitatively determined. Modelling was not appropriate for responding to the research aims, which is concerned with characterising the ventilation practices of actual occupants and experienced IEQ in real dwellings. Furthermore, there is an abundance of modelled data and a dearth of empirical data on overheating, IAQ, noise, and ventilation in the UK, and this research responded directly to the calls by Crump (2011); Sundell et al. (2011); AECOM (2012*b*,*a*); Mylona and Davies (2015) for further research on the relationship between ventilation and IEQ derived from primary empirical data. In order to collect data on the social factors associated with the ventilation practices, both quantitative and qualitative social data was collected using the same questionnaire developed for the survey of ventilation provision and use in British homes

(Van Rooyen and Sharpe, 2024). This survey included details of perceived use, drivers, and barriers for ventilation and enables comparison with a larger sample.

This research employed a case study approach, which is "a strategy for doing research which involves an empirical investigation of a particular contemporary phenomenon within its real life context using multiple sources of evidence." Yin (2009) (as cited in Robson 2011). This choice of strategy is justified below.

Section 2.2 in the previous chapter (Figures 2.2, 2.3, 2.4, and 2.6) highlighted that the relationship between ventilation and IEQ involves the complex interaction of numerous internal and external factors. Therefore, in order to disentangle this complex relationship, this research adopted a case study approach, which enabled the careful and detailed exploration of these complex interactions within their real life context (Flyvbjerg, 2006; Yin, 2009).

Empirical research into ventilation and IEQ is necessary to expand our understanding of occupants ventilation behaviour beyond the context independent and simple rule governed acts constrained by a theory only framework (Flyvbjerg, 2006). The detailed investigation of this phenomena using a case study approach in real occupied homes enables this phenomena to be researched in its real context and allows for the "development of a nuanced view of reality" (Flyvbjerg, 2006, p. 223), which can allow our knowledge to "develop from rule-based beginners to virtuoso experts" (Flyvbjerg, 2006, p. 221). Although case study research cannot be readily or simply generalised to a wider population, the detailed investigation of case study research brings about a deeper context dependent understanding of the phenomena. Expert knowledge is gained from context dependent knowledge and the collective knowledge in a particular field is comprised of the accumulative knowledge from many individual cases.

Empirical socio-technical research into ventilation and IEQ is expensive. Buswell et al. (2017) estimated the labour and equipment costs for rolling out a 2 year monitoring campaign to be between £22,000 and £27,000 per house in the UK. Additional costs would need to be factored for analysis and dissemination. The high labour and equipment costs associated with empirical socio-technical research in part might explain why much of the existing research was limited to smaller samples.

Finally, considering timescales, the literature review highlighted that ventilation behaviours are dependent on season and outdoor temperature (2.2.2), therefore, it was important to collect longitudinal measurements of IEQ and ventilation practices over a period of time that included the key seasons (summer and winter) and a range of outdoor temperatures (Liu et al., 2022). Ideally, social data would also be captured with high temporal and spatial resolutions over the same period of time; however, this was not practical, and social data was collected once at a single point in time. The temporal differences in the social and technical data are discussed later in this chapter and also in Section 5.5

The sections below present the methods used to collect data (3.2.1, 3.2.2, 3.2.3), the methods used to analyse the data (3.2.4), the recruitment of and detailed descriptions of the case studies (3.2.6).

3.2 Methods and method development

The previous section of this chapter described the mixed methods approach adopted, which can be broadly categorised as technical and social. The technical methods used in this project were building surveys (3.2.1), measurements of IEQ, windows and doors (3.2.2). A detailed questionnaire (3.2.3) was used to collect social data on the provision and use of ventilation in each case study.

3.2.1 Building survey

In order to provide context and facilitate interpretation of the measurements and questionnaire responses, it was necessary to collect information on the physical characteristics and services of all case studies. Technical building surveys are a widely used method for collecting this type of information and have been used in similar research projects by Mavrogianni et al. (2016); Wright et al. (2018), and MHCLG (2019). Building surveys are typically conducted by trained building surveyors but can also be inferred from photographs or from occupant questionnaires; however, the latter can lead to errors and inaccuracies.

The researcher is experienced in conducting building surveys and conducted detailed surveys at the end of each monitoring campaign, when national COVID restrictions allowed - see timescales in Figure 3.25, on page 151. Risk assessments were completed for conducting the surveys, with specific control measures for COVID-19 infection prevention - for example, pre-survey PCR test, FFP2 mask, hand and equipment disinfecting. Prior to each survey, a checklist was prepared, which provided an aide-mémoire for pre-survey tasks, tasks to complete during the survey, and an equipment checklist to ensure that equipment locations were recorded and removed from each case study. An example of this checklist is provided in appendix C on page 357.

During the survey, a detailed floor plan was prepared and measurements of all rooms and windows were taken using a laser measuring device and tape measure. Locations of all monitoring equipment was documented. The construction materials and details of the building fabric (e.g., glazing, facade materials, etc.) were photographed and recorded. Ventilation devices were inspected and details recorded, including: window type and opening style, how far each window opened, if the windows could be securely 'locked' open (providing secure ventilation), model numbers of all mechanical ventilation equipment and cooker hoods, trickle vent sizes/details/positions and ventilation controls. Other dwelling features that could impact ventilation were also documented, such as: locations and types of blinds/curtains, door undercuts measured and locations of self closing doors. Finally, a subjective assessment of indoor and outdoor sources of heat, air pollutants, and noise/sound was undertaken.

Records were stored in accordance with the data management plan and GDPR requirements (3.2.5 on page 149). All floor plans were drafted into an electronic format using AutoCAD and are presented

along with a description of each case study in Section 3.2.6 (page 150).

3.2.2 Technical data collection

The previous chapter and the previous section argued that empirical measurements of IEQ and ventilation are required to respond to the research questions. This section (3.2.2) describes how these components of IEQ were measured.

3.2.2.1 Temperature and IAQ measurements

Measurands

Section 2.1.2.3 (page 53) in the previous chapter described the many potential component parts of IAQ and identified the most prevalent and important components for occupant health, which are summarised in the list below. This list forms the basis of the measurements taken in this research.

1. Moisture and humidity
2. Particulate matter
3. Tobacco smoke
4. Nitrogen dioxide
5. Carbon monoxide
6. Biological agents
7. VOCs
8. Radon
9. Ozone
10. Sulphur dioxide
11. Carbon dioxide

The case study dwellings were located in London and Oxford, which both have low background levels of radon (UKHSA, 23/08/2022). Similarly, ambient concentrations of SO_2 are low in London (1.5 - 3 $\mu g.m^{-3}$ - Air Quality England (2022)) and substantially lower than the WHO (2021*a*) guideline values (40 $\mu g.m^{-3}$). Due to the lack of significant indoor or outdoor sources, both radon and SO_2 were not measured.

The case studies were located in environments near roads (discussed in Section 3.2.6.4), where vehicle emissions scavenge ozone, resulting in low potential for outdoor sources. Additionally, indoor sources of ozone were expected to be low. Ozone was not measured and remains a limitation of the technical monitoring. The questionnaire described in Section 3.2.3 and the building surveys collected data on prevalence of damp and mould.

Of the IEQ components identified above, the temporal and spatial variation of relative humidity, particulate matter, nitrogen dioxide, carbon monoxide, TVOCs, and carbon dioxide were quantified

through the use of technical monitoring equipment. Below are details of where, when, and how these measurements were taken.

Location of measurement within homes

This research is concerned with ventilation and IEQ from the perspective of occupants' health, and therefore, monitoring of IEQ is important in all spaces which people occupy and are exposed to IEQ. People spend the longest uninterrupted periods at home in their bedrooms, which equates to between 7 and 8 hours a day (Sharpe et al., 2014). Bedrooms are particularly important for young, elderly, and infirm occupants, who are likely to spend longer than this in their bedrooms. In addition to bedrooms, kitchens and bathrooms contain important sources of pollutants, particularly peaks of pollutants, that are associated with occupants' activities.

The previous chapter outlined that ventilation can cause the movement of pollutants between the indoor and outdoor environments, and also that outdoor conditions are an important driver and barrier for ventilation behaviour. Therefore, measurements of the outdoor environment were necessary to identify relative concentrations and likely sources of pollutants, as well as potential barriers and drivers for behaviours.

With the introduction of national lockdowns throughout the UK at the time of monitoring (see timescales in Figure 3.25, on page 151), people were expected to remain indoors and at home most of the time. None of the participants worked in protected occupations and were not required to travel to work, therefore were present in their homes for most of the monitoring in this research. The lockdown(s) resulted in homes transforming into workplaces and make-shift schools, with people spending almost all of their time in their homes and using spaces for different and multiple purposes/activities. This meant it was important to include the main spaces that the occupants were present in for most of the time they were in their homes, in order to capture data relevant to their exposure. However, an important limitation to state here is that this research, and much other research, does not capture information on the temporal and spatial movement of occupants in their homes and is therefore unable to accurately relate IEQ measurements to personal exposure.

In this research, measurements were taken in bedrooms, living rooms, kitchens, and bathrooms. The next Section (3.2.2.2) describes the equipment used in each room type, and Section 3.2.6.4 provides detailed floor plans for each case study, showing the locations of equipment, and Section E presents schematic drawings showing the various measurements for each space in each case study.

Finally, the literature review (2.2.2) identified season as a key factor for ventilation behaviour, and therefore, the monitoring was planned to take place over longitudinal monitoring campaigns covering as much of the winter and summer seasons as possible. Figure 3.25, on page 151, provides an overview of the monitoring campaign durations for each case study.

Measurement instrumentation

Due to the specific considerations described below and equipment availability, a range of different

equipment was deployed to the case studies.

In living spaces, kitchens, and outdoors, Eltek AQ110A instruments (Figures 3.3a, 3.3b, and 3.3c) were used to measure all of the previously identified priority pollutants, namely: temperature, relative humidity, carbon monoxide, carbon dioxide, particulate matter ($PM_1, PM_{2.5}, PM_{10}$), nitrogen dioxide, and VOCs. The AQ110A were placed inside of a weatherproof box (Figure 3.3c) to enable measurements outdoors, and a bespoke 12V 'ribbon cable' was manufactured (Figure 3.3f) to allow power to be routed through a closed window/door. Eltek AQ110A instruments have been used in IEQ research (Stamp et al., 2021, 2022; Wang et al., 2022a; Wang et al., 2022b), and the Alphasense gas sensors within these instruments are also used in other equipment (Cross et al., 2017; Jain et al., 2019; Asumadu-Sakyi, 2019; Few, 2021; Tryner et al., 2021; Du et al., 2021; Sá et al., 2022; Tahmasebi et al., 2022) and Chatzidiakou et al. (2019).

Eltek AQ110A and GD47AC instruments were paired by radio frequency to a SRV250 logger (Figure 3.3e), which has a 3G modem. The modem was configured to upload IEQ measurements to an Amazon EC2 server every 10 to 30 minutes (varied to avoid clashes between different loggers). A second virtual Linux server was configured to backup data, check data, and provide a web based graphing function using an Influx time series database (InfluxData, 12/08/2022) and Grafana graphing dashboard (Grafana Labs, 16/08/2022). This graphing facility enabled the daily checking of all data streams for missing and erroneous data. Furthermore, a Python script was developed to check incoming data every hour for any missing data and send email notifications if data was missing. A number of instances occurred throughout the campaigns where equipment was accidentally turned off or there were electrical power cuts, and this code enabled the timely resolution and prevented any substantial loss in data. The time series database, graphing functions, and checking scripts have been uploaded to GitHub (https://github.com/cairanvanrooyen) and publicly shared for other researchers to make use of (Van Rooyen, 2021).

It was not possible to measure particulate matter in bedrooms as the PM sampling fans produced a high pitched noise, this limited the equipment to the Onset HOBO MX1102 (Figure 3.4b) or Eltek GD47AC (Figure 3.3d), which measured temperature, relative humidity, and carbon dioxide. Onset HOBO MX1102 and Eltek GD47AC have been used in other IEQ research by (Ortiz, 2019; Men et al., 2020; Few, 2021; Wang, Cooper, Tahmasebi, Taylor, Stamp, Symonds, Burman and Mumovic, 2022). Of the important components of IAQ previously identified, bedrooms were not expected to contain substantial sources of carbon monoxide or nitrogen dioxide but could have sources of VOCs from personal hygiene products and other consumer goods. However, due to equipment availability, it was not possible to measure VOCs in bedrooms, which is a limitation of this monitoring campaign.

Due to practical constraints and electrical safety it was not possible to install mains powered equipment in wet spaces. Battery powered ONSET HOBO U12-012 (Figure 3.4c) loggers were used to measure temperature, relative humidity, and light levels in all bathrooms - these devices are widely

used in IEQ research (Gauthier and Shipworth, 2014; Mavrogianni et al., 2015; Pathan et al., 2017; Mavrogianni et al., 2016; Hviid et al., 2019; Asumadu-Sakyi, 2019; Du et al., 2021; Ahmed et al., 2022). Many wet spaces have extract fans that are operated by a light switch, and it was expected that light measurements would enable mechanical ventilation operation to be inferred. However, in practice, the majority of bathrooms also had exterior windows, making it challenging to disentangle daylight from artificial light.

A 5 minute logging interval was selected for all measurements. This logging interval is a compromise between data storage, battery life, disruption to participants (replacement due to battery and internal memory), and cost. However, this logging interval is considered relevant for capturing the variation of ventilation and IEQ parameters and is widely used in other research (Claude-Alain and Foradini, 2002; Few and Elwell, 2019; Few et al., 2019; Few, 2021; Ortiz, 2019; MHCLG, 2019; Wang, Cooper, Tahmasebi, Taylor, Stamp, Symonds, Burman and Mumovic, 2022; Kim et al., 2022).

Table 3.1 provides a summary of the monitoring instruments and the manufacturers stated accuracies. Table 3.2 provides details of the IAQ sensors drift and life.

Table 3.1: Stated accuracy for all instruments and their sensors

Instrument (Sensor)	Measurand	Accuracy
Eltek AQ110 (No data)	Temperature	± 0.5°C (5°C to 45°C)
Eltek AQ110 (No data)	Humidity	± 2% (10 to 90% RH)
Eltek AQ110 (Alphasense OPC-N3)	PM1 (0-1 μm)	No data
Eltek AQ110 (Alphasense OPC-N3)	PM2.5 (1-2.5 μm)	No data
Eltek AQ110 (Alphasense OPC-N3)	PM10 (2.5-10 μm)	No data
Eltek AQ110 (Alphasense CO-A4)	Carbon monoxide	220 to 275 nA/ppm @ 2ppm [1]
Eltek AQ110 (No data)	Carbon dioxide	< ± 50ppm + 3% of measured value
Eltek AQ110 (Alphasense NO2-A43F)	Nitrogen dioxide	-175 to -450 nA/ppm @ 2ppm [1]
Eltek AQ110 (Alphasense PID-AH2)	Total VOC	No data
Eltek GD47AC (No data)	Temperature	± 0.4°C (-5°C to 40°C)
Eltek GD47AC (No data)	Humidity	± 2% (10 to 90% RH) ± 4% (0 to 100% RH)
Eltek GD47AC (No data)	Carbon dioxide	< ± 50ppm + 3% of measured value
HOBO MX1102A	Temperature	± 0.21 °C from 0°C to 50°C
HOBO MX1102A	Humidity	± 2% from 20% to 80% typical to a maximum of ± 4.5% including hysteresis at 25°C; below 20% and above 80% ±6% typical
HOBO MX1102A	Carbon dioxide	±50 ppm ±5% of reading at 25°C , less than 90% RH non-condensing and 1,013 mbar
HOBO U12-012	Temperature	± 0.35°C (0°C to 50°)
HOBO U12-012	Humidity	± 2.5% from 10% to 90% typical to a maximum of ± 3.5% including hysteresis at 25°C; below 10% and above 90% ±5% typical
HOBO U12-012	Light	Designed for relative light level measurements
HOBO UX90-001M	State/time	± 1 minute per month at 25°C
RPi Noise	Sound	See Section 3.2.2.6

[1] Note 1: Nanoamperes per part per million of concentration.

Table 3.2: Sensor drift and sensor life of the integral Eltek AQ110 air quality sensors

Sensor	Zero drift	Sensitivity Drift	Operating Life
Alphasense CO-A4	< ± 100 PPB change/year	< 10 % change/year	> 36 months until 50% original signal (24 months warranted)
Alphasense NO2-A43F	0 to 20 PPB change/year	< -20 to -40 % change/year	> 24 months until 50% original signal (24 months warranted)



(a) Eltek AQ110A transmitter.



(b) Eltek AQ110A transmitter, with the case open, showing the sensors.



(c) Eltek AQ outdoor enclosure (with AQ110A inside) and ribbon cable below.



(d) Eltek GD47AC transmitter.



(e) Eltek Squirrel SRV250 logger.



(f) Ribbon cable manufactured to provide power to outdoor AQ110A.

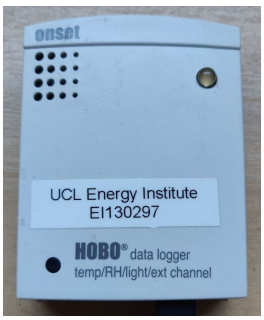
Figure 3.3: Photographs of Eltek equipment.



(a) Onset UX90-001M event sensor/logger and magnet installed on a window.



(b) Onset HOBO MX1102 sensor/logger.



(c) Onset HOBO U12-012 sensor/logger.

Figure 3.4: Photographs of Onset equipment

3.2.2.2 Temperature and IAQ instrument co-location and cross comparison

This section describes the methods which were used to compare and check measurements from field instruments with reference instruments ('co-location'). A number of different error types are discussed below, and Figure 3.5 provides a reference illustration of the common types of sensor/measurement error alongside the ideal response of the sensor/instrument.

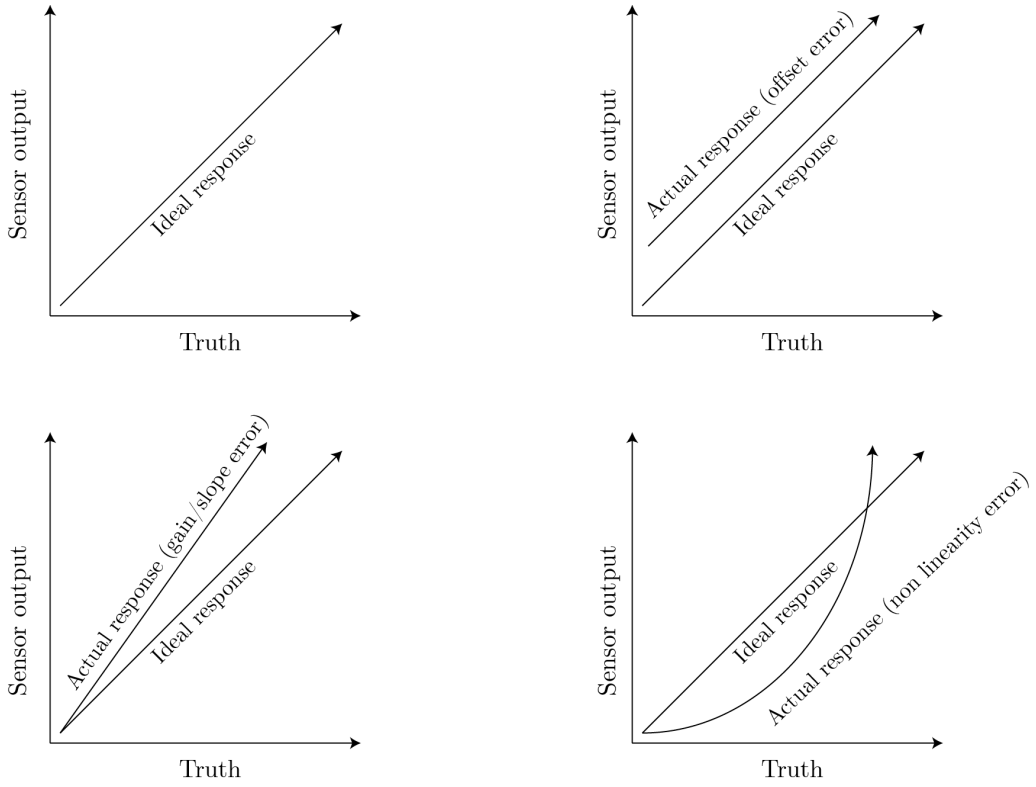


Figure 3.5: Examples of sensor error.
Examples of different forms of sensor error, showing the ideal response from the sensor output for the measured parameter (top left), offset error (top right), gain/slope error (bottom left), and non-linear error (bottom right) (reproduced from Adafruit Learning System (2021)).

Ideally, prior to field monitoring, all field instruments and all sensors would be sent to the manufacturers or a specialist certified laboratory to check all sensor outputs against certified, calibrated reference instruments ('truth'). Depending on the nature of the error (see Figure 3.5), the laboratory would adjust and calibrate the measurements across the operational range of the sensors. This process can be time-consuming, and for instruments with multiple sensors, this can be complex and costly.

Due to project timescales, cost constraints, and national COVID lockdown restrictions, it was not possible to have all sensors in all measurement devices calibrated prior to the field work (see Figure 3.25). Instead, all instruments were co-located with each other for a period of two weeks in the researchers home prior to and following the main campaign. Additionally, following the campaign, all instruments were co-located with a calibrated TSI Q-Trak indoor air quality monitor (7575), with 982 (carbon monoxide) and 986 (TVOC) probes and a TSI DustTrak aerosol monitor - these two TSI instruments are referred to as the 'reference instruments' hereafter. Figure 3.6 is a photo of the

post-campaign co-location of all field instruments with the Q-Trak. Co-locating in an environment that has conditions representative of those measured during the monitoring campaign has an advantage over laboratory calibrations, as this exposes the sensors to actual indoor pollutants in similar temperatures and humidities as the main monitoring (Chatzidiakou et al., 2019). However, a key limitation of conducting co-location in an occupied setting and for a limited time period, is that it is not possible to expose the sensors to the full range of environmental conditions, particularly high and low temperatures and high concentrations of hazardous pollutants. The resulting dataset was highly skewed, with many observations at low concentrations and very few at mid/high concentrations, and if this was used for creating a correction model, the resulting linear model error calculations would be disproportionately affected by the small number of high concentrations. Chatzidiakou et al. (2019) explain that the linear models for corrections should (ideally) "not be extrapolated beyond the range of the observations (including meteorological conditions)", and therefore, in this research, the results of the co-location data are used to explore the drift and uncertainty in the measurements within the available ranges and not used to correct the raw measurements.



Figure 3.6: Photograph showing the post-campaign co-location of all field equipment with the TSI Q-Trak (reference) IAQ instrument.

Stamp et al. (2021) and Chatzidiakou et al. (2019) compared measurements from field instruments with each other (inter-comparison) and with reference instruments using a range of different metrics, including Pearsons correlation (R^2), root mean squared error (RMSE), mean bias error (MBE) and means. The same approach is used in this research to carry out inter-comparison pre-campaign and both inter comparison and comparison with reference instruments post-campaign.

Table 3.3 shows the numerical results of the analysis, comparing the temperature measurements from all field instruments with the reference instruments and with each other (inter-comparison). Following the measurement campaigns, the sensors were exposed to temperatures between 19 and 27°C ($\bar{T}$ = 23°C, σ_T = 1.1°C), which is representative of indoor temperatures for most case studies. However,

Table 3.3: Table showing the results of inter-comparison and comparison with reference for temperature for the different types of instruments.

Instrument	Quoted accuracy	Comparison to reference	Inter-comparison
U12-012 (n=18)	± 0.35°C (0°C to 50°)	$\bar{T}_{ref}$ = 23.0 °C $\bar{R}^2$ = 0.91 (0.80-0.97) $\bar{RMSE}$ = 0.6 (0.3-1.2) °C $\bar{MAE}$ = 0.5 (0.2-1.1) °C	$\bar{T}_{inter}$ = 23.2 °C $\bar{R}^2$ = 0.98 (0.93 - 1.00) $\bar{RMSE}$ = 0.4 (0.2-0.7) °C $\bar{MAE}$ = 0.4 (0.1-0.7) °C
MX1102 (n=7)	± 0.21°C (0°C to 50°)	$\bar{T}_{ref}$ = 23.0 °C $\bar{R}^2$ = 0.91 (0.86-0.96) $\bar{RMSE}$ = 0.6 (0.3-0.8) °C $\bar{MAE}$ = 0.5 (0.2-0.7) °C	$\bar{T}_{inter}$ = 23.3 °C $\bar{R}^2$ = 0.98 (0.97 - 0.99) $\bar{RMSE}$ = 0.3 (0.2-0.5) °C $\bar{MAE}$ = 0.3 (0.2-0.5) °C
AQ110A (n=11)	± 0.5°C (5°C to 45°)	$\bar{T}_{ref}$ = 23.0 °C $\bar{R}^2$ = 0.97 (0.92-0.99) $\bar{RMSE}$ = 0.6 (0.3-0.9) °C $\bar{MAE}$ = 0.5 (0.2-0.9) °C	$\bar{T}_{inter}$ = 23.5 °C $\bar{R}^2$ = 0.97 (0.95 - 0.98) $\bar{RMSE}$ = 0.3 (0.2-0.5) °C $\bar{MAE}$ = 0.3 (0.1-0.4) °C
GD47AC (n=8)	± 0.4°C (-5°C to 40°)	$\bar{T}_{ref}$ = 23.0 °C $\bar{R}^2$ = 0.93 (0.91-0.95) $\bar{RMSE}$ = 1.5 (1.0-1.9) °C $\bar{MAE}$ = 1.4 (1.0-1.8) °C	$\bar{T}_{inter}$ = 24.4 °C $\bar{R}^2$ = 0.98 (0.98 - 0.99) $\bar{RMSE}$ = 0.9 (0.5-1.3) °C $\bar{MAE}$ = 0.9 (0.4-1.3) °C

these temperatures were not representative of outdoor temperatures, which often exceed this range. There is a high correlation between each instrument and the mean of all instruments ($\bar{R}^2$ = 0.97 to 0.98) and a high correlation between each instrument and the reference instrument ($\bar{R}^2$ = 0.91 to 0.97). The average MAE between all of the U12-012 & AQ110A vs reference instruments is comparable with the stated accuracy, but the average MAE is much higher than the stated accuracy for all of the MX1102 & GD47AC vs reference instruments (0.5°C vs 0.2°C and 1.4°C vs 0.4°C respectively). Table 3.3 highlights that there is greater uncertainty for temperature in bedrooms (GD47AC), particularly when the temperature difference (guideline and measurements) was less than 1.5 °C.

Following the measurement campaign, the sensors were exposed to relative humidity of between 34% and 78% ($\bar{RH}$ = 57%, σ_{RH} = 7%), providing a range of relative humidity representative of typical indoor RH for most case studies. Similar to above, Table 3.4 shows the results of comparing the relative humidity measurements from the field instruments with each other and the reference instrument. This shows a high level of correlation between each instrument and the mean RH of all instruments ($\bar{R}^2$ = 0.99) and a high level of correlation between each instrument and the reference ($\bar{R}^2$ = 0.97 to 0.99). Most instruments have an average MAE close to or below their stated accuracy, apart from the U12-012 and GD47AC instruments, which has an average MAE higher than their stated accuracy. Table 3.4 highlights that the uncertainty of the measurements is small when compared to the range of relative humidity the sensors were exposed to. Differences in RH, of less than 4%, should be treated with care.

Table 3.4: Table showing the results of inter-comparison and comparison with reference for relative humidity and the different types of instruments.

Instrument	Quoted accuracy	Comparison to reference	Inter-comparison
U12-012 (n=18)	± 2.5% (10% to 90%)	$\bar{RH}_{ref}$ = 57 % $\bar{R}^2$ = 0.97 (0.92-0.99) $\bar{RMSE}$ = 4 (2-8) % $\bar{MAE}$ = 3 (2-7) %	$\bar{RH}_{inter}$ = 60 % $\bar{R}^2$ = 0.99 (0.96 - 1.00) $\bar{RMSE}$ = 2 (1-6) % $\bar{MAE}$ = 2 (1-6) %
MX1102 (n=7)	± 2% (20% to 80%)	$\bar{RH}_{ref}$ = 57 % $\bar{R}^2$ = 0.97 (0.96-0.99) $\bar{RMSE}$ = 3 (3-3) % $\bar{MAE}$ = 3 (2-3) %	$\bar{RH}_{inter}$ = 60 % $\bar{R}^2$ = 0.99 (0.90 - 1.00) $\bar{RMSE}$ = 2 (1-3) % $\bar{MAE}$ = 1 (1-2) %
AQ110A (n=11)	± 2% (10% to 90%)	$\bar{RH}_{ref}$ = 57 % $\bar{R}^2$ = 0.99 (0.97-1.00) $\bar{RMSE}$ = 1 (1-2) % $\bar{MAE}$ = 1 (1-2) %	$\bar{RH}_{inter}$ = 57 % $\bar{R}^2$ = 0.99 (0.99 - 0.99) $\bar{RMSE}$ = 2 (1-2) % $\bar{MAE}$ = 1 (1-2) %
GD47AC (n=8)	± 2% (10% to 90%)	$\bar{RH}_{ref}$ = 57 % $\bar{R}^2$ = 0.98 (0.97-0.99) $\bar{RMSE}$ = 4 (2-5) % $\bar{MAE}$ = 3 (1-5) %	$\bar{RH}_{inter}$ = 54 % $\bar{R}^2$ = 0.99 (0.99 - 1.00) $\bar{RMSE}$ = 4 (2-6) % $\bar{MAE}$ = 4 (2-6) %

Further to the monitoring campaign, the sensors were exposed to CO_2 concentrations between 423 and 1,358ppm ($\bar{CO}_2$ = 560ppm, σ_{CO_2} = 139ppm). These conditions are representative of low/mid range of indoor CO_2 from most case studies ($\bar{CO}_2$ = 775ppm, σ_{CO_2} = 388ppm), but not representative of the high indoor CO_2 concentrations observed in some case studies (up to 5,000ppm). Table 3.5 shows the results of comparing the CO_2 measurements from the field instruments with each other and the reference instrument. This shows a high level of correlation between the instruments and the mean CO_2 of all instruments ($\bar{R}^2$ = 0.99-1.00) and the instruments and the reference ($\bar{R}^2$ = 0.99). The average MAE of all instruments is below the quoted accuracy.

During the post-campaign co-location, the sensors were exposed to concentrations of PM_1 between 0 and 109μg.m^{-3} ($\bar{PM}_1$ = 1.3μg.m^{-3}, σ_{PM_1} = 3.5μg.m^{-3}), $PM_{2.5}$ between 0 and 120μg.m^{-3} ($\bar{PM}_{2.5}$ = 1.5μg.m^{-3}, $\sigma_{PM_{2.5}}$ = 3.7μg.m^{-3}), and PM_{10} between 0 and 126μg.m^{-3} ($\bar{PM}_{10}$ = 2.2μg.m^{-3}, $\sigma_{PM_{10}}$ = 4.6μg.m^{-3}). The mean concentrations of particulate matter during the post-campaign co-location was approximately half of that measured during the main monitoring campaign ($\bar{PM}_1$ = 3.8μg.m^{-3}, $\bar{PM}_{2.5}$ = 5.7μg.m^{-3}, $\bar{PM}_{10}$ = 11.4μg.m^{-3}) and with limited elevated concentrations. The consequence is that it was not possible to investigate the uncertainty of measurements of elevated concentrations of particulate matter.

Table 3.5: Table showing the results of inter-comparison and comparison with reference for CO_2 and different types of instruments.

Instrument	Quoted accuracy	Comparison to reference	Inter-comparison
MX1102 (n=7)	± 50ppm	$C\bar{O}_{2\text{ref}}$ = 560 ppm $\bar{R}^2$ = 0.99 (0.98-0.99) $R\bar{M}SE$ = 54 (33-69) ppm $M\bar{A}E$ = 48 (26-65) ppm	$C\bar{O}_{2\text{inter}}$ = 512 ppm $\bar{R}^2$ = 0.99 (0.98 - 0.99) $R\bar{M}SE$ = 32 (22-42) ppm $M\bar{A}E$ = 27 (17-39) ppm
AQ110A (n=11)	± 50ppm	$C\bar{O}_{2\text{ref}}$ = 560 ppm $\bar{R}^2$ = 0.99 (0.99-0.99) $R\bar{M}SE$ = 48 (18-129) ppm $M\bar{A}E$ = 43 (14-128) ppm	$C\bar{O}_{2\text{inter}}$ = 535 ppm $\bar{R}^2$ = 1.00 (1.00 - 1.00) $R\bar{M}SE$ = 40 (9-102) ppm $M\bar{A}E$ = 39 (7-101) ppm
GD47AC (n=8)	± 50ppm	$C\bar{O}_{2\text{ref}}$ = 560 ppm $\bar{R}^2$ = 0.99 (0.99-0.99) $R\bar{M}SE$ = 46 (26-93) ppm $M\bar{A}E$ = 40 (18-90) ppm	$C\bar{O}_{2\text{inter}}$ = 546 ppm $\bar{R}^2$ = 1.00 (0.99 - 1.00) $R\bar{M}SE$ = 43 (13-65) ppm $M\bar{A}E$ = 42 (10-64) ppm

Table 3.6: Table showing the results of inter-comparison and comparison with reference for $PM_{1,2.5\&10}$ and AQ110's.

Instrument	Quoted accuracy	Comparison to reference	Inter-comparison
AQ110A (n=11) PM_1	No data	$P\bar{M}_{1\text{ref}}$ = 1.3 μg.m^{-3} $\bar{R}^2$ = 0.58 (0.48-0.68) $R\bar{M}SE$ = 3.0 (2.4-3.4) μg.m^{-3} $M\bar{A}E$ = 1.6 (1.3-2.1) μg.m^{-3}	$P\bar{M}_{1\text{inter}}$ = 1.6 μg.m^{-3} $\bar{R}^2$ = 0.94 (0.88 - 0.97) $R\bar{M}SE$ = 1.0 (0.4-1.4) μg.m^{-3} $M\bar{A}E$ = 0.7 (0.2-1.1) μg.m^{-3}
AQ110A (n=11) $PM_{2.5}$	No data	$P\bar{M}_{2.5\text{ref}}$ = 1.5 μg.m^{-3} $\bar{R}^2$ = 0.59 (0.47-0.71) $R\bar{M}SE$ = 2.4 (2.7-4.1) μg.m^{-3} $M\bar{A}E$ = 2.3 (1.8-3.1) μg.m^{-3}	$P\bar{M}_{2.5\text{inter}}$ = 3.0 μg.m^{-3} $\bar{R}^2$ = 0.91 (0.81 - 0.97) $R\bar{M}SE$ = 1.1 (0.7-1.6) μg.m^{-3} $M\bar{A}E$ = 0.7 (0.4-1.1) μg.m^{-3}
AQ110A (n=11) PM_{10}	No data	$P\bar{M}_{10\text{ref}}$ = 2.2 μg.m^{-3} $\bar{R}^2$ = 0.59 (0.37-0.72) $R\bar{M}SE$ = 7.9 (5.2-9.5) μg.m^{-3} $M\bar{A}E$ = 5.0 (3.3-6.1) μg.m^{-3}	$P\bar{M}_{10\text{inter}}$ = 6.8 μg.m^{-3} $\bar{R}^2$ = 0.74 (0.55 - 0.83) $R\bar{M}SE$ = 5.4 (4.0-7.4) μg.m^{-3} $M\bar{A}E$ = 3.1 (2.5-4.1) μg.m^{-3}

Field and reference instruments measuring different sizes:
Alphasense OPC-N2 measures 0.3μm to 17μm
Dusktrak 8533 measures 0.1μm to 15μm.

Table 3.6 shows the results of comparing the $PM_{1,2.5\&10}$ measurements from the field instruments with each other and the reference instrument. Generally, there is a high level of correlation between the field instruments and the mean of the field instruments ($\bar{R}^2 = 0.74$ to 0.94). However, the correlation between the field instruments and the reference instrument is lower ($\bar{R}^2 = 0.58$ to 0.59). The correlation values for PM_1 and PM_{10} with the reference instruments are similar to those reported by Stamp et al. (2021), which use the same PM sensor. However, correlation between $PM_{2.5}$ and the reference instrument is lower than reported by Stamp et al. (2021). The performance of these PM sensors relative to reference instruments has been shown to have high variability and is subject to a number of factors surrounding the environment and data collection procedures (Chatzidiakou et al., 2019; Stamp et al., 2021). Stamp et al. (2021) explained that particles exposed to high humidity experience hygroscopic growth, which leads to mass overestimation, and as there is no particle drier in the AQ110 instruments, PM measurements where RH > 85% (88% in Stamp et al. (2022)) are filtered out - this has been implemented throughout this research. A key possible reason for lower correlations between field instruments and the reference instrument is that the field instruments (Alphasense OPC-N2) and reference instruments (Dusktrak 8533) measure different particle sizes and have different binning - the former measure particles sizes ranging from 0.3μm to 17μm and the latter measures 0.1μm to 15μm, so differences in the measurements for PM_1 and PM_{10} are to be expected (Stamp, 2019).

During the post-campaign co-location, the NO_2 sensors were setup in close proximity to each other to enable comparison between instruments; however, the radio frequency communication electronics caused interference with the NO_2 sensors and the resulting data for NO_2 was not usable. Measured concentrations of NO_2, however, were low for most case studies (mean indoor NO_2 of all case studies = 15.6μg.m^{-3}) and below the relevant health guidelines (25μg.m^{-3}) for most of the time.

Table 3.7 shows the results of the comparison of the field instruments with each other and the reference instrument for carbon monoxide and TVOCs. Indoor concentrations of carbon monoxide during the co-location were very low and below the level of detection (LOD) for the reference instrument, so it was not possible to compare the measurements of carbon monoxide for field and reference instruments. For the inter comparison, there is a high level of correlation between the instruments. Similar to NO_2 above, measured concentrations of CO were low for most case studies (mean indoor CO of all case studies = 399μg.m^{-3}) and below the relevant health guidelines (4,000μg.m^{-3}) for most of the time. Measured concentrations of TVOCs were also low during the co-location and ranged between 0 and 1ppm ($\bar{TVOC}$s = 0.1ppm, σ_{TVOCs} = 0.1ppm). The co-location highlighted two failed VOC sensors, which have been removed from this analysis and the data removed from the main campaign. Table 3.7 shows that there is a high correlation between the measurements of TVOC from the field instruments and the reference instrument ($\bar{R}^2 = 0.78$ to 0.97) and also a high correlation between the field instruments and the mean concentration of TVOC from all field instruments ($\bar{R}^2 = 0.78$ to 0.95).

For research concerning the health impacts of IEQ, the uncertainty of measurements which are

Table 3.7: Table showing the results of inter-comparison and comparison with reference for CO and TVOC for the AQ110's.

Instrument	Quoted accuracy	Comparison to reference	Inter-comparison
AQ110A (n=11) CO	No data	Concentrations below LOD	$\bar{CO}_{inter}$ = 316 μg.m^{-3} $\bar{R}^2$ = 0.91 (0.78 - 0.95) $\bar{RMSE}$ = 139 (88-415) μg.m^{-3} $\bar{MAE}$ = 108 (68-354) μg.m^{-3}
AQ110A (n=11) TVOCs	No data	$\bar{TVOCs}_{ref}$ = 0.12 ppm $\bar{R}^2$ = 0.90 (0.78-0.97) $\bar{RMSE}$ = 0.10 (0.04-0.14) ppm $\bar{MAE}$ = 0.06 (0.02-0.09) ppm	$\bar{TVOCs}_{inter}$ = 0.07 ppm $\bar{R}^2$ = 0.97 (0.90-0.99) $\bar{RMSE}$ = 0.04 (0.01-0.07) ppm $\bar{MAE}$ = 0.03 (0.01-0.05) ppm

well below guideline values are less important than the uncertainty of measurements near or exceeding health related guideline values. Furthermore, there is a need to exercise caution when interpreting IEQ data, where the uncertainty of a measurement is greater than the difference between a measurement and the respective guideline value for that variable. In these situations, it is difficult to draw conclusions with confidence due to the uncertainty of the measurements relative to the guideline.

Measurement drift

The sensitivity of sensors can change over time and cause the measurements to 'drift'. This drift can result in the offset and slope errors to also change over time. The amount and rate of change of drift is dependant on the type and manufacture of each sensor, the measurement sampling interval, and the measurement environment (including concentration of certain variables).

For sensors that have a linear degradation of sensitivity over time, drift can be corrected by linear interpolation of the offset and slope prior to and following the monitoring campaign - this can be calculated using a reference instrument and each field instrument. Of the sensors used in this research, non-dispersive infrared sensors (NDIR for CO_2) and electro-chemical sensors (carbon monoxide and nitrogen dioxide) are known to drift as the light source (NDIR) and chemical compositions (electro-chemical) change over time.

As mentioned above, there was no opportunity to obtain pre-campaign co-location data with reference instruments, so an alternative approach was used to calculate sensor drift over the monitoring campaign. All instruments (using different sensor types and ages) were co-located for a period of two weeks prior to and following the monitoring campaign in the researchers home, this co-location allowed each instrument output to be compared with the mean output of all instruments. It is recognised that all sensors could drift over time 'together' and therefore the mean of all instruments could exhibit this drift error. However, this error is minimised by using the mean of a range of different instruments as a reference, where this includes different types and ages of sensors measuring the same variables.

The mean absolute error was calculated for each instrument and for the mean of all instruments for

Table 3.8: Table showing the results of analysis of the drift, pre and post campaign. The results are the median (and IQR) difference in the pre and post campaign MAE for each instrument type and each measurand. * post correction - see Section 3.2.4.1.

Measurand	U12-012 (n=18)	MX1102 (n=8)	AQ110A (n=11)
Temperature	0.14 °C (0.14)	0.16 °C (0.14)	0.06 °C (0.10)
RH	0.46 % (0.94)	0.58 % (0.22)	1.09 % (0.78)
CO_2		2.95 ppm (8.06)*	7.32 ppm (13.44)
PM_1			0.65 $\mu g.m^{-3}$ (0.28)
$PM_{2.5}$			0.61 $\mu g.m^{-3}$ (0.19)
PM_{10}			2.31 $\mu g.m^{-3}$ (0.62)
NO_2			27.58 $\mu g.m^{-3}$ (13.35)
CO			27.73 $\mu g.m^{-3}$ (25.48)
TVOC			0.01 ppm (0.00)

the co-location before and after the main monitoring campaign. The difference between the MAE of each instrument and the mean MAE of all instruments was calculated and then the difference between the post- and pre-campaign MAE was calculated for each instrument. Following this, the median difference and interquartile range (pre vs post) MAE for each instrument type and each measurand are presented in Table 3.8. The median difference in MAE for all measurands is below the stated accuracy (where available) of the instruments and also below the MAE calculated against the reference instruments.

Non-dispersive infrared sensors (NDIR sensors) are known to drift over time, as the strength of the infrared light source deteriorates - this results in a change in the offset and slope of the measurement error over time, but in a known direction (Few, 2021). NDIR sensors were used for measurements of CO_2 and because there was no pre and post co-location data with reference instruments, a novel method for correcting the drift was developed. This method is based on the assumption that indoor CO_2 concentrations will reduce to the background outdoor concentrations when the dwellings are unoccupied for extended periods of time. More detail of this method and an example are presented in Section 3.2.4.1.

3.2.2.3 Qualitative laboratory analysis of VOCs

The Eltek AQ110's use a photo-ionisation detector (PID) for measuring TVOCs. This detector estimates the total absolute concentration of all VOCs with ionisation potentials < 10.6 eV, which does include some harmful VOCs but not others such as formaldehyde, methane, or carbon monoxide (there is a separate sensor for CO in AQ110A). The sensor is calibrated with isobutylene, and this provides an equivalent measurement for this gas, which is an approximation of total VOC concentrations. Due to the sensor measuring all VOCs, it is not possible to identify individual VOC compounds or their individual concentrations, and so it is not possible to understand potential health impacts from TVOC measurements alone (Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi, 2019). However,

measurements of TVOCs are useful, particularly as an indication of the variation of VOCs over time, identifying peaks, specific events and also investigating the variation relative to other events, such as ventilation.

In order to seek a deeper understanding of the VOC species that comprise the total VOCs present, and therefore understand the potential health implications, this research used passive sampling sorbent tubes (Figure 3.7) for VOC monitoring in some of the case studies (Gradko, ND). Passive sampling sorbent tubes work by molecular diffusion and collecting compounds on a solid polymer absorbent inside the tube. These tubes were analysed in a certified laboratory, identifying the top 10 compounds in the absorbent and qualitatively ranking these according to their relative concentration.



Figure 3.7: Sorbent tube (sealed) before dispatching to participant

3.2.2.4 Window and door events

Most homes in the UK and the case study dwellings (described later 3.2.6) are naturally ventilated and rely on opening windows for ventilation. In order to relate this ventilation practice to other IEQ variables and answer the research questions, it was necessary to collect data on when windows were opened and closed.

The times when a window is opened or closed can be recorded manually by the participants or by researchers recording this by observing window positions at different times of the day; however, this is very labour-intensive (Fox, 2008). Furthermore, Kukadia and White (2006) found that occupant diaries suffered from a lack of completeness and accuracy, as it was not always convenient for occupants to record these activities. Window and door events can also be recorded by using electronic devices which record movement using accelerometers (Andersen et al., 2013) or the change in state using reed switches. Modern electronic event sensors are reliable, cost effective, and nonintrusive (Liu et al., 2022).

ONSET HOBO UX90-001M electronic reed switch event data loggers (Figure 3.4a) were used to record the time when windows, internal and external doors were opened and closed. During the pilot study (P1), an event sensor was attached to the movable section of the cooker hood to record when the cooker hood was operated; however, the heat and products from cooking led to the failure of this event sensor, and so, event sensors were not used for measuring cooker hood operation in the other case

studies.

ONSET HOBO UX90-001M event sensors are known to suffer from time drift (Few, 2021), and this drift was accounted for in the analysis and is detailed in Section 3.2.4. The sensor can also suffer from repeated measurements (split seconds apart) when the magnet is close to the internal reed switch, these events were filtered after ingesting.

Internal doors enable the flow of air and pollutants between spaces in dwellings, and so, where these doors are frequently used, it was important to collect data on when they were opened and closed. Internal door events were also important for identifying when the case studies were occupied - the occupancy detection algorithm is described below in Section 3.2.4.2. However, despite deploying a large number of event sensors, there was an insufficient quantity available to monitor all internal doors in all case studies.

3.2.2.5 PIR occupancy sensors

Due to the limited availability of event sensors for the occupancy algorithm, participants were questioned about their use of internal doors, and where internal doors were not used, a limited number of PIR sensors were deployed. The ONSET HOBO UX90-006 occupancy data loggers were used to detect the presence of occupants, typically near the main entrance to the dwelling. Two case studies contained pets, so these devices were not deployed or the data was later discarded. During the campaign, it was discovered that these devices suffered from a limited battery life and given the nature of the longitudinal remote monitoring campaign, they provided a limited amount of useful data.

3.2.2.6 Sound Pressure Level Loggers

During the pilot study (P1) and the development of the novel method for inferring window positions (Chapter 4), a RIONOTE was used for simultaneously measuring sound indoors and outdoors. The RIONOTE is a calibrated and certified (class 1) multi-function instrument which can provide detailed (waveform and FFT) high-quality measurements of sound (RION, 2020). However, the RIONOTE is highly specialised and expensive. Additionally, the participant in the pilot case study reported that the conventional sound measurement setup of a microphone and a wind shield installed on a tripod was intrusive and acted as a constant reminder that sound was being measured in their home - see Figure 3.8.

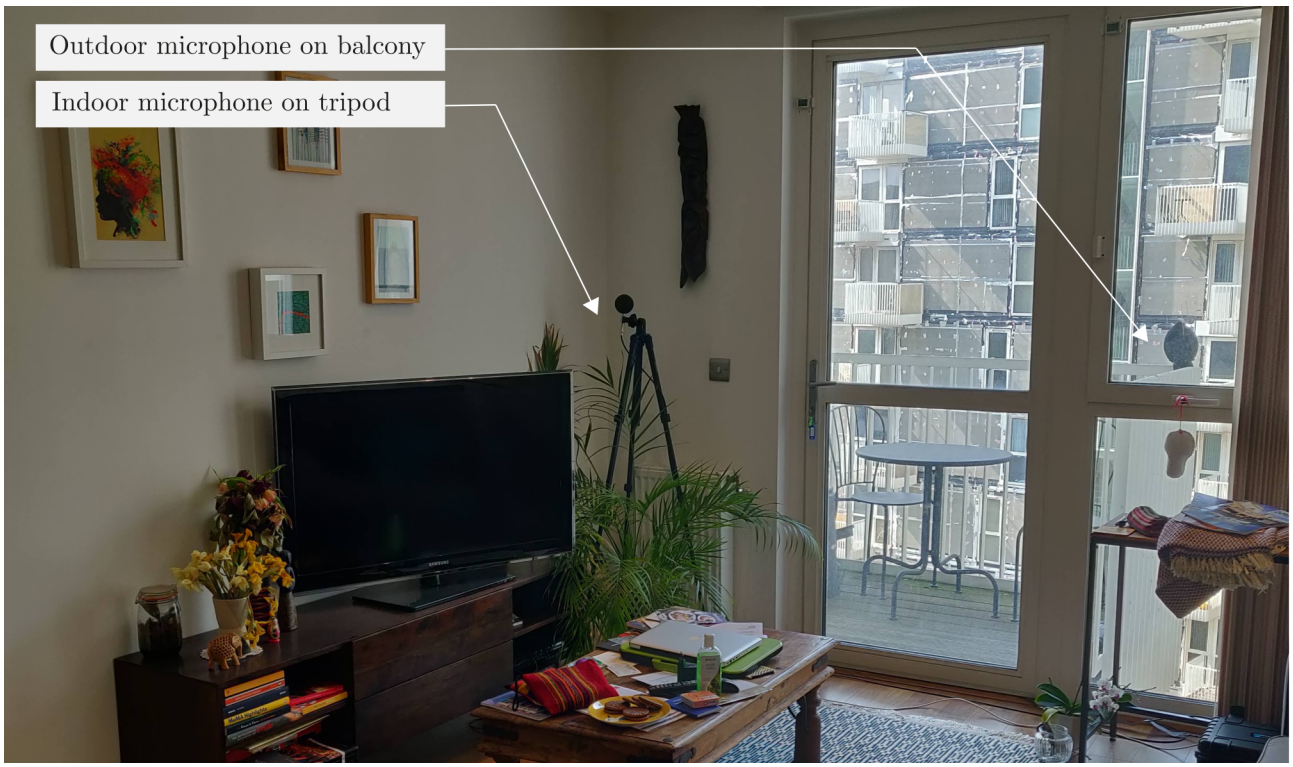


Figure 3.8: Photograph showing the indoor and outdoor microphones installed in the living room and balcony of P1. The participant reported the equipment was intrusive and a constant reminder that sound was being measured in their home.

For these reasons, a bespoke noise measurement platform was designed and manufactured by Dr Benjamin Fenech of UKHSA and support from the author. The system was based off the Raspberry Pi (RPi) small computer, off-the shelf components, and a small number of bespoke 3D printed interfacing elements. The system fits under Category 3 of the classification system proposed by Wessels and Basten (2016) - low cost acoustic sensor networks for pervasive use. The developed noise platform was similar to the devices described by Noriega-Linares and Navarro Ruiz (2016) and was designed to provide a balance between hardware cost, flexibility, reliability, and accuracy.

Briefly, the system consists of (1) microphones, (2) data acquisition, processing and transmission, and (3) power supply. The microphone sub-system consisted of PUI Audio AOM-5024L-HD-R omni-directional microphones which have high sensitivity and signal-to-noise ratio (PUI Audio, 2017). Microphone preamplifiers based on the TL07xx family of low-noise FET-Input operational amplifiers were used, and together with the microphone, they were housed in a custom-designed, 3D-printed assembly (Texas Instruments, 2023). The indoor microphone was installed in a smaller foam wind shield and was attached directly to an indoor surface (see Figure 3.9a). The outdoor microphone was mounted inside a cylindrical open cell foam wind shield and attached to a twist-locking suction cup base (see Figure 3.9b). The data acquisition, processing, and data transmission sub-system consists of (1) a Raspberry Pi 4B ,(2) a two-channel data acquisition card based on the WM8960 audio codec, and (3) a 3G dongle (Raspberry Pi, 2019; Cirrus Logic, 2016; Three, 2023).

Audio streams were continuously recorded simultaneously from both outdoor and indoor microphones in five minute blocks and immediately post-processed using a Python script. The post-processing consists of (1) load data and apply a microphone system sensitivity factor, (2) calculate one-third octave spectra at 100ms intervals between 25Hz and 10kHz, (3) save the "population distribution" in 0.5dB bins for each one-third octave band, and (4) delete audio recordings. Audio was immediately processed on board and deleted (not stored) for all 5 minute blocks to protect the privacy of the participants - this is discussed more in the section on ethics (3.2.5).

Data was then transmitted to a cloud-based server every 24hr over a secure connection. The one-third octave spectra "population distribution" enabled the calculation of any percentile in post-processing. This data was processed into 5 minute measurements of L_{eq}, L_{max}, L_{min}, L_5, L_{10}, L_{50}, L_{90}, and L_{95} for one third octaves between 25Hz and 10kHz.

The power system consists of (1) an external DC power supply, (2) a power interface card (MoPi 2) that provides power to the RPi and sound card from a wide input voltage range (7-22V) and provided emergency safe shutdown capability via battery backup), and (3) passive power noise filtering for the data acquisition card and the microphone preamplifiers (Sheffield Pi-Tronics, 2023).

The only user interface is a single button that is used to switch on and safely shut down the system. No displays, LEDs or speakers are included to minimise the intrusion on the indoor environment.

The data acquisition and powering sub systems are housed in a sealed box that is located adjacent to a window (see Figure 3.9c). Both microphones (Figures 3.9a and 3.9b) are connected to the main unit using miniature screened microphone cable with an external diameter of 2mm, which allows most window types to be closed with negligible air gaps. The noise floor of the system is approximately 25dBA.

Measurements of noise were typically taken inside the living rooms and outdoors adjacent to the living room (P1, P3, P4, P5). Sound was measured inside and outside (outdoors) of bedrooms of two case studies (P2 & P6), the kitchen of P2 and the dinning room of P7. Section 3.2.6.4 provides descriptions of the case studies and locations of all measurement equipment.



(a) Indoor microphone. To be attached to indoor surface using adhesive strips.



(b) Outdoor microphone with twist-locking suction cup base to be attached to window surface.



(c) RPi Noise measurement processing unit, containing the Raspberry Pi, data acquisition, processing and transmission electronics.

Figure 3.9: Photographs of bespoke noise measurement platform, specifically designed and manufactured for this research.

All five RPi noise platforms were calibrated pre- and post-campaign by Dr Ben Fenech (Fenech, 2022) using two types of calibration: (1) using a piston phone, which generates a known level at a single frequency (Figure 3.10a) and (2) generating multiple frequencies and comparing this with a calibrated class 1 sound meter (Figure 3.10b). The corrections to all devices were calculated from the piston phone results and applied retrospectively during the analysis. Calibration using the piston phone was carried out pre- and post-campaign and demonstrated that there was no significant drift in the microphone response. For two of the worst-affected microphones, there was a discrepancy of 1dB between pre- and post-deployment.

All RPi noise measurement platforms were compared with a Class 1 Castle Mirus sound level meter with diffuse field microphone correction. Test and reference microphones were mounted on a vertical plane in a ring with microphone diaphragms approximately 10mm from an imaginary centre - see Figure 3.10b. A sound source consisting of sequential white, pink, and brown noise, each at four different levels, was generated (Fenech, 2022). When the overall A-weighted (LA_{eq5s}) measurements for the reference and test devices are compared, there is a very high co-efficient of determination of 0.99 for all.

All noise measurement platforms provided measurements where, between 69% and 96% of A-weighted values above 30dB (A) were within ± 1.5dB of the class 1 device (Fenech, 2022). Similarly all devices provided measurements where, between 90% and 97% of A-weighted values above 30dB (A) were within ± 2.0dB of the class 1 device (Fenech, 2022).

Based on the above information and following the calibration corrections, for non-impulsive sounds with short-term (5s) energy averaged A-weighted levels of 40 to 85dB(A), 90-95% of the measurements recorded by the RPi platform are within ± 3dB(A) of levels that would be obtained from a Class 1 sound level meter.



(a) RPi calibration 1 - using piston phone.



(b) RPi calibration 2 - using Class 1 Castle Mirus sound level meter.

Figure 3.10: Photographs of RPi calibration (Fenech, 2022).

3.2.2.7 Technical data outputs

The combined measurements from the above sections are illustrated in Figure 3.11. This figure shows a schematic of the equipment installed within a typical case study, the measurands for each item of equipment, and the path the data takes from measurement to storage and processing. This diagram illustrates the common rooms in the case studies and the variables measured in those rooms. Section E provides similar schematic drawings for each case study.

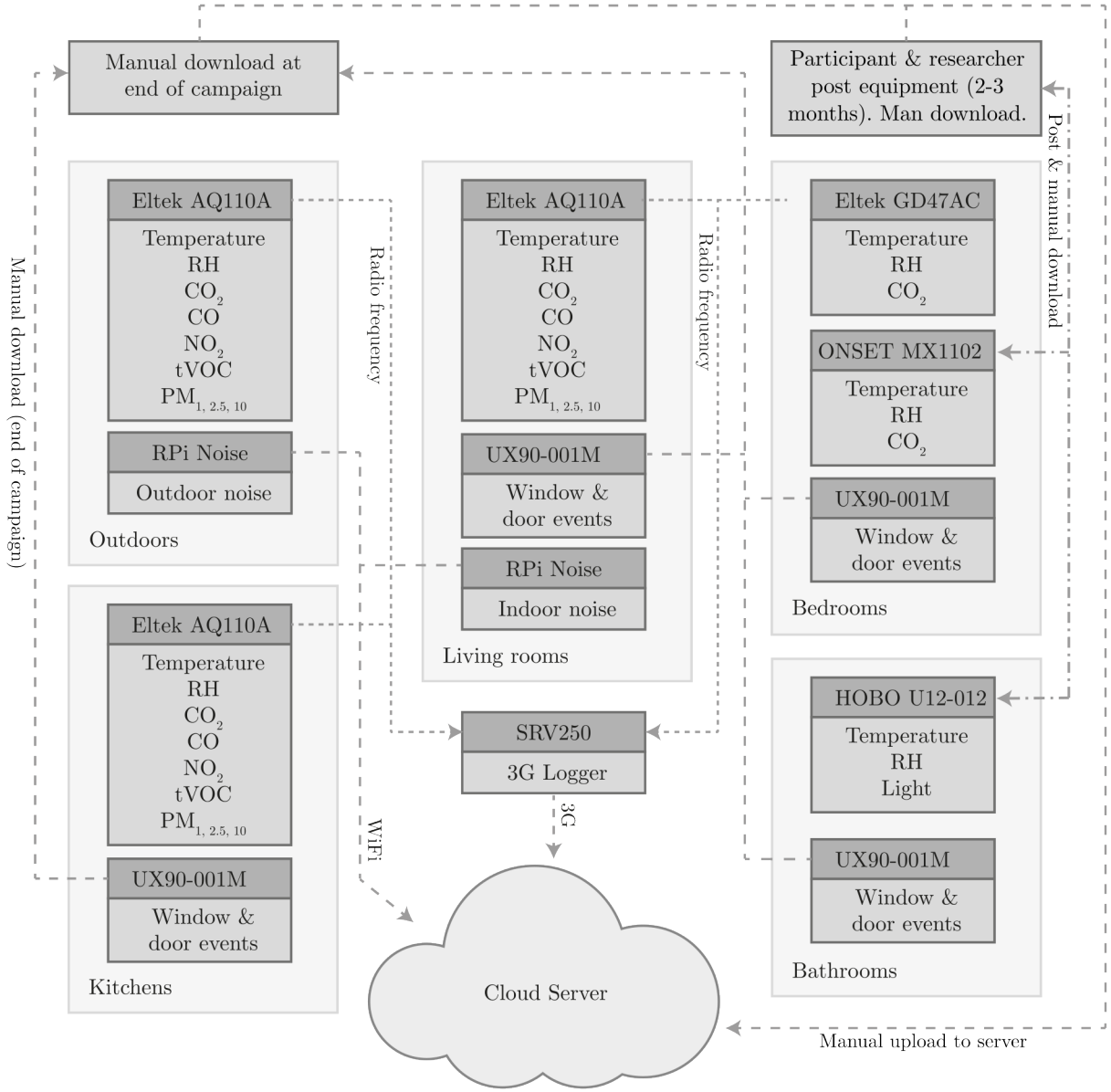


Figure 3.11: Schematic diagram of typical equipment installed in each room in each case study, the measurands for the equipment and data flow to cloud server.

3.2.3 Social data collection

At the beginning of this chapter (3.1) buildings were conceptualised as 'complex socio-technical systems' (Lowe et al., 2018) involving human actors and their interaction with the built environment infrastructure and technologies (Love and Cooper, 2015). The previous chapter highlighted that the literature frequently describe occupants' behaviour (humans interaction with the building/services) as the most important factor for ventilation, AER, and IEQ. It is therefore important to investigate the occupant's behaviour in order to bring about a deeper and more nuanced understanding of the relationship between ventilation and IEQ as a part of this 'complex socio-technical system'. To explore occupant behaviours, it was necessary to collect social data from participants on their

attitudes/perceptions/beliefs of ventilation and IEQ.

The most common methods for collecting social data are: questionnaires, observations, interviews, or diaries (Balvedi et al., 2018). With the extensive technical monitoring, observations were considered to be too labour-intensive, disruptive for occupants, and not likely to bring any further useful information. Participant diaries are considered to be very insightful for recording events, barriers, and drivers, particularly from the perspective of the participants, but again, this was considered to be too onerous and time-intensive for the participants, especially alongside the intense and intrusive technical monitoring. In addition, Kukadia and White (2006) found that participant diaries suffered from incompleteness and inaccuracy. Questionnaires, on the other hand, can be completed at a time and place convenient to the participants and can provide the social information sought by this research. Questionnaires have been widely used in IEQ research (Van Dongen and Phaff, 1989; Coward et al., 2001; Frontczak et al., 2012; Brown et al., 2015).

The questionnaire from the survey of ventilation provision and use in British homes was adapted and used in this research, with the aim of drawing insights across the case studies and the population (Van Rooyen and Sharpe, 2024). The questionnaire used by Van Rooyen and Sharpe (2024) was developed from the findings of the literature review in this thesis, and the questionnaire was shaped through consultation with experts from University of Leeds, University of Strathclyde, and UKHSA. Many questions were replicated directly from other IEQ and ventilation research to enable direct comparison. Socio-economic and household information was collected using standardised and common questions from Government Statistical Service (29/05/2020*b*). The questionnaire, along with justifications and sources of questions, can be found in Appendix D on page 368.

There are a number of measurements using technical instruments that might be considered social data - these measurements can inform the researcher of participants presence, actions, and/or consequences of their actions. These measurements include: window and door openings (ventilation practices using event sensors), operation of mechanical ventilation systems (using event sensors), occupancy of rooms and the dwelling as a whole (using event and occupancy sensors), internally generated pollutants and internally generated sound (using IAQ and noise sensors).

3.2.4 Data analysis framework

Figure 3.12 provides a graphical representation of the analysis framework used in this research. This figure shows the data inputs on the left, the core processing and analysis functions in the centre, and on the right, are the outputs/results and the themes that these results relate to. The preceding sections of this chapter have described the methods that were used to collect the raw data contained in the left box of Figure 3.12, the processing and analysis functions in the central box are described in this section. The data for each case study was sequentially 'passed' through the framework as a whole in order to generate the results, which are presented throughout Chapter 5. Together, this section and the next

section provide an overview of the methods that were used to store, process, analyse, and interpret the data, describing how the data was used to respond to the research questions.

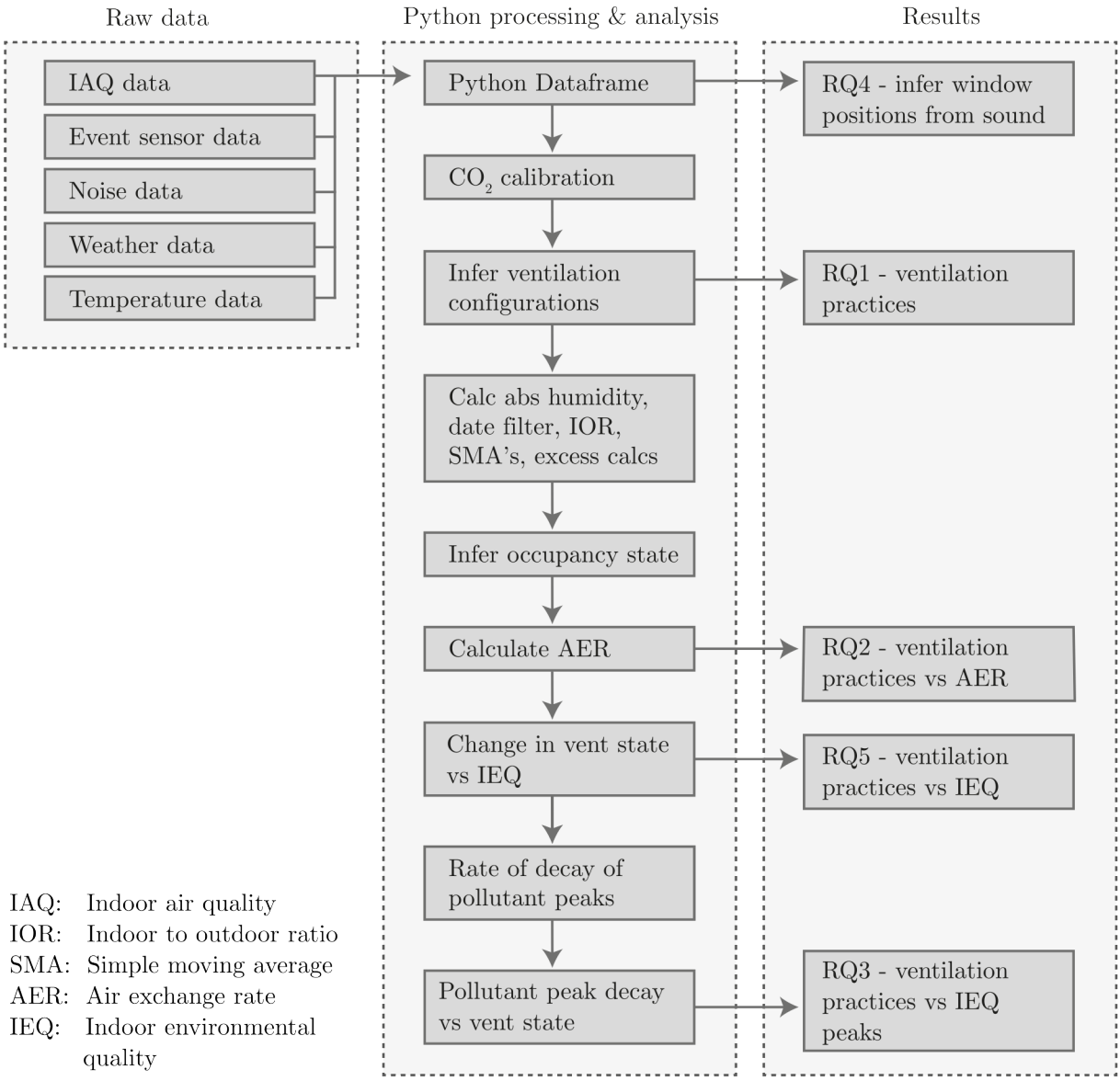


Figure 3.12: Illustration of the analysis framework with input data, Python processing, analysis, and results

The comprehensive longitudinal monitoring campaigns in the seven case studies resulted in over 32 million data points, and over 27,000 lines of Python code were written to ingest, shape, and analyse the data presented throughout this thesis. This data and code will be shared publicly for others to use.

3.2.4.1 Ingest, process, merge, and correct CO_2 drift

Initially, data from all air quality instruments were ingested and shaped. Local Met Office weather datasets were downloaded from the Centre for Environmental Data Analysis (CEDA) (CEDA, 2019) for each location - these datasets contained wind direction, wind speed, temperature, dewpoint, wet bulb temperature, pressure and CO_2. This weather data, event sensor data and noise data were ingested,

shaped and preprocessed. Finally, data from all sensors and the weather data were merged into a common datetime indexed dataframe in Python.

As described in Section 3.2.2.1, checks of all data streams were conducted on a daily basis and erroneous data was identified and recorded in Grafana - these records were used to discard problematic data in the merged datasets. Forward interpolation was limited to 6 points (30 minutes) for all variables.

Next, the drift of CO_2 measurements were corrected (previously mentioned in Section 3.2.2.2), based on the simplifying assumption that indoor CO_2 concentrations will decay to the background outdoor concentrations when the dwellings are unoccupied for long periods of time.

First, all extended periods (multiple days) during which each case study was unoccupied were manually identified from the carbon dioxide and occupancy data. These periods had durations of multiple days, where the indoor CO_2 concentrations have sufficient time to decay to the outdoor concentrations. During the identified unoccupied periods, the median outdoor CO_2 concentration was used to characterise the 'background' outdoor concentration for each period. The use of the median over a number of days reduces the effect of the daily variation.

The 10th percentile of CO_2 measurements for each indoor sensor was used to characterise the 'settled' indoor CO_2 concentrations during each unoccupied period. The 10th percentile was chosen as this uses the lowest 10 percent of the indoor CO_2 measurements during each unoccupied period and effectively ignores the decaying CO_2 from when the occupants leave their home. Other percentiles were briefly explored, but shown to be influenced by the initial CO_2 decay when the dwelling becomes unoccupied. This method could be potentially improved by developing an algorithm that discards the initial decay to characterise the settled CO_2 concentrations.

The 10th percentile measurements from each indoor sensor were corrected to the median outdoor concentrations during all unoccupied periods - the difference between the 10th percentile and the median outdoor concentration is termed the 'offset'. Linear interpolation of the offsets between consecutive unoccupied periods enabled the measurements during the occupied periods to be linearly corrected.

This method makes the simplifying assumption that the outdoor instruments do not drift, however in reality they will, but this is considered negligible. The NDIR sensors in the outdoor AQ110A instruments are of a higher quality than the indoor sensors, and their drift is very small over the longitudinal campaigns (7.3ppm - Section 3.2.2.2) when compared with the quoted accuracy of the sensors (50ppm).

CO_2 measurements from the MX1102 instruments, exhibited substantial drift. Figure 3.13 shows this function correcting indoor CO_2 measurements for participant 1 (P1) from one MX1102 instrument (red line) over a period of almost 9 months. Only the drift of the indoor instruments were corrected.

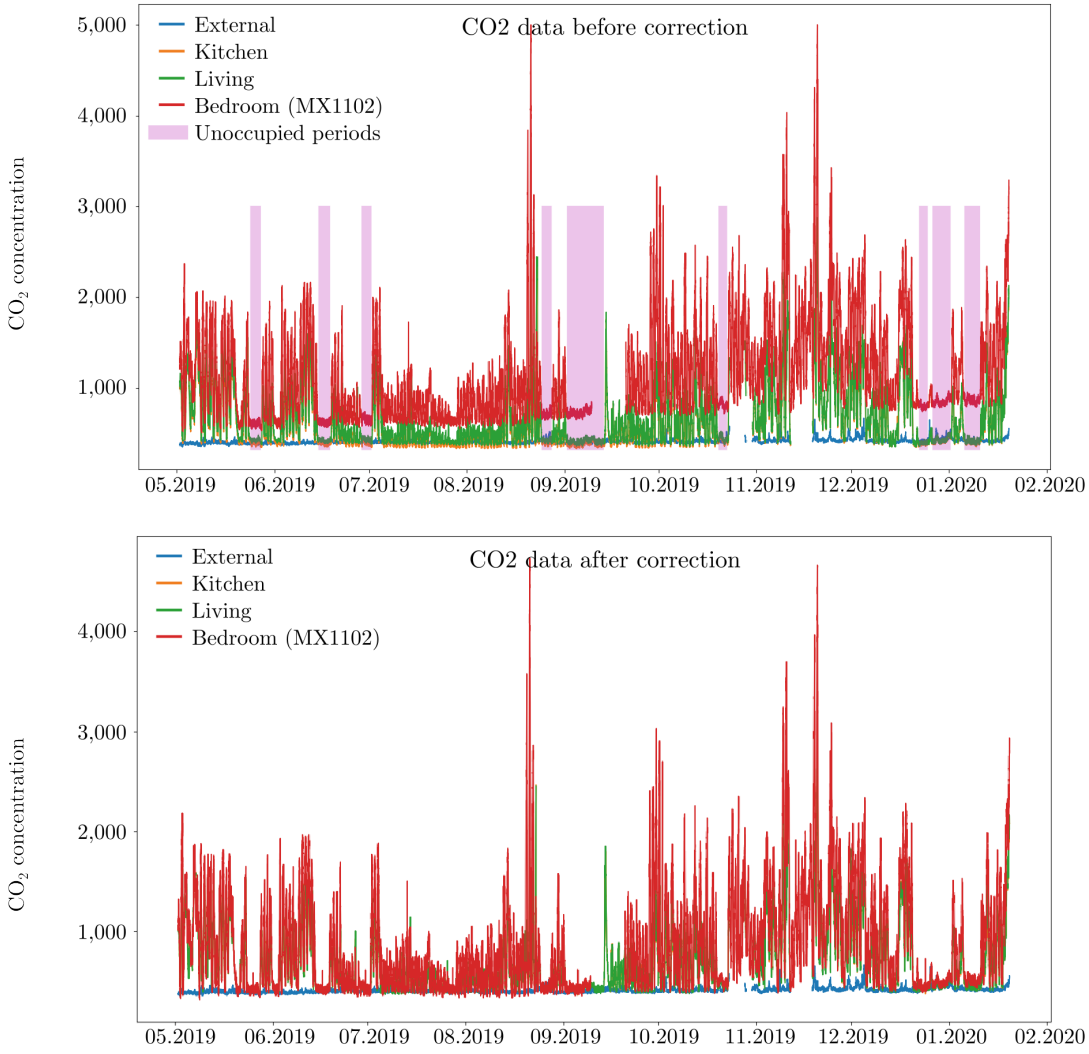


Figure 3.13: Illustration of the drift correction to CO_2 measurements in P1 - the red line indicates the measurements from an MX1102 instrument used to measure CO_2 in the bedroom of P1.

3.2.4.2 Analysis method development - ventilation practices

Research question 1 is 'How do participants ventilate their homes when they are occupied and how does this vary over time?'.

In order to answer this research question, it was necessary to determine when each case study was occupied. Occupancy information could have been obtained by participant diaries, but suffers from the limitations described in Section 3.2.3. PIR sensors were deployed to determine occupancy times in three case studies (P5, P6 and P7), however, as described in Section 3.2.2.5, these devices suffered from very limited battery life. A recent innovative study by Fritz et al. (2023) merged GPS data from mobile devices to determine occupancy and other data from wearable fitness trackers to determine periods of sleep, but this is an intrusive method of collecting this data.

In this research, occupancy periods were determined by adapting the improved 'occupancy status algorithm' developed by Few and Elwell (2019); Few (2021). This algorithm assesses the periods of

time between the front door closing and the next time it opened and determines occupancy status based on if there has been any activity indoors (from event sensors) or if the gradient of indoor CO_2 concentration exceeded a threshold value. This threshold value was selected to identify if metabolic CO_2 is being released in the dwelling. If there was any event sensor activity in the time between the front door closing and opening again and/or the threshold is exceeded during this period, the algorithm classified the dwelling as occupied.

CO_2 measurements from the MX1102 instruments were noisy and as such, Few and Elwell (2019); Few (2021)'s method was modified to operate with this noisier data. In particular, the period of the moving average was increased from 15 to 30 minutes and the threshold values were determined empirically. In most case studies, there are extended periods when the occupants left their home and these periods are used as a reference for iteratively calibrating the value for this threshold. Few (2021) used a threshold of 100 ppm per hour, whereas in this research, values of 120 to 180 ppm per hour were used. The algorithm was modified to ignore a period ('buffer') at the beginning and end of the assessment time period. This buffer was calculated from the stated drift in the manufacturers literature and manually adjusted based on inspection of the event sensor data. Figure 3.14 illustrates the logic of this occupancy algorithm. Figure 3.15 illustrates this algorithm applied to case study 1, with the top panel containing CO_2 measurements from the kitchen, living room, and bedroom, the middle panel showing the status from the algorithm and the bottom panel showing all internal events measured from the event sensors.

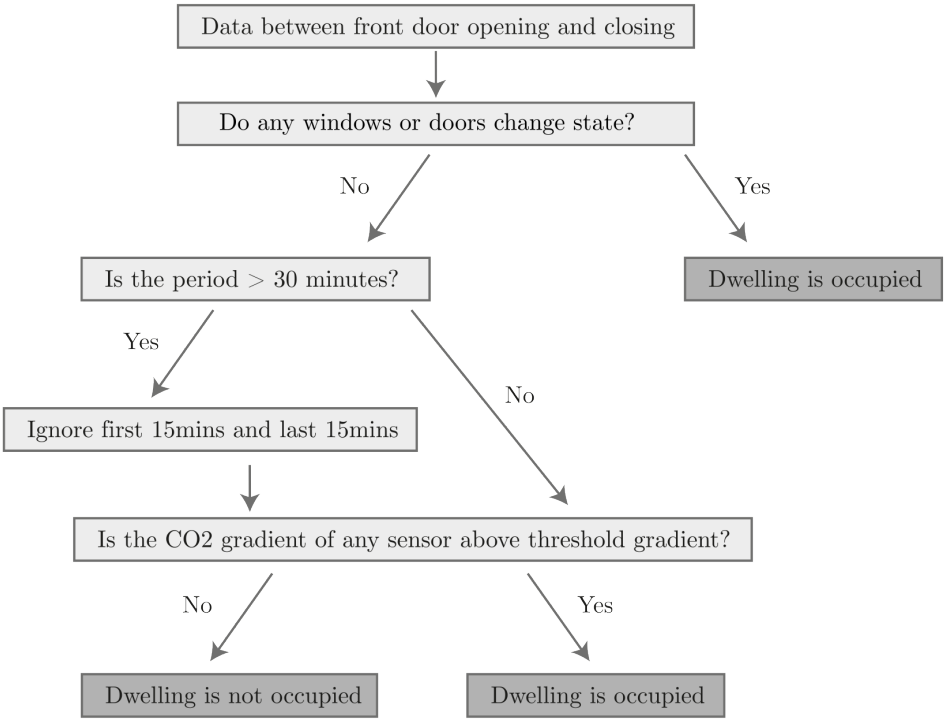


Figure 3.14: Illustration of the occupancy algorithm logic, partially reproduced from Few (2021).

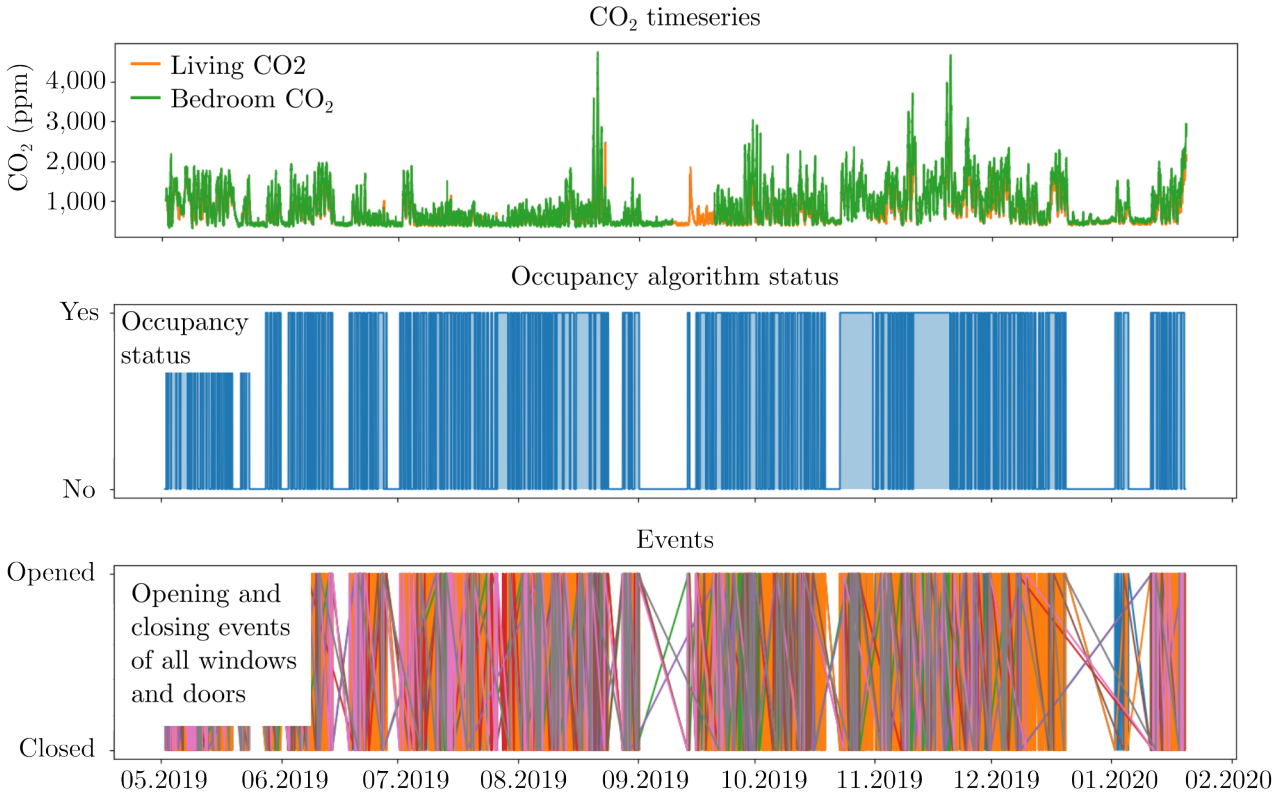


Figure 3.15: Example of the occupancy algorithm in use for case study P1.

After determining the occupied periods, the most common ventilation configurations were determined for each case study, where each ventilation configuration is a unique combination of open/closed windows and doors. The amount of occupied time that each case study dwelling was in each of the ventilation configurations was calculated for the summer and winter seasons. For the purposes of this analysis, summer and winter both included half of the preceding and following shoulder seasons. In addition to the amount of occupied time in each configuration, the number of times and the amount of time each window and door was opened during each season were calculated.

The results of this analysis are described in Section 5.1 (page 212).

3.2.4.3 Analysis method development - ventilation and AER

Research question 2 is 'What are the ventilation rates for common ventilation configurations/practices and are homes in the UK adequately ventilated?'. In the previous analysis method, periods of occupancy and common ventilation configurations/practices were established for each case study. In order to answer research question 2, it was necessary to calculate AER and relate these to the configurations/practices.

The use of tracer gases is the one of the most common methods for estimating ventilation rates (Breen et al., 2014; Carrer et al., 2015; Few, 2021). In this research, air exchange rates (AER) were calculated using a modified version of the 'automatic analysis method' developed by Few (2021) which is based on the CO_2 tracer gas decay technique. This method analyses the rate of decay of CO_2 after

the dwelling becomes unoccupied to estimate the AER. Few (2021) defines the end of the 'decay episode' as the end of the monotonically reducing 3 period (15 minutes) simple moving average. Long decays are split into 60 minute sections and if each meets a set of conditions, the AER is estimated for each shorter decay. This calculation method is illustrated in figure 3.16.

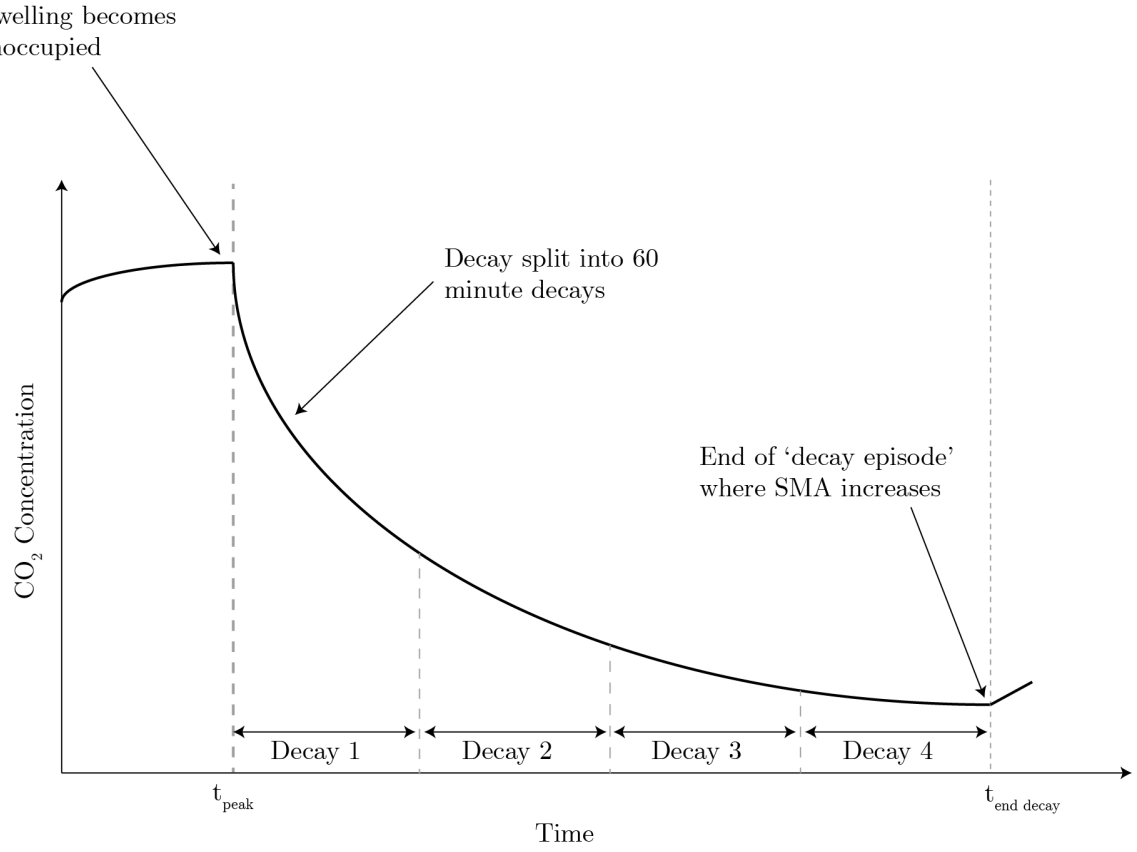


Figure 3.16: Illustration of the AER calculation on an example CO_2 decay episode.

The first condition used by Few (2021), tests if CO_2 is well mixed and is defined as "adequately spatially homogeneous if the CO_2 concentrations (of different sensors) were within the larger of 40 ppm or 10% of each other" (Few, 2021). The 10% threshold is derived from standard test method ASTM E741 (ASTMI International, 2011). In the case of Few's (2021) research, the case study dwellings were either single bedroom flats or studio flats, which were assumed to act as single zones - these dwellings had a small volume and less potential for spatial inhomogeneity of CO_2 than larger dwellings or dwellings with a larger number of zones. The estimated uncertainty associated with spatial inhomogeneity varies across different research, which is likely to be due to the variation in conditions. Few (2021) estimated this uncertainty to be between 9% and 13%, Westgate and Ng (2022) 7% and (Santamouris et al., 2008) between 4 and 7%.

CO_2 tracer gas decay models are single zone and there is a critical issue when using this model for characterising AER across multiple zones (Nazaroff, 2021). This presents a methodological issue when using this method with the case studies in this research, which have multiple zones - multiple floors, bedrooms, large internal volumes and a higher potential for inhomogeneity of CO_2 across the

whole dwelling. Despite this limitation, this research characterises whole dwelling AER by estimating AER from the sum of CO_2 from all spaces. This summed CO_2 is not volume-weighted, as the whole dwelling is being simplified and treated as a single zone. By using the sum of CO_2 from all occupied spaces, uncertainty associated with inter-zonal flow is reduced, but the assumption of a well mixed single zone is violated. In all cases, CO_2 was measured in rooms where occupants were expected to spend most of their time (all bedrooms, living rooms and kitchens), but not in all rooms (e.g.: hallways). Therefore, there are a small number of spaces where CO_2 measurements were not recorded, but these spaces were expected to be occupied for less time and also have lower concentrations of CO_2. Because of this, the estimated whole house AER are likely to contain a systematic bias, whereby the results are systematically higher than the 'true' values. This is because, when the dwelling becomes unoccupied, the initial part of the CO_2 decay is likely to be characterised by a combination of inter-zonal dispersion and AER. In a similar way to Nazaroff (2021), in addition to whole house AER, this research estimates AER for individual rooms. However, there is expected to be a systematic bias in the AER for individual rooms, depending on the sources of CO_2 during the occupied period and inter-zonal flows when the dwelling becomes unoccupied. It is expected that the uncertainty associated with whole house and individual room AER will be lower for lower volume case studies. The uncertainty associated with this bias is not estimated because it would be variable across the case studies and would require extensive further monitoring to accurately characterise it.

The uncertainties described above might limit the accuracy of the estimated AER, but does illustrate how conditions in the rooms change with time and therefore how the conditions the occupants experience changes with time.

The second condition in the method by Few (2021), was to only carry out calculations on decays where the difference between outdoor and indoor CO_2 was above 50ppm, and this same threshold is used in this research. The third condition, was to only carry out calculations on decays where the duration of the decay was more than 40 minutes and a maximum duration of 60 minutes. Long decays lasting more than 60 minutes were split into one-hour-long decays and the final decay was allowed to be 1hr 40mins - 1 hour decay lengths are deemed appropriate by Nazaroff (2021). The reason for splitting the long decays into shorter decays, was so that the driving forces behind the decays could be assumed to be constant over the duration of that decay, therefore minimising the impact of changing wind, temperature gradients etc. The final condition, was to only carry out calculations on decays where the variation of outdoor CO_2 was less than 40ppm, and this same threshold value is used in this research.

If the decay meets the above three conditions, a linear regression model is fitted using numpy.polyfit (NumPy Developers, 2022) to the natural logarithm of the ΔCO_2 and the AER is estimated from this linear model - this is a well established and widely used standard method for calculating AER (Sherman, 1990; Persily, 1997, 2016, 2022; Few, 2021). In each case study, there is a large volume of data with potentially hundreds of decays, which means that it was not practical to carry out this analysis

manually, therefore, an automated algorithm was developed to identify these decays and estimate the AER - Figure 3.17 provides an illustration of the logic for this algorithm. Figure 3.18 shows one example (of a total of 921 calculations for P1) of a CO_2 decay calculation (using sum of CO_2 from all rooms) for case study P1.

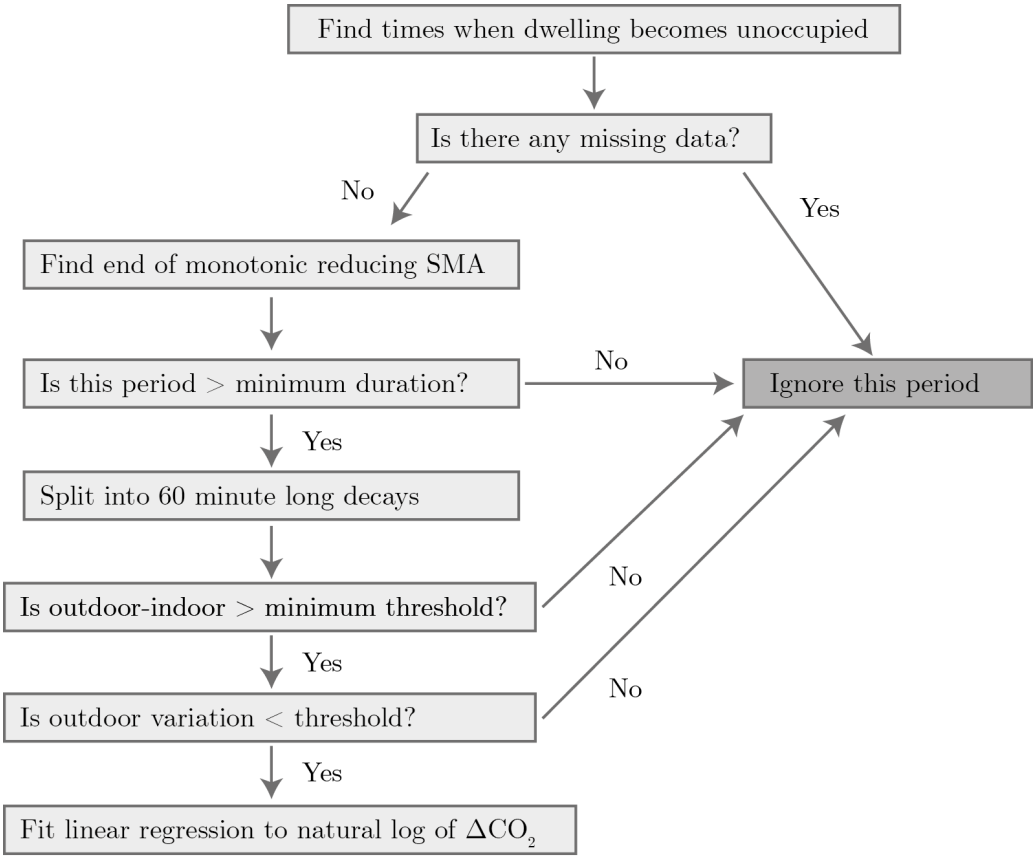


Figure 3.17: Illustration of the AER algorithm logic.

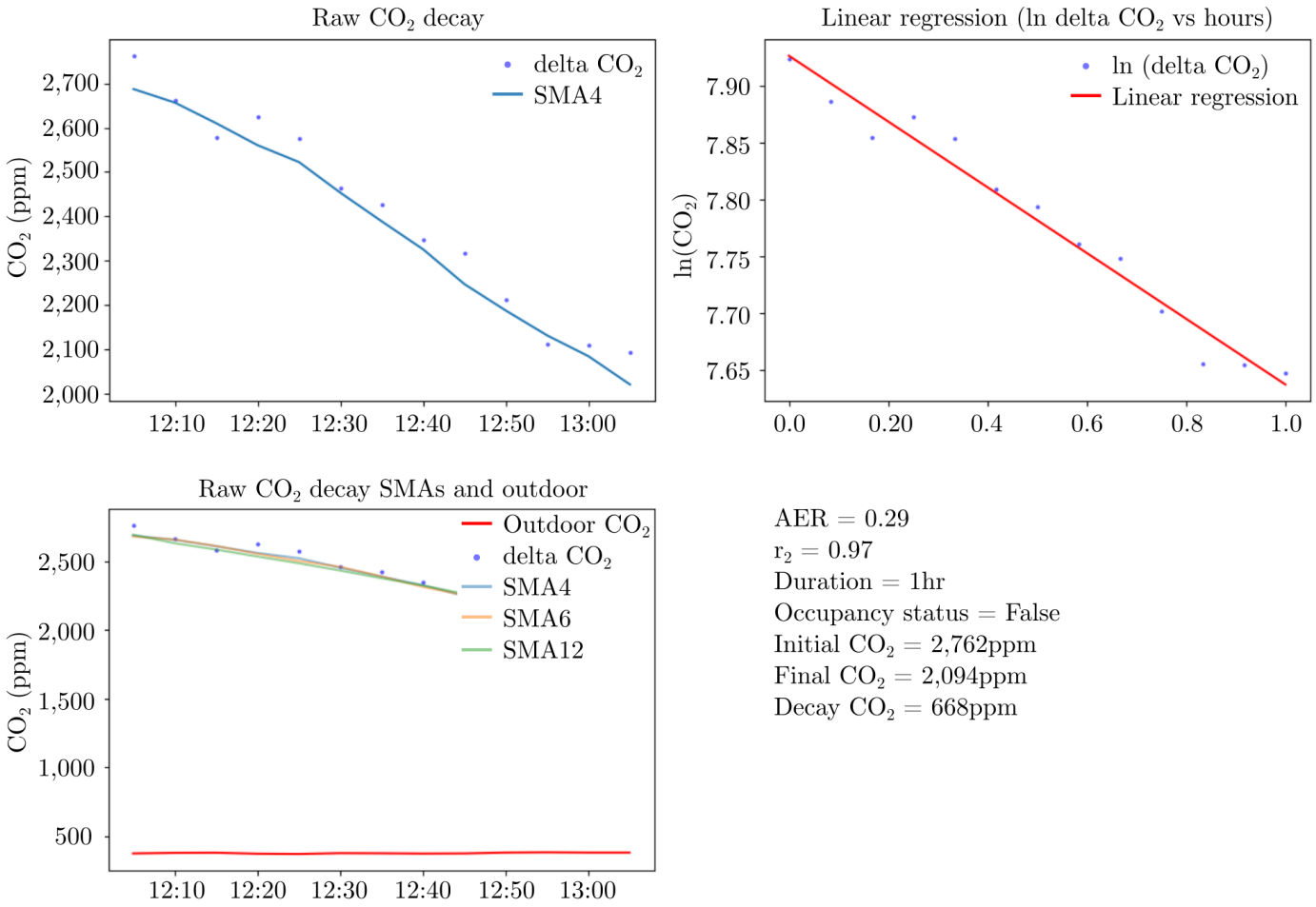


Figure 3.18: One example (of a total of 921 calculations for P1) of a CO_2 decay calculation (using sum of CO_2 from all rooms) for case study P1. Top left panel is the (excess) ΔCO_2 (indoor - outdoor) and the 4 period SMA, the top right panel is the linear regression applied to the natural log of the ΔCO_2, and the bottom left panel shows the outdoor CO_2 concentration, ΔCO_2, and a number of other SMA's, the bottom right panel gives summary information for this particular decay - showing an AER of $0.29h^{-1}$.

The estimated individual room and whole house AER were related to different ventilation configurations and practices to respond directly to the research gap and research question. The results of this analysis are presented in Section 5.2 and from this, the key limitation that emerged, is that the configurations that participants leave their homes in are not representative of the configurations when the participants are present in their home. This resulted in a very limited number, or no observations of AER for certain configurations, discussed further in Section 5.2.

As identified in the previous chapter, AER are important factors influencing IAQ, exposure and health, but are "not of primordial importance" (Nazaroff, 2021, p. 196) - in light of this, the following two analysis methods focuses on the relationship between ventilation, IEQ and exposure.

3.2.4.4 Analysis method development - ventilation state and IEQ

Research question 5 is 'What is the impact of ventilation on each component of IEQ after different ventilation events?'. This question primarily aims to establish the direction of change and secondarily to establish an indication of the magnitude of change of all IEQ components with changes in state of ventilation devices. The method described below responds directly to this question, by considering the change in state of each ventilation device and how this is related to changes in IEQ during occupied periods. This analysis uses the temporal component of the high resolution time series data to investigate the impact of the transition of a window or door from one state to another (opened to closed or closed to open). This approach does not use the average conditions during a single state, which can be problematic as the state impacts IEQ, with the "consequence that the predictive variables are influenced by the state that they are trying to predict" (Fabi et al., 2012, p. 196).

An automated algorithm was compiled to iterate over the times that every window and door was opened and closed ('ventilation event') and calculate the median concentration of all IEQ variables in that room in the time period (up to one hour) before each 'ventilation event' and (up to one hour) after each ventilation event. This algorithm ignores a ('buffer') period of 5 minutes after each event in order to enable a new flow regime to become established and also to exclude the effects of the transient. The reason for selecting an hour period is (1) to allow for the new flow regime to have an effect on IEQ, (2) to avoid transients, (3) this is a timescale that is relevant to occupants, and (4) so that this effect can be related to AER, which are measured per hour. The algorithm calculates the difference between the median concentrations of all variables in the period after and the hour before the event, resulting in a magnitude and direction for the change in each variable each time a window or door opens or closes. Figure 3.19 illustrates how this algorithm works.

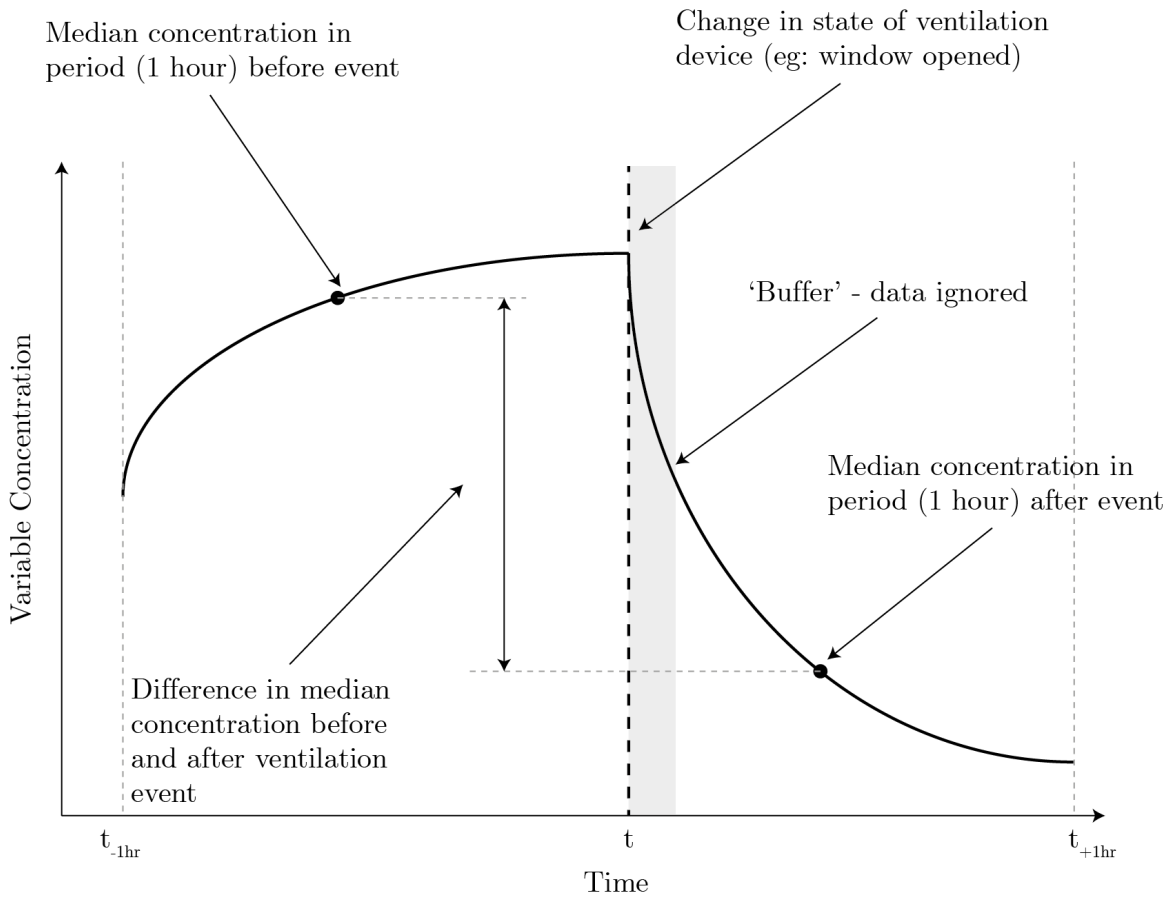


Figure 3.19: Illustration of the change in state VS IEQ algorithm for a single ventilation event on a time series graph.

In certain cases, there was a short space of time between ventilation events, such as a window closing shortly after being opened, and therefore, the algorithm incorporated a minimum time threshold to the next change in state. The reason for including a minimum threshold was that it is expected that there is a minimum amount of time for the new flow regime to become fully established and to ensure that the analysis was not biased towards short duration events, which could have a limited impact on IEQ. Further analysis of the data could investigate the changes in IEQ for events of a short duration, however, this analysis is focussed on quantifying the larger changes in IEQ. The algorithm ignored events where the duration between events was less than this threshold. Table 3.9 shows the total number of change in states for the external windows and doors for case study 1 and the amount of change in states that were filtered for 3 different minimum time thresholds. 10 minutes was selected as the threshold, as this provides the required minimum of two data points to calculate the average without filtering out a large number of observations.

Table 3.9: Table showing the total number of events and the number of events that were filtered, using different minimum time thresholds.

Event	Total observations	Filtered (>5mins)	Filtered (>10mins)	Filtered (>15mins)
Bedroom window	211	18 (9%)	27 (13%)	36 (17%)
Balcony door	295	47 (16%)	63 (21%)	79 (27%)
Living window	254	22 (9%)	37 (15%)	45 (18%)

3.2.4.5 Analysis method development - ventilation and peak decay

Section 2.2.2.2 highlighted the lack of ventilation knowledge among building occupants; this final analysis presents a framework for empirically deriving data that can be used to inform ventilation advice for occupants with the aim of reducing exposure to peaks of pollutants. Section 5.6.2 presents an extended discussion of how this advice might be practically disseminated to occupants with varying characteristics (ventilation provision, dwelling archetype, etc.).

This final analysis builds on the previous analyses and considers the relationship between the ventilation configuration of each case study and the time for short-term peaks (shape and duration described below) of each IEQ variable to decay below the health threshold for each variable. Figures 3.20 and 3.21 provide an overview of the algorithm logic and an illustration of the calculation used by the algorithm on a time series graph for a peak.

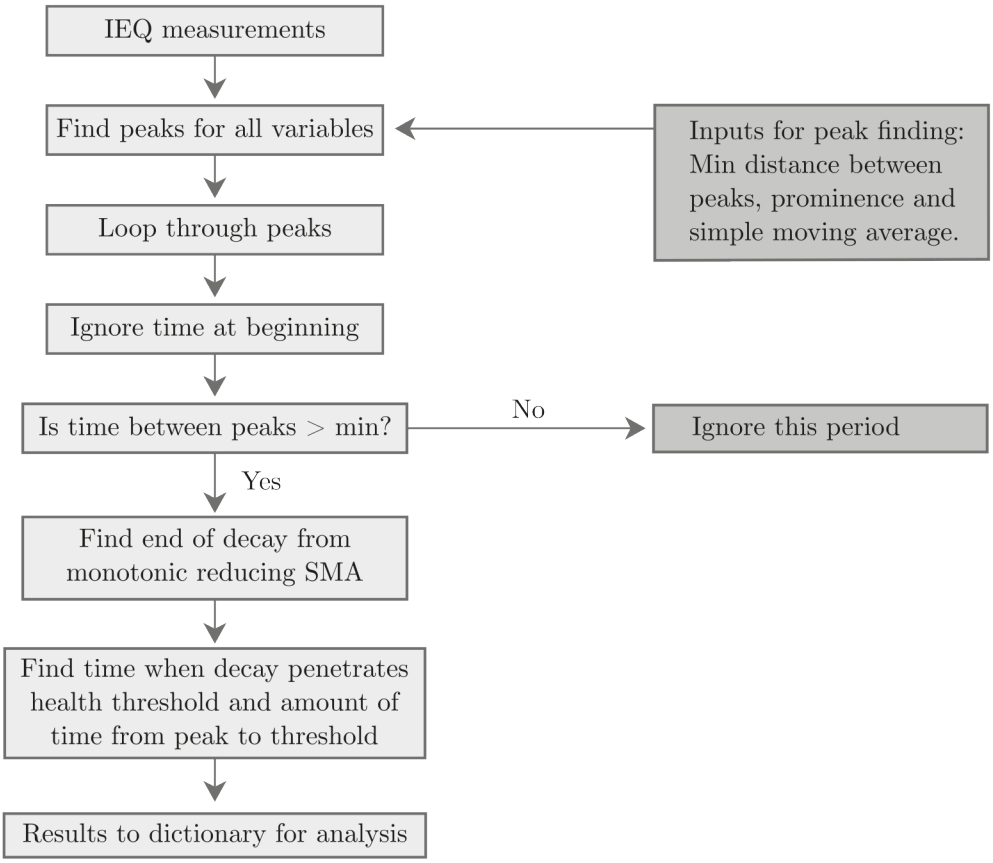


Figure 3.20: Simple flow diagram of the logic used by the algorithm to calculate the time for peaks of pollutants to decay to the health threshold.

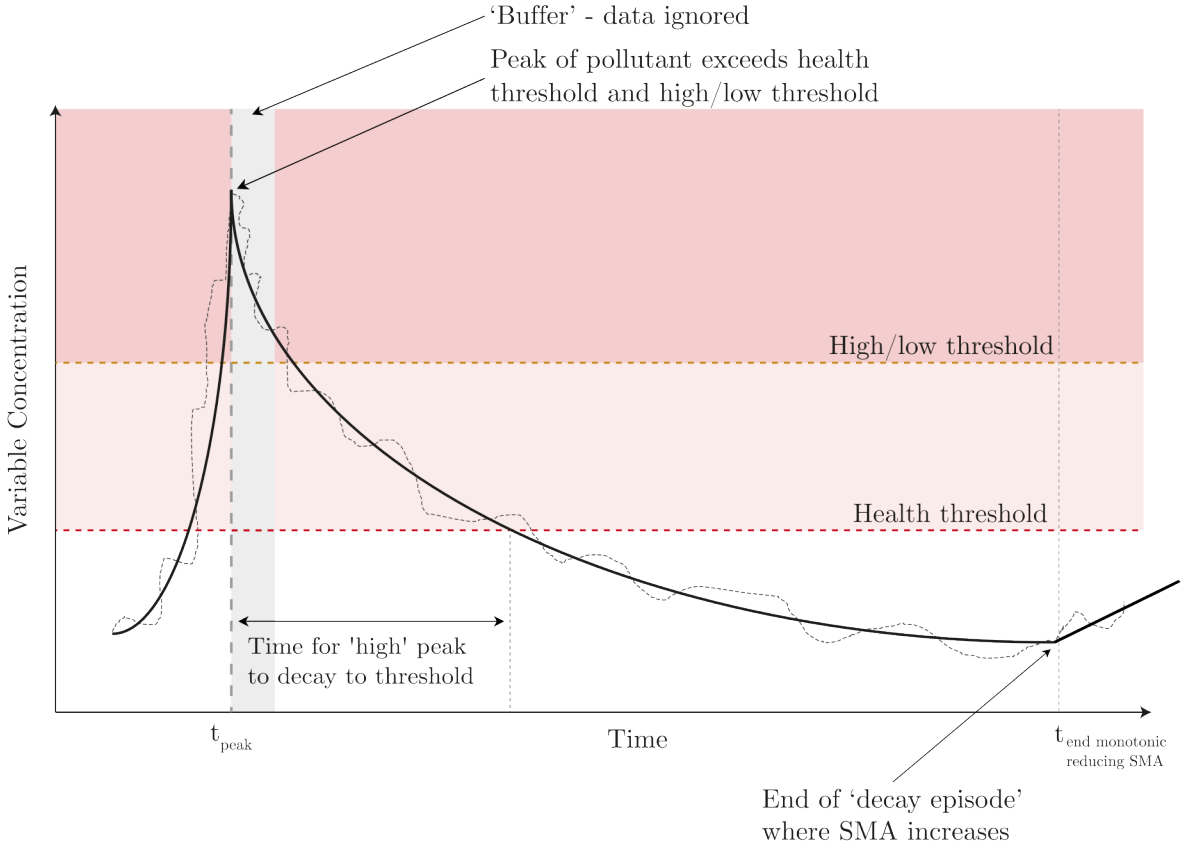


Figure 3.21: Illustration of the algorithm for calculating the time for pollutant peaks to decay to health thresholds, for an example single peak on a time series graph.

The first step for this analysis was to determine the times of all peaks for all variables; this was completed using the scipy.signal.find_peaks package by The SciPy community (2022). This package determines peaks as any observation with two direct neighbours that have a smaller amplitude. Peaks of pollutants are highly variable due to many covarying factors, including: occupancy, strength and emission profile of sources, latency of measurements, mixing and inter-zonal dispersion. Due to the short-term variation, it was necessary to smooth the signal in order to identify major peaks - the 60 minute simple moving average was used. Furthermore, the time between peaks was constrained to a minimum of 60 minutes. This package uses an input argument for the 'prominence of a peak', which is the amount that a *"peak stands out from the surrounding baseline of the signal and is defined as the vertical distance between the peak and its lowest contour line"* (The SciPy community, 2023). Prominence values were highly variable across case studies, room types and IEQ variables. Due to this variability, the minimum prominence of peaks was manually resolved by visually inspecting graphs of the peak-finding algorithm whilst iteratively exploring different values of prominence - this was done separately for each participant, each room, and each variable. Figure 3.22 illustrates an example of the visual inspection of peaks of $PM_{2.5}$ in the kitchen of P1.

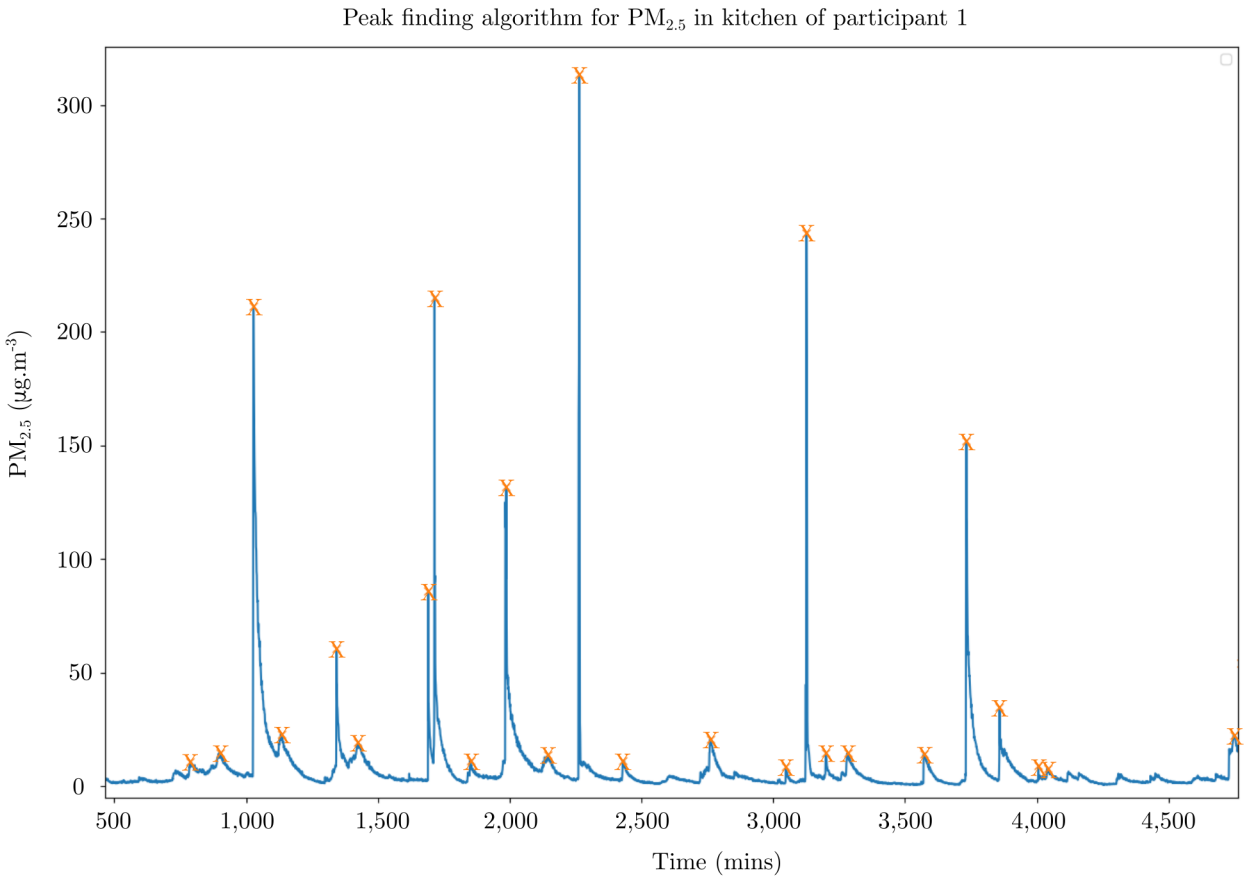


Figure 3.22: Example of peak finding algorithm for concentrations of $PM_{2.5}$ in the kitchen of case study P1 - the peaks identified by the algorithm are shown with an orange X

Similar to the AER algorithm discussed in Section 3.2.4.3, this analysis uses a simple moving average (SMA) to smooth the data and calculates the time when the SMA stops reducing (monotonic reducing function) - this is defined as the 'end' of the decay for each peak (see Figure 3.21). It is worth noting that it is very challenging to determine exactly when each decay ends, particularly when the gradient of the decay has reduced and the concentration does not reduce much with time. Further complicating this is the highly variable nature of the decays, as described in the paragraph above. However, despite the apparent challenge, this analysis is focussed on the time for the elevated concentrations to decay to safe levels, which is typically less influenced by the exact end of decays. The rate of decay is dependant on a number of dynamic factors, including the background concentration of the pollutant, volume of air in the room/dwelling, and the air exchange rate. When windows are open, the air exchange rate is expected to increase and so the rate of decay will also be influenced by outdoor concentrations. This highlights the need for interpreting the results of this analysis in the context of the local dynamic environmental factors, whilst accounting for ventilation configuration.

The selection of the period of the SMA is important and has a corresponding impact on the estimated duration of each decay - this is illustrated using a real example in Figure 3.23. Low SMAs are relatively easily influenced by this variation and can begin to increase before the 'actual' end of

the decay, resulting in a shorter and inaccurate characterisation of the decay. On the other hand, long SMAs can continue to reduce after the 'actual' end of the decay and also give an inaccurate decay. The selection of SMA used in this research aims to balance this and was selected through the visual inspection of different SMAs (example in Figure 3.23) and their ability to smooth out noise whilst not impacting the monotonic reducing function. In addition, a numerical sensitivity analysis was carried out (on P1) to establish the impact of the SMA on the number of decays and the time to decay to the threshold. Table 3.10 displays a summary of the sensitivity analysis and shows a lower number of decay periods and a bias towards lower decay times for lower SMAs.

The method developed for this analysis used a 12 period SMA (60 minute), which was empirically determined using the actual equipment and real data from P1. This SMA provided a balance between including relevant decays and accurately determining the end of the decays whilst not overestimating the end time.

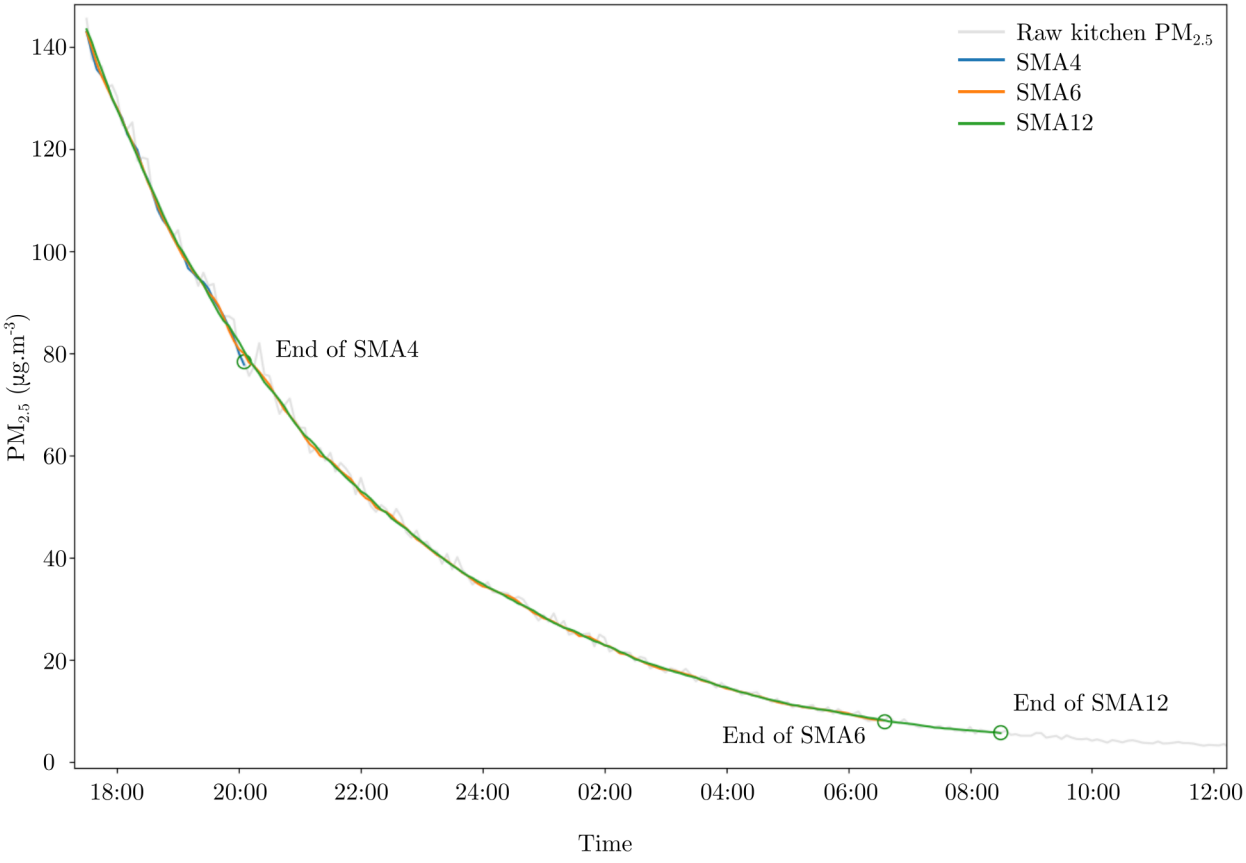


Figure 3.23: Example of a decay of a peak of $PM_{2.5}$ in the kitchen of case study 1, highlighting the times when the SMA4, 6, and 12 end monotonically reducing.

Table 3.10: Table showing the number, median, and interquartile range (IQR) of the time for peaks to decay to the relevant health threshold (see Table 2.3 and Table 3.11), when using different SMAs for the kitchen of case study 1.

Variable	6 period SMA (30 minutes)			12 period SMA (60 minutes)			30 period SMA (150 minutes)			Units
	n	median	IQR	n	median	IQR	n	median	IQR	
Temperature	50	35	61	53	45	90	56	58	106	°C
RH	28	10	12.5	33	15	35	38	15	75	%
CO_2	88	53	116	106	85	173	117	115	210	ppm
PM_1	39	35	63	58	68	138	59	95	133	$\mu g.m^{-3}$
$PM_{2.5}$	17	40	85	18	45	98	17	50	105	$\mu g.m^{-3}$
PM_{10}	90	0	5	83	0	5	62	0	8.75	$\mu g.m^{-3}$

After the algorithm established relevant decays, their start and end times, the algorithm filters all decays to retain only the decays where (1) the peak concentration is above the relevant health threshold for that variable and (2) the concentration at the end of the decay is less than the health threshold. The algorithm then finds the time where the decay passes through the health threshold - this is the time for the peak to decay to the health threshold (see Figure 3.21). During this period, the descriptive statistics for IEQ are recorded, along with the mode of all ventilation devices and the outdoor concentrations of each variable during the decay.

It was hypothesised that the time for a peak to decay was dependent on the initial (highest) concentration of the peak, where higher peaks will take longer to decay because they emit a higher mass of pollutant into the space, which will cause the indoor concentrations to remain elevated for a longer period of time. In order to test this hypothesis, a second threshold was empirically derived to classify each peak as high or low. The concentrations of all peaks that exceeded the health thresholds were found to have a positively skewed distribution, which is left truncated at the threshold - Figure 3.24 shows this shape for peaks of $PM_{2.5}$ from all case studies. The high/low threshold should lie towards the outer edge of the main distribution of data, in order to explore the full range of peak concentrations and also adequately differentiate between the high and low peaks. Initially, the median was explored as a threshold, but due to the skewed distribution, the median was located within the main bulk of the distribution and did not provide an effective way of capturing the difference between the high and low peaks. Typically, this was also the case for the 50th and 66th percentiles. Figure 3.24 shows the distribution of peaks of $PM_{2.5}$ from all case studies and illustrates this point. The selected threshold for most variables was based on the 75th percentile. However, temperature, humidity and NO_2, high/low thresholds were based on the 66th percentile, due to the reduced range and lower skew in the distribution. Table 3.11 summarises the health thresholds, the 50th, 66th, and 75th percentiles of peaks above the health threshold and the high/low threshold used for this analysis.

Most health thresholds were selected based on the 24-hour mean, which provides the same time average for different pollutants, thereby enabling their comparison to those of recognised health thresholds. However, it is recognised that this 24-hour health threshold does not directly transfer to the much shorter exposures and durations associated with ventilation practices. Ideally, it would have been possible to use 1-hour health thresholds for all pollutants, but evidence on such thresholds is not available in the literature for all pollutants.

One issue with the guideline values is that they use simple 24 hour averages, which does not adequately account for short term acute exposure. An illustrative example of this might be someone exposed to a concentration of PM over one hour that is 22 times higher than the 24 hour threshold, but when averaged over 24 hours, this exposure does not exceed the threshold. The acute exposure to an extremely high concentration in a short space of time could be very damaging to health, potentially more damaging than if a person was exposed to the threshold over 24 hours. The future development of short term exposure thresholds could be valuable to IEQ research and the development of guidance that can support healthy environments.

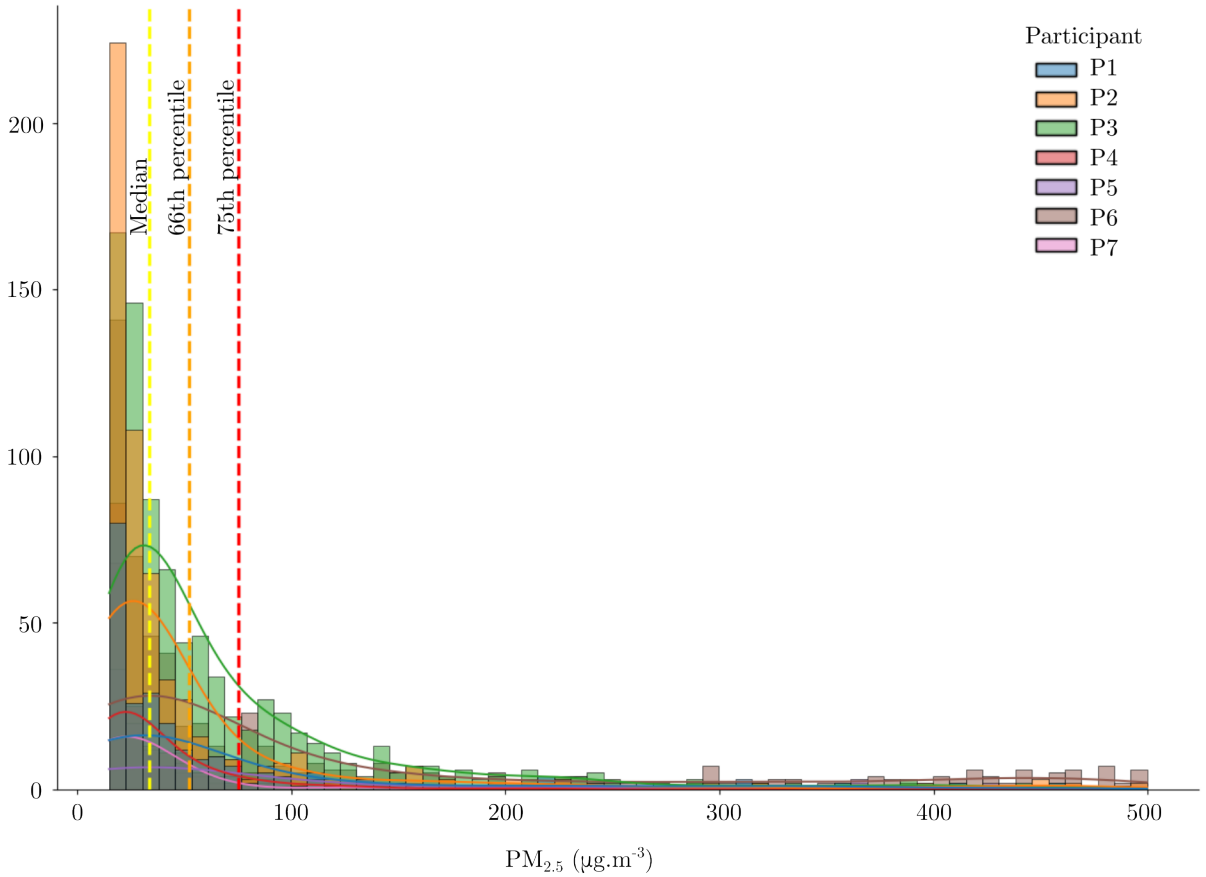


Figure 3.24: Distribution of peaks of $PM_{2.5}$ from all case studies which have exceeded the health related threshold. This figure shows the positively skewed distribution which is left truncated at the health threshold. The yellow vertical line is the median, orange is the 66th percentile, and red is the 75th percentile.

Table 3.11: Table showing the health related threshold values, empirically derived percentiles of peaks above the health thresholds, and the proposed high/low thresholds for all variables.

				Percentiles (exceedances)			
Variable	Units	Health threshold	n	50th	66th	75th	High/low threshold
Temperature	°C	26 [1]	658	27.2	27.8	28.1	28
RH	%	80% [1]	1560	86	88	88	88
CO_2	ppm	900 [2]	11086	1221	1385	1514	1500
CO	$\mu g.m^{-3}$	4000 [3]	263	5961	6915	7974	8000
PM_1	$\mu g.m^{-3}$	5 [4]	4965	12.1	18.04	24.48	25
$PM_{2.5}$	$\mu g.m^{-3}$	15 [3]	2692	33.9	52.5	75.3	75
PM_{10}	$\mu g.m^{-3}$	45 [3]	5790	78.5	104.5	131.2	130
NO_2	$\mu g.m^{-3}$	25 [3]	3200	60	83.6	110.3	85

[1] CIBSE (2015)
[2] Wargocki (2013)
[3] WHO (2021*a*) 24 hour mean
[4] Currently, there is no recognised air quality guideline for PM_1. However, a threshold is necessary for this method, and an arbitrary threshold used was calculated, based on the prevailing ratio of the short term thresholds for $PM_{2.5}$ and PM_{10}. 45 $\mu g.m^{-3}$ (PM_{10}) / 15 $\mu g.m^{-3}$ ($PM_{2.5}$) = ratio of 3. 15 $\mu g.m^{-3}$ ($PM_{2.5}$) / 3 = 5 $\mu g.m^{-3}$.

Section 5.4 of Chapter 5 presents the results of this analysis.

3.2.5 Research ethics

The research was designed to ensure that no harm would come to the participants or the researcher.

Three potential concerns were identified that might have arisen from participants, relating to privacy and security. First, participants might be concerned that their activities could be discerned from the IEQ data; however, in reality, it would be very challenging to accurately infer this from the data, particularly given the dynamic nature and high variability of IEQ measurements. Furthermore, this research did not use data for inferring activity, and the data will be fully anonymised before sharing. Secondly, noise measurements and the noise measurement system might present a privacy concern to the participants. The noise measurement equipment does not save audio recordings, only average noise levels over a 5-minute interval, and it is not possible to reconstruct audio from this numerical data - this was communicated to participants. Last, it might be possible to infer occupants' typical patterns of movement to and from the dwelling, which could pose a security concern to the occupants. To overcome this, data was pseudo-anonymised and securely stored.

The pilot project was completed, following approval from The Bartlett School of Environment, Energy and Resources (BSEER), UCL ethics co-ordinator in February 2019. The ethics application was then revised in early 2020 and again at the end of 2020, incorporating specific measures to mitigate risks associated with COVID-19, which are discussed in more detail in Section 3.2.6.2. Following approval of the revised ethics application, the main monitoring campaign (P2-P7) began in early 2021. See Figure 3.25 for a timeline of this project.

Physical risks associated with the monitoring campaign were controlled and managed through risk assessments, which included control measures for COVID-19 infection prevention (discussed more in sections 3.2.6.1 and 3.2.6.2).

All technical and social data was collected and stored in strict accordance with EPSRC and UCL Data Protection requirements. A data management plan was developed in accordance with EPSRC requirements and approved by UCL. This research project was registered with the UCL data protection team on 06.02.2022, number Z6364106/2020/02/17. All data was held and processed in accordance with the Data Protection Act and was compliant with the GDPR regulations.

3.2.6 Case study dwellings and data collected

This section describes the recruitment of participants, the modifications to initial plans to accommodate changes due to the COVID-19 pandemic in the UK and also provides a description of each case study dwelling.

3.2.6.1 Recruitment

Following ethics approval, a single dwelling was recruited for a pilot study (case study P1) in March 2019. The pilot study included a full scale monitoring campaign with the aim of (1) testing the monitoring equipment in a real occupied environment, (2) collecting preliminary data, and (3) to develop and assess data analysis techniques and methods. The findings of the pilot study were used to shape both the technical and social data collection methods - these findings are discussed in Section 3.2.6.4. This recruitment was carried out by email to a convenience sample of staff and students within The Bartlett School of Environment, Energy and Resources (BSEER), UCL. The recruitment email included an information sheet (see Appendix A on page 320), which provided background information on the project, implications for participants taking part in the project, how to complain, how data will be handled and disseminated, and finally how to contact the researcher.

During early 2020, the author had partnered with Oxford City Council (OCC) and identified a particular site for conducting this research. The site was selected following a multi-criteria decision analysis (MCDA) and appraisal of two potential residential sites. Recruitment letters were prepared for the preferred site, after which, all fieldwork was suspended at UCL due to the beginning of the COVID-19 pandemic in the UK. The suspension of fieldwork caused a delay to the recruitment and subsequent monitoring of this project. Unfortunately, due to the ongoing pandemic, OCC was unable to continue to support this project.

Due to the ongoing COVID-19 pandemic, the monitoring aspect of the project was redesigned to be carried out entirely remotely (discussed more in the following section), as national travel restrictions prohibited non-essential travel. Recruitment of participants for the main monitoring campaign was conducted by email to all staff and students in BSEER (UCL) along with all staff in the UK Health

Security Agency (UKHSA) (see Appendix A on page 320 for the emailed information sheet). Respondents were requested to carry out their own COVID risk assessment to ensure that no participants in the high-risk category (elderly, pregnant, clinically vulnerable) were included in the research.

Data was collected from respondents on their location, type of dwelling, and if it was possible to safely install equipment directly outside their dwelling. All respondents where it was not possible to install outdoor equipment were omitted. A qualitative assessment was made of the outdoor noise environment using information from Extrium (Extrium, No Date) and air pollution data from the London Air Quality Network (Environmental Research Group, Imperial College London, 2021) and Oxfordshire AirQuality (Oxfordshire AirQuality, 2021). Environmental noise, outdoor air pollution, and the potential for overheating was given a qualitative score of between 0 and 3 (0 - no information, 1 - low, 2 - medium, 3 - high), these scores then formed the basis of a multi criteria decision analysis, which ranked all the dwellings using equal weighting for each criteria. The top 4 dwellings were recruited (case studies 2 to 5), 2 participants dropped out before the installation of the equipment, and the next 2 highest scoring participants were recruited in their place. Participant P5 dropped out after 86 days, and a further participant was recruited in their place (case study P6). Around this time, additional equipment became available and a further, final participant was recruited (case study P7). Figure 3.25 provides an overview of the monitoring periods for each participant and also indicates the COVID-19 national lockdowns in the UK.

All selected participants were required to complete consent forms and were encouraged to ask any questions or clarifications about the research before any equipment was sent to them.

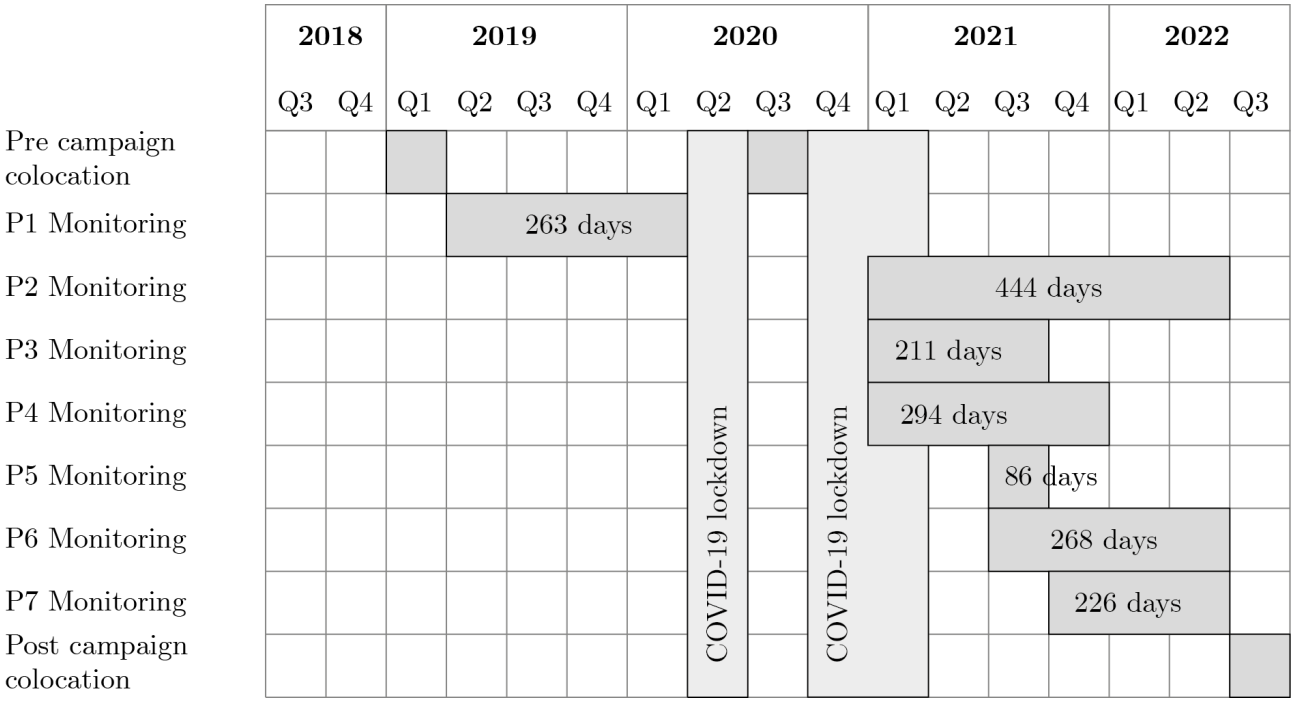


Figure 3.25: Timeline of monitoring for all case study dwellings.

There are a number of factors that mean that the sample of seven homes in this research is not

representative of the population in the UK and the sample is biased - these factors are discussed below.

The recruitment was carried out using a convenience sample of students, academics, and scientists at UCL and UKHSA. The resulting sample includes participants who are likely to be more aware of the relationship between ventilation and IEQ than the rest of the population. It is therefore expected that their ventilation practices will not be representative of the wider population. Furthermore, the intensive and intrusive monitoring campaign involved a high participant burden, which is likely to have also influenced those who chose to take part in this research (discussed more in Section 3.2.6.2). Finally, as described above, the participants in the sample were specifically selected for having a higher potential of poor outdoor air quality, high outdoor noise, and a higher potential of overheating, as these dwellings would allow the researcher to study the interaction between ventilation and these features. Flyvbjerg (2006) defines this case study selection as 'information oriented selection' and it this is also referred to as 'purposive sampling' (Wright et al., 2018), where these cases were selected with an expectation of the insights they might provide on the relationship between IEQ and ventilation. This non-probability convenience and purposive sample selection will bias the results and not be representative of or readily generalised to the wider population (Wright et al., 2018).

3.2.6.2 Equipment installation, managing monitoring, and data validity during COVID-19 pandemic

All equipment for the first case study dwelling (P1) was installed by the author. The author also visited the case study dwelling every month to check the operation and battery levels, replace batteries, and to download data from the equipment with internal memory. At the end of the campaign, the author conducted the building survey and uninstalled all equipment in person.

The COVID-19 pandemic and national lockdowns in the UK made it impossible for the author to visit each case study home in person, therefore the monitoring component of the research was redesigned to be conducted entirely remotely, with no physical contact between the researcher and the participants. At the time, conducting a remote campaign with the large quantity of complex monitoring equipment was highly unusual.

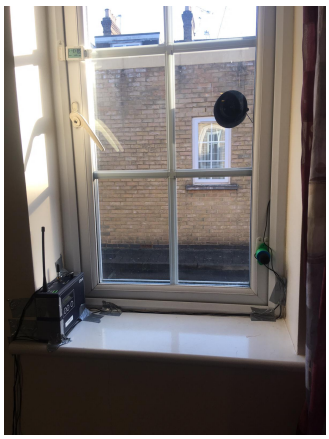
All equipment was carefully tested and preconfigured as far as practically possible to minimise the burden on the participants. Equipment was carefully disinfected (Figure 3.26a), packaged, and posted to participants by courier. On receipt, participants quarantined the equipment for 7 days, before unpacking. In one situation, equipment was damaged by couriers whilst in transit to the participant (Figures 3.26b and 3.26d). A comprehensive set of instructions was prepared for the participants to follow for unboxing, identifying, and installing all equipment, including their placement - see Appendix B on page 326. Almost all the equipment was installed successfully and appropriately by the participants (Figure 3.26c). Throughout the monitoring phase, one sensor was broken in transit, one event sensor was lost and another event sensor was damaged from exposure to high temperatures from a cooker.



(a) Author disinfecting equipment.



(b) Box damaged in transit to participant.



(c) Example of equipment correctly installed by participant 4.



(d) Sensor broken in transit.



(e) Event sensor installed incorrectly (90°) - sensor showing window as open.



(f) Outdoor noise microphone hanging from the one participants window (Google, 2022).

Figure 3.26: Photographs of the remote monitoring campaign.

Throughout the installation and monitoring phases of the project, the researcher and participants used WhatsApp messaging service for secure instant communications. During the installation, participants asked questions, called the author using video chats, sent photos and videos of installation issues/questions. Photos from participants during the installation phase were important for identifying and rectifying incorrectly installed sensors. Figure 3.26e is an example of an incorrectly installed event sensor, which was identified after this photo was shared with the author following their initial installation. During the monitoring phase, the researcher contacted participants to resolve issues, for example, when the data checking algorithm detected missing data, this was raised and investigated with the participants. Despite sharing installation photos and preparing detailed installation instructions, some equipment was not installed correctly or was altered during the long campaign. An example of this was noticed by chance, when the researcher noticed on Google Streetview (Google, 2022) an outdoor microphone had become loose and was hanging from the first floor window - see Figure 3.26f.

Section 3.2.2.1 explained that in certain rooms, battery-powered equipment with on-board memory was used. In most cases, the battery and/or memory on these devices would last a maximum of 3

months. Due to COVID restrictions, it was not possible for the author to attend the case study dwellings to replace this equipment, so every 2 to 3 months, replacement equipment was preconfigured, packaged and posted to each participant with return packaging and prepaid postage to enable the replacement of all battery-powered equipment.

The large amount of complex equipment, its nature, and the need for participant installation resulted in a monitoring campaign with a high burden on the participants. This high burden is unusual and restricted participants to those prepared to take part in this research.

3.2.6.3 Data set validity and COVID

The nature of the data collected during this campaign is unique, as it was collected during the COVID-19 pandemic in the UK, and most notably, data was collected during extended national lockdowns, where the participants were restricted to their homes for most of the day. Many participants in this research spent most of their time in their homes working during the monitoring campaign.

One potential issue with the data collected during this campaign, is that it is not likely to be representative of the way people used their homes, IEQ, or ventilation practices before COVID - Tahmasebi et al. (2022) found occupants of 8 flats in London opened their windows for far shorter periods of time during lockdown than before lockdown. Tahmasebi et al. (2022) also observed increased indoor concentrations of CO_2 during lockdown. The measurements, however, are potentially more representative of conditions in homes after COVID and into the future, as people continue to work from home.

The large percentage of time that occupants were confined to their homes during lockdown is an advantage to this research, as the IEQ closely reflects the occupants' personal exposure to many of the IEQ variables measured. Additionally, the lockdowns resulted in a dataset with more participant interactions with their ventilation systems and more indoor pollution events than if they were at work and not at home. However, lockdowns are likely to have resulted in a substantial reduction in traffic from all sources of transport, which would have had a corresponding reduction in outdoor noise and air pollution.

One limitation of the data collected during lockdown is that the case studies were infrequently unoccupied, and this had an impact on meeting the conditions required to calculate AER (3.2.4.3).

3.2.6.4 Description of case study homes

This section provides a brief description of each of the case study dwellings and the data collected from each. Table 3.12 provides an overview of each case study, their location, dwelling type, and details of the occupants, Table 3.13 an overview of the ventilation provision, Table 3.14 an overview of the monitoring campaigns, Table 3.15 the building fabric and finally, Table 3.16 a subjective assessment of external sources of heat gain, pollutants, and noise for each of the case studies.

P1 was the pilot case study, which included a detailed technical monitoring campaign, using the same instrumentation described earlier in this chapter. The monitoring campaign highlighted a number of limitations when using electronic event sensors for determining when windows and doors were open or closed - this was a motivating factor in developing a new novel method for inferring if a window or door is open, ajar, or closed from sound measurements inside and outside of a dwelling - this method is described in the next chapter (4).

This pilot study also highlighted issues around collecting technical information alone, where it was challenging to reconcile and interpret the technical data without social insights from the occupants - this helped shape the questionnaire (D). Feedback from the participants on the intrusiveness of the tripod mounted microphone shaped the discrete design of the microphones used in the RPi equipment (described in Section 3.2.2.6).

An event sensor measuring when the cooker hood was opened was destroyed by heat and cooking by-products, and no further attempts were made to measure cooker hood operation. Lastly, lessons were learned on how to configure (and pre-configure) and use each item of equipment efficiently and effectively, along with resolving issues remotely.

Table 3.12: Table summarising the location, dwelling type, and occupants for all case studies.

	Location	Type	Area	Constructed	Occupants
P1	East London	1 storey 6th floor flat	$50m^2$	2012	2 adults
P2	Oxford	2 storey semi detached	$83m^2$	1919-1944	1 adult + 2 cats
P3	North London	1 storey ground floor flat	$43m^2$	Unknown	2 adults
P4	West London	1 storey bungalow	$63m^2$	1991-2015	1 adult
P5	Central London	1 storey top floor flat	$69m^2$	2014	2 adults
P6	North London	2 storey semi detached	$112m^2$	Unknown	4-5 adults + 1 dog
P7	East London	2 storey terraced	$84m^2$	pre 1919	2 adults 1 infant

Table 3.13: Table summarising the ventilation provision for all case studies.

	Windows	Trickle vents	Cooker hood	Mech bathroom	Other passive
P1	Tilt-turn	Yes - open	Extract outside	MEV - not working	-
P2	Outward side hung	No	Recirculating	No	Airbrick bathroom
P3	Outward side hung	Yes - permanently open	Recirculating	Yes - light switch control	-
P4	Outward side hung	Yes - open	Recirculating	Yes - light switch control	-
P5	Mainly inward bottom hung	Yes	Recirculating	MEV - working	NA
P6	Tilt-turn	Some	Recirculating	Yes - light switch control	Airbrick bedroom
P7	Mixed	Only rear	Recirculating	Yes - not working	NA

Table 3.14: Table summarising the monitoring campaign dates and measurements for all case studies.

	Installed	Uninstalled	Observations (5min)	Variables	Measurements
P1	Apr-19	Nov-19	75,745	57	4,317,465
P2	Jan-21	May-22	127,994	72	9,215,568
P3	Jan-21	Sep-21	60,769	50	3,038,450
P4	Jan-21	Nov-21	84,792	70	5,935,440
P5	Feb-21	Jun-21	24,769	60	1,486,140
P6	Jul-21	May-22	52,993	77	4,080,461
P7	Sep-21	May-22	65,089	61	3,970,429

Table 3.15: Table summarising the dwelling fabric for all case studies.

	Walls	Floor	Windows	Roof
P1	Insulated cladding	NA - internal	Double UPVC	NA - internal
P2	Rendered masonry	Unknown	Double UPVC	Pitched
P3	Rendered masonry	Unknown	Single timber framed	NA - internal
P4	Masonry	Unknown	Double UPVC	Pitched
P5	Insulated cladding	NA - internal	Double UPVC	Unknown
P6	Rendered masonry	Unknown	Double UPVC	Pitched
P7	Rendered masonry	Unknown	Mostly triple acoustic	Pitched

Table 3.16: Table summarising the researchers subjective assessment of potential external sources of heat gain, pollutants, and noise for all case studies. This assessment was undertaken during the building survey.

	Heat gain sources	Pollutant sources	Noise sources
P1	Communal heating	New cladding	Adjacent road and rail
P2	Solar gains to South facade	Busy road	Busy road
P3	NA	Busy road, smokers	Busy road
P4	Conservatory	Busy road	Busy road
P5	Communal heating		Road at GF
P6	NA	Busy road	Busy road
P7	NA	Busy road front	Busy road front

On the following pages, Figures 3.27, 3.28, 3.29, 3.30, 3.31, 3.32, 3.33, 3.34, 3.35, and 3.36 present the floor plans for each case study. In Appendix E (page 387) Figures E.1, E.2, E.3, E.4, E.5, E.6, and E.7 present schematic drawings, detailing the instruments that were used inside and outside of each case study and all variables measured in each space.

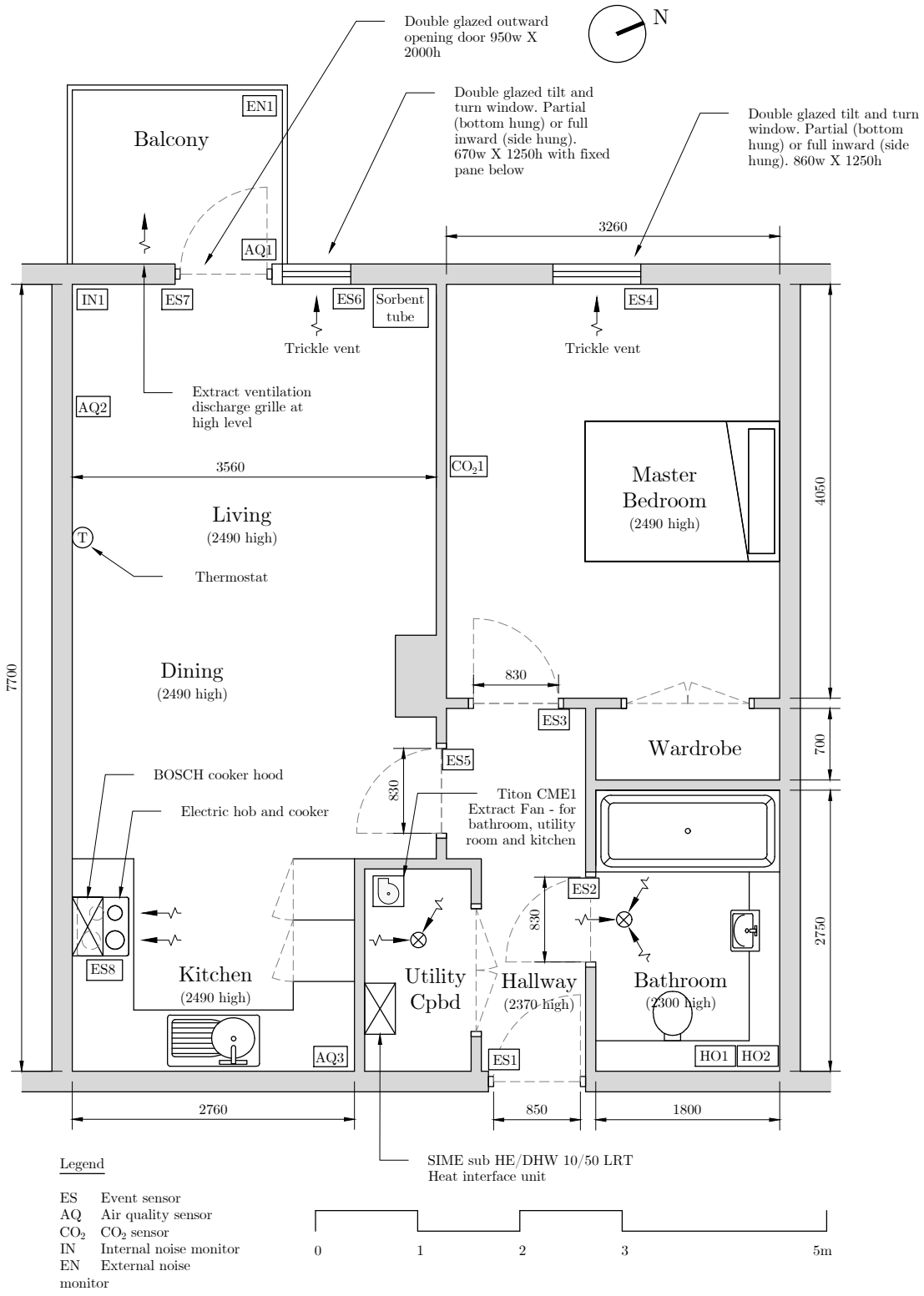


Figure 3.27: Floorplan for P1 (6th floor). Units in mm.

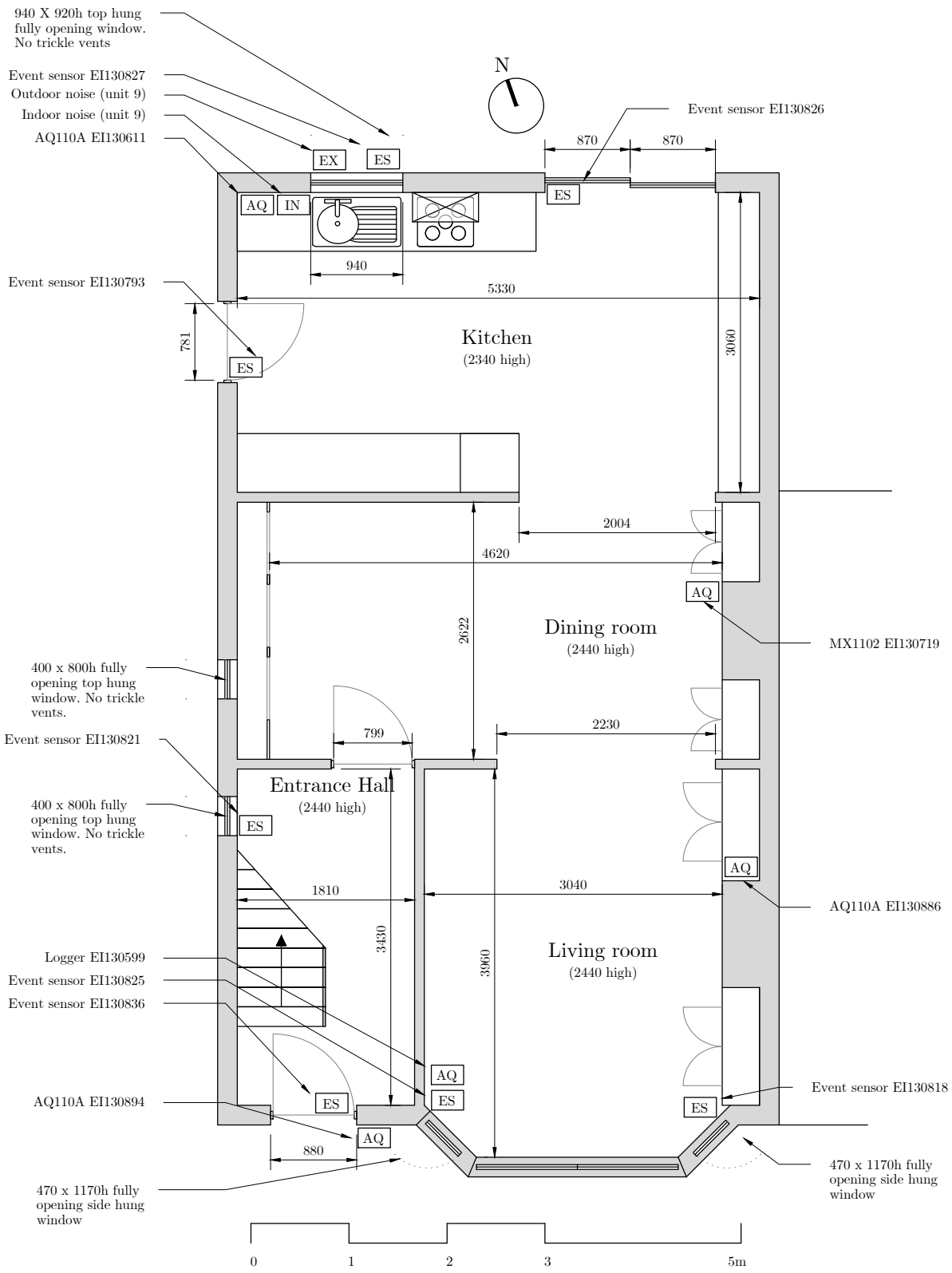


Figure 3.28: Ground floor of case study P2. Units in mm.

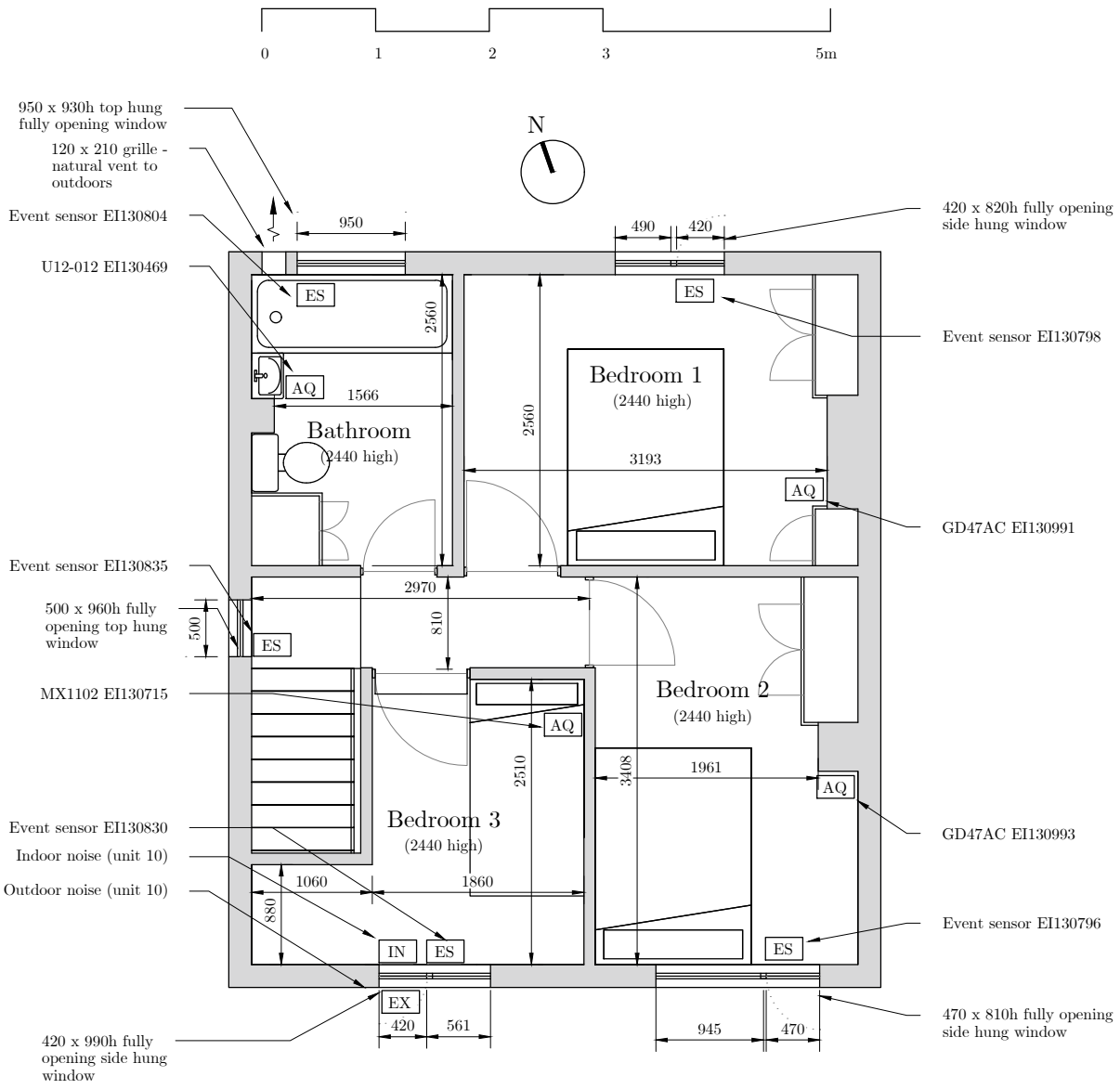


Figure 3.29: First floor of case study P2. Units in mm.

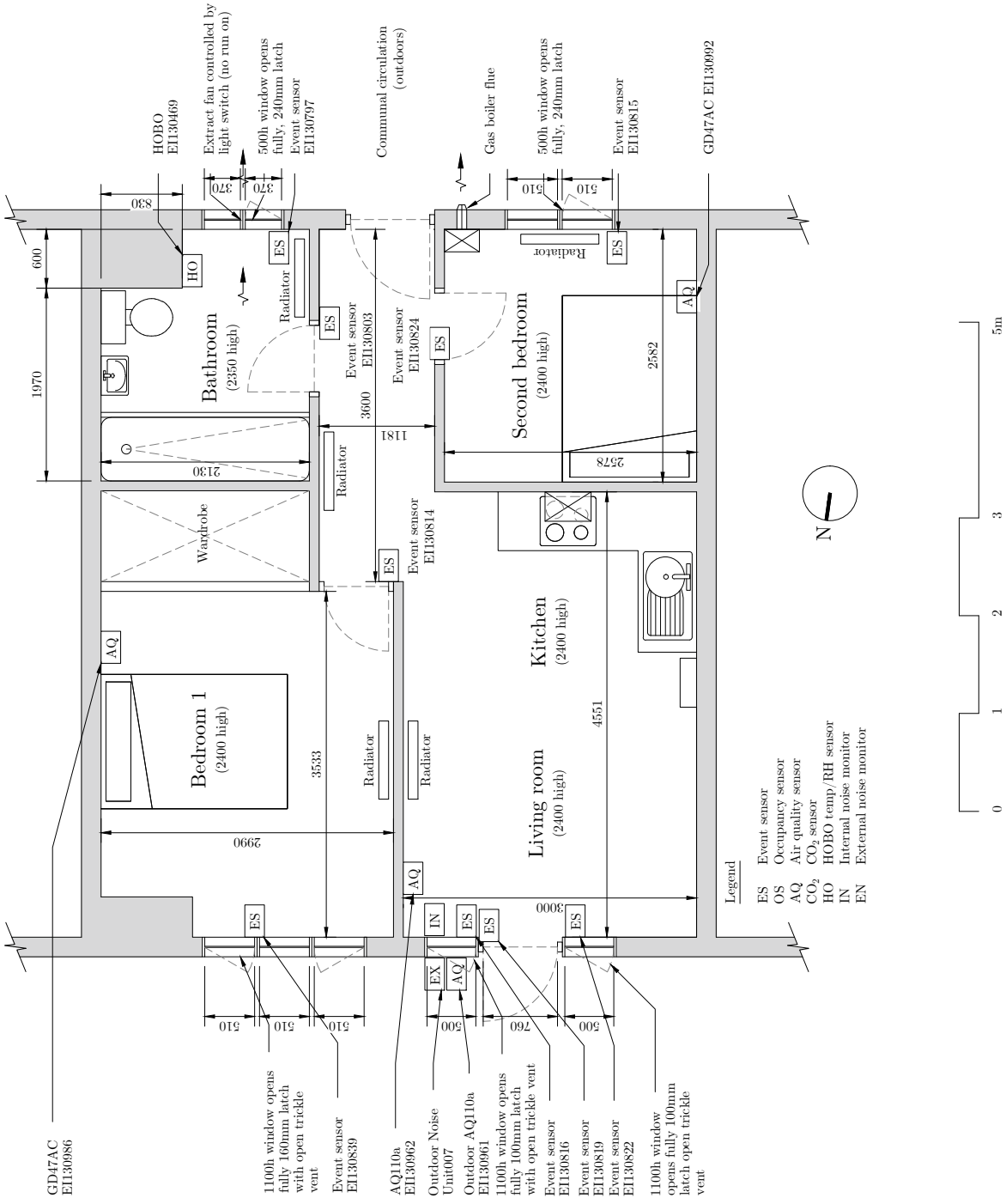


Figure 3.30: Floorplan of case study P3. Units in mm.

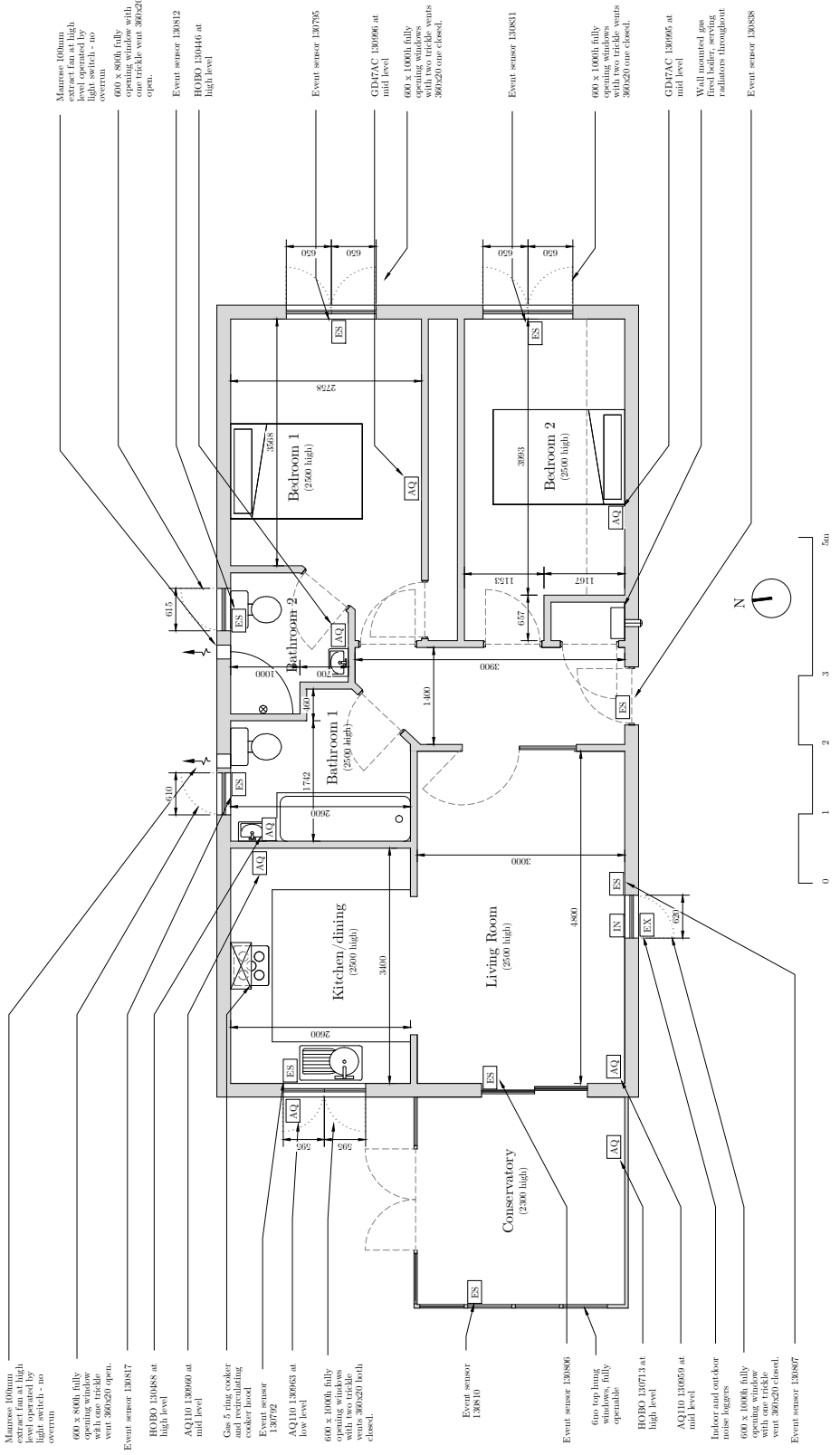


Figure 3.31: Floorplan of case study P4. Units in mm.

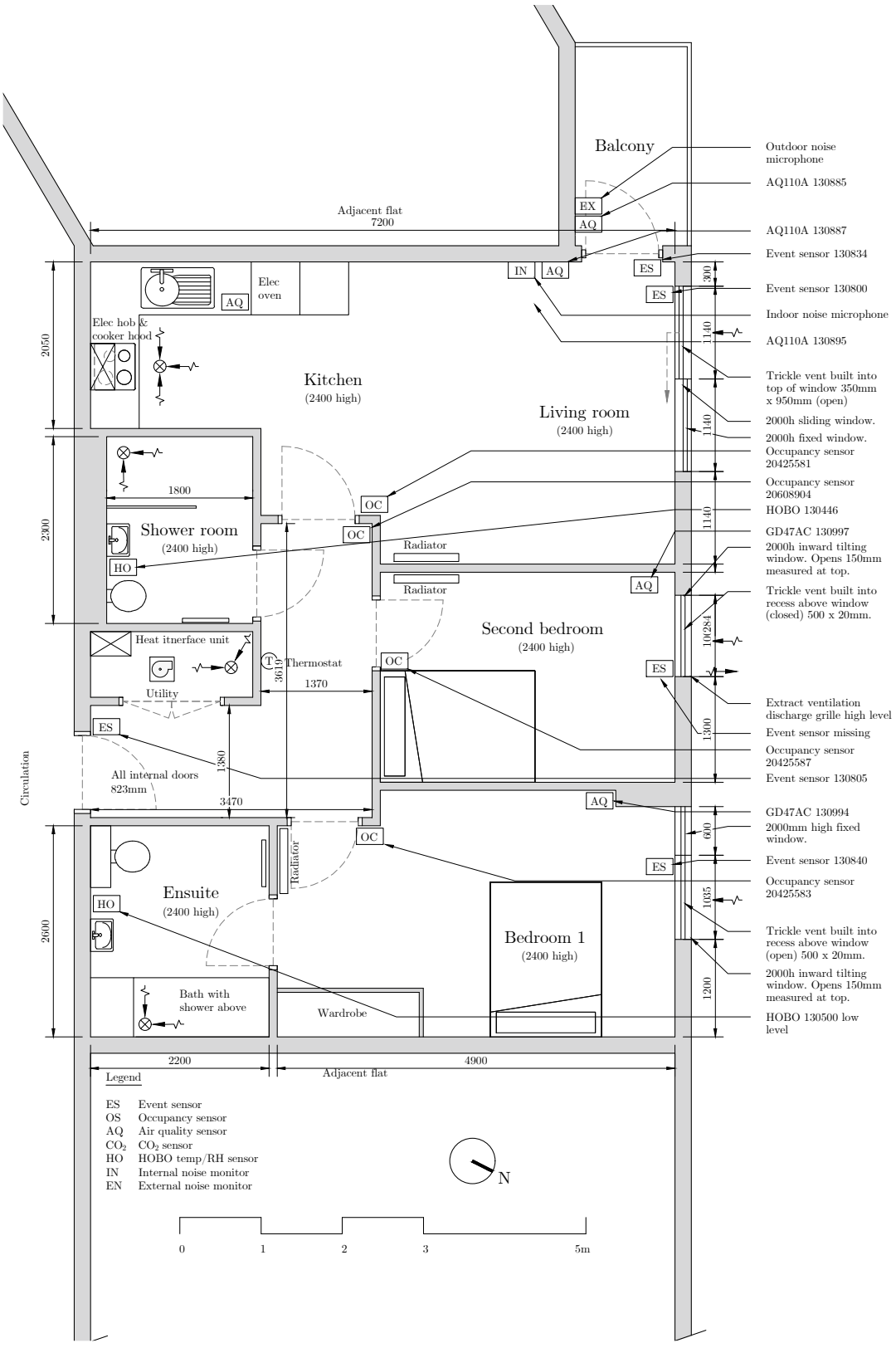


Figure 3.32: Floorplan of case study P5. Units in mm.

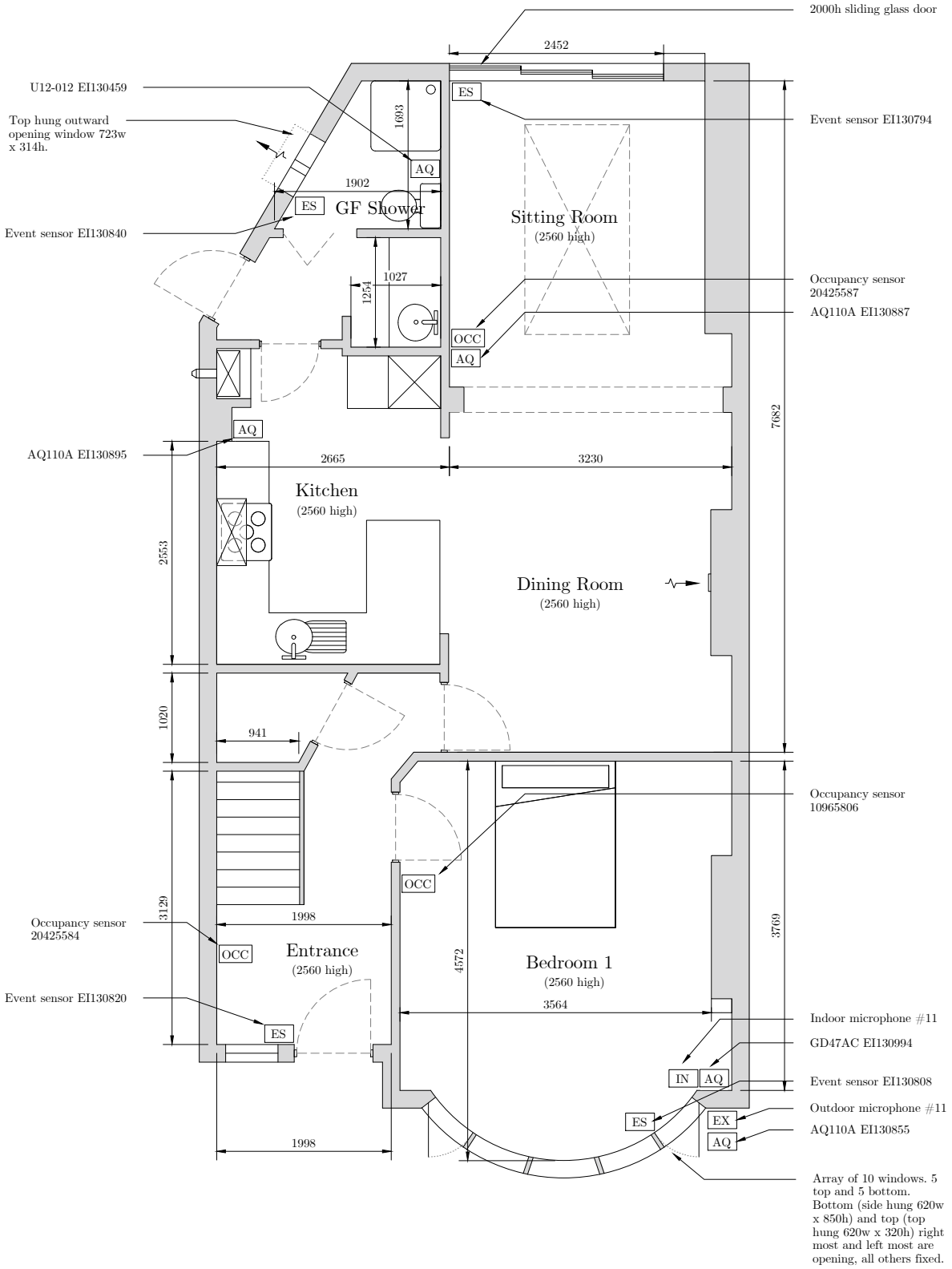


Figure 3.33: Ground floor of case study P6. Units in mm.

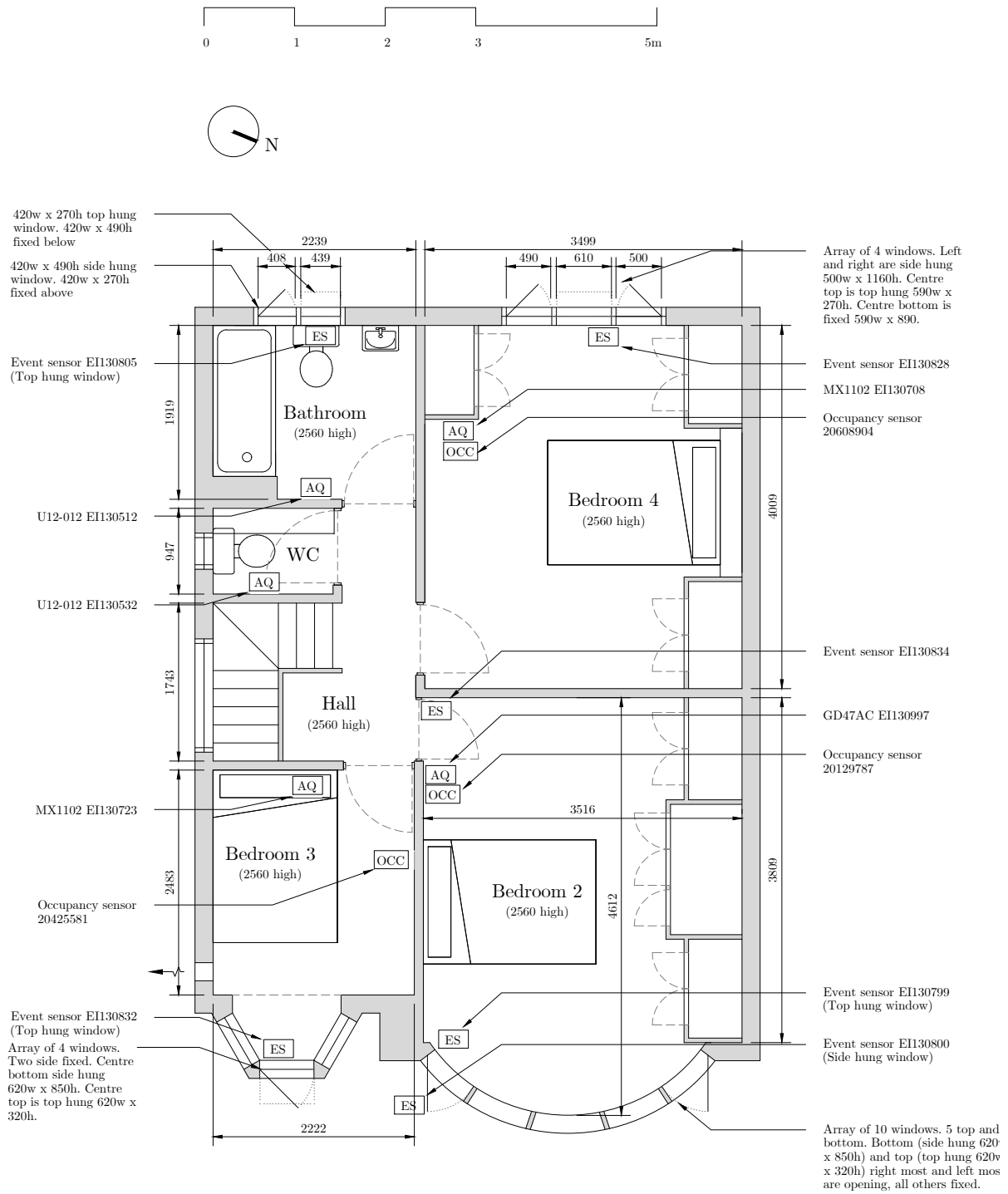


Figure 3.34: First floor of case study P6. Units in mm.

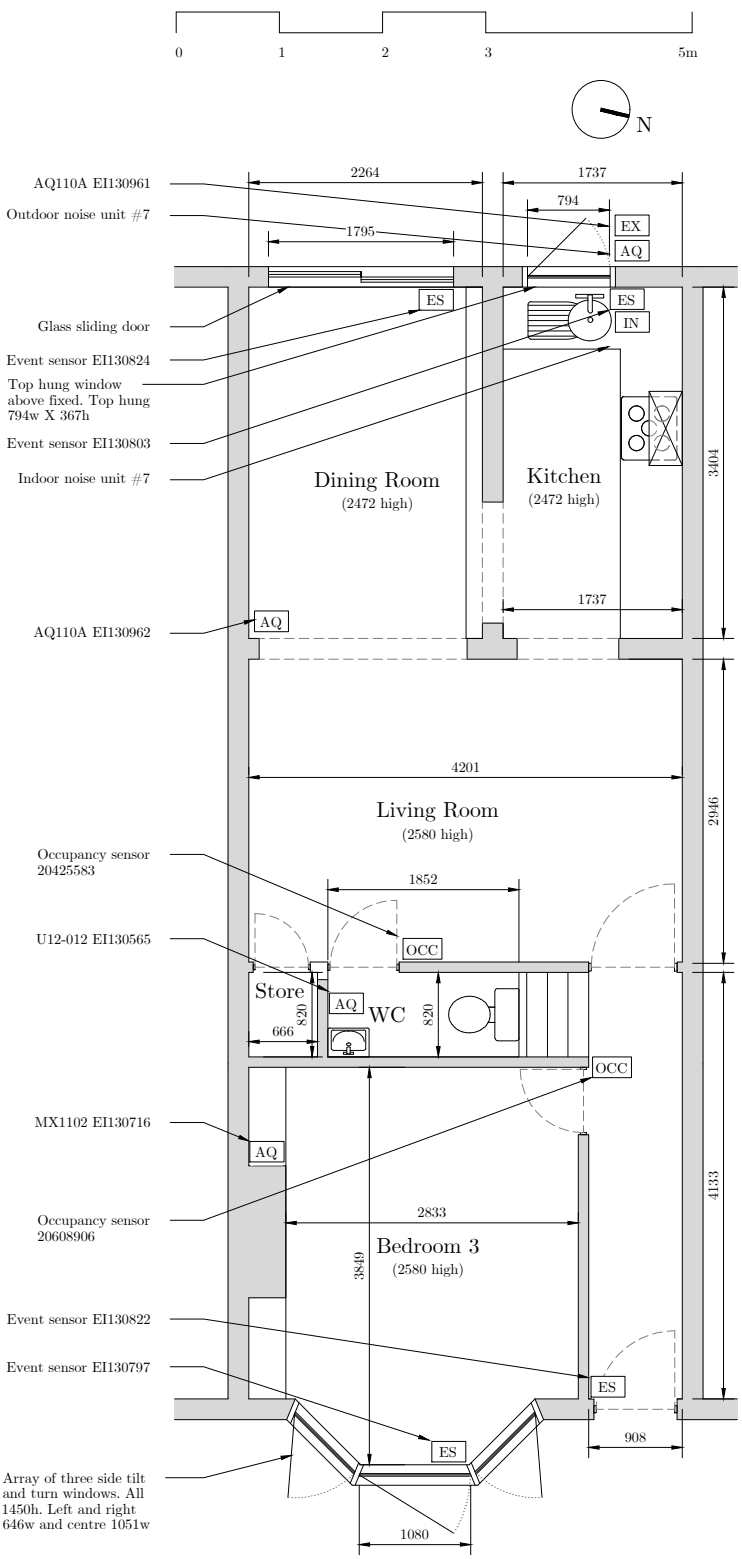


Figure 3.35: Ground floor of case study P7. Units in mm.

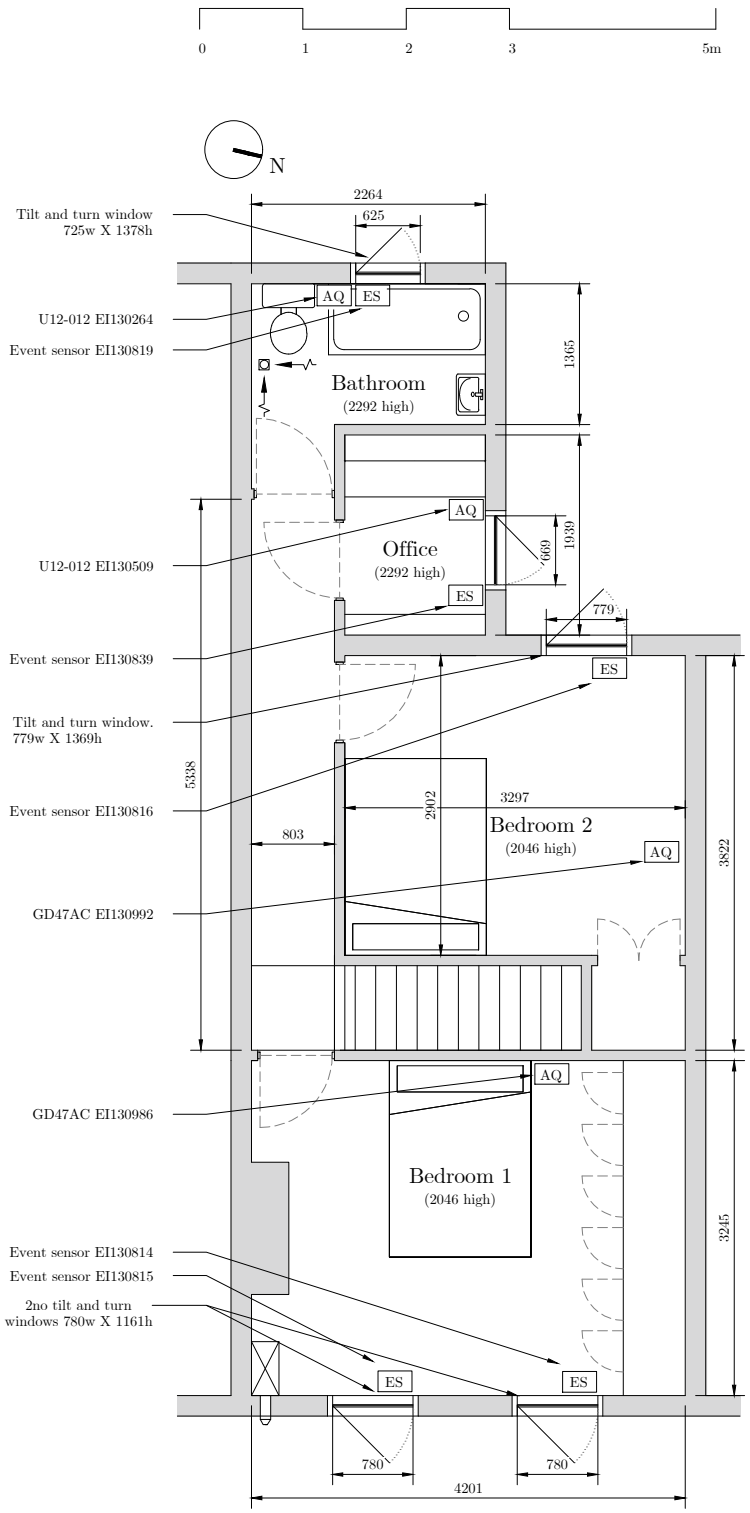


Figure 3.36: First floor of case study P7. Units in mm.

3.3 Summary

This chapter introduces and discusses the methodology, methods and case study dwellings used in this research. This chapter discusses the choice of an empirical, multi case study, mixed methods approach with longitudinal measurements. This approach addresses the literature gaps identified in Chapter 2, and allowed the researcher to study, in detail, the many complex social and technical factors that impact the relationship between ventilation and IEQ. Key limitations and ways in which this approach adds value to the existing literature are discussed.

Technical and social data collection methods were presented. Technical data collection methods include: building surveys, measurements of temperature, air quality, noise, VOCs, occupancy, window and door events. Questionnaires were used for obtaining data from participants on their household, home, ventilation provision and its use. The conceptual causal diagram from the previous chapter (Figure 2.8) has been updated (Figure 3.37) to show the variables that were measured and the methods used in this research. Following a discussion of the data collection methods, there was a detailed discussion of the data analysis methods that were developed to answer the research questions.

The final section of this chapter presented details of the research ethics and descriptions of the seven different case studies that were recruited from a convenience sample to take part in this research. The impact of the COVID-19 pandemic was discussed, along with the redesign of the monitoring campaign to be carried out entirely remotely through the postal system and the installation of equipment by the participants.

The next chapter (4) combines the development of a novel method with the results from its application in two occupied homes.

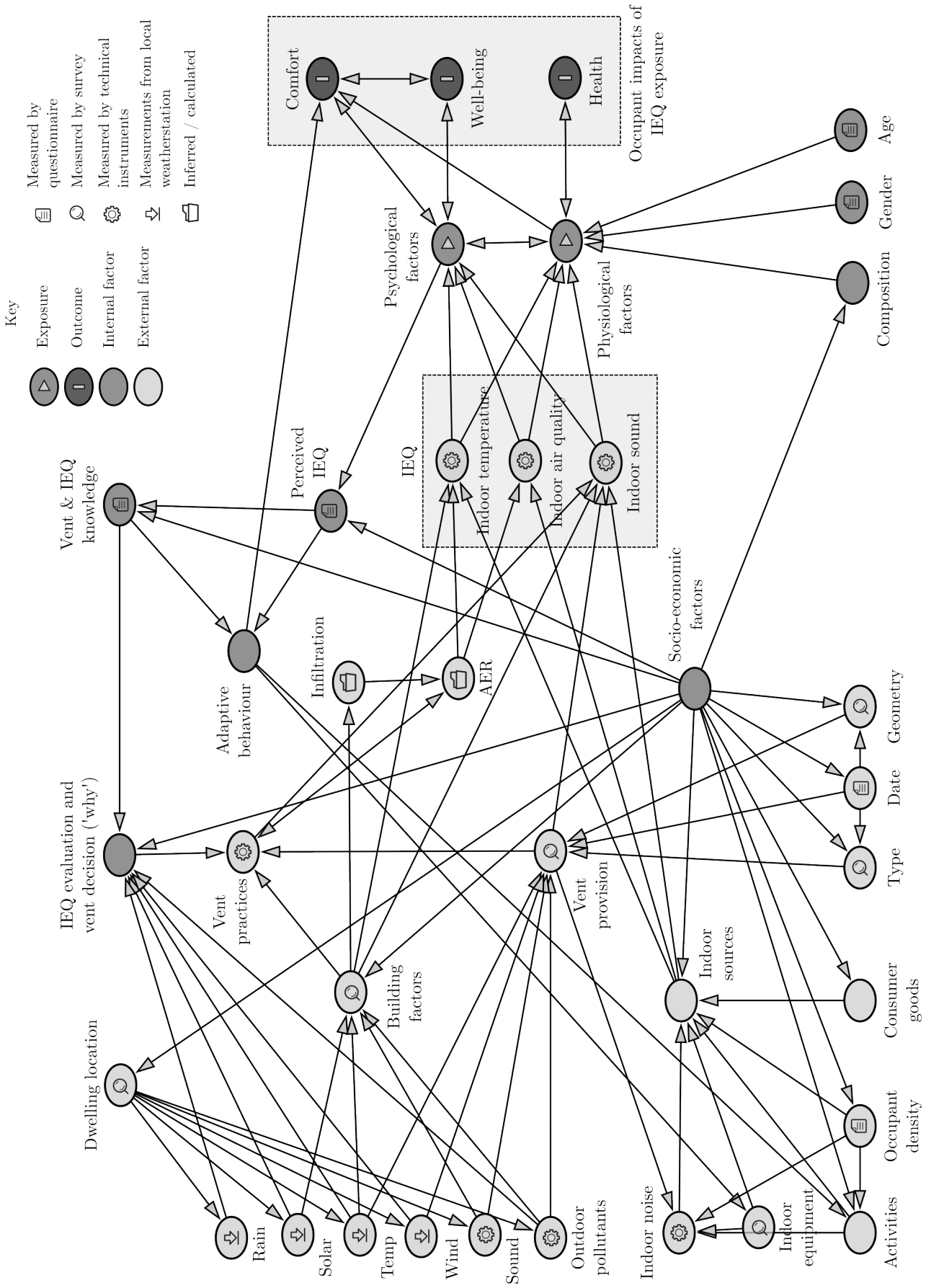
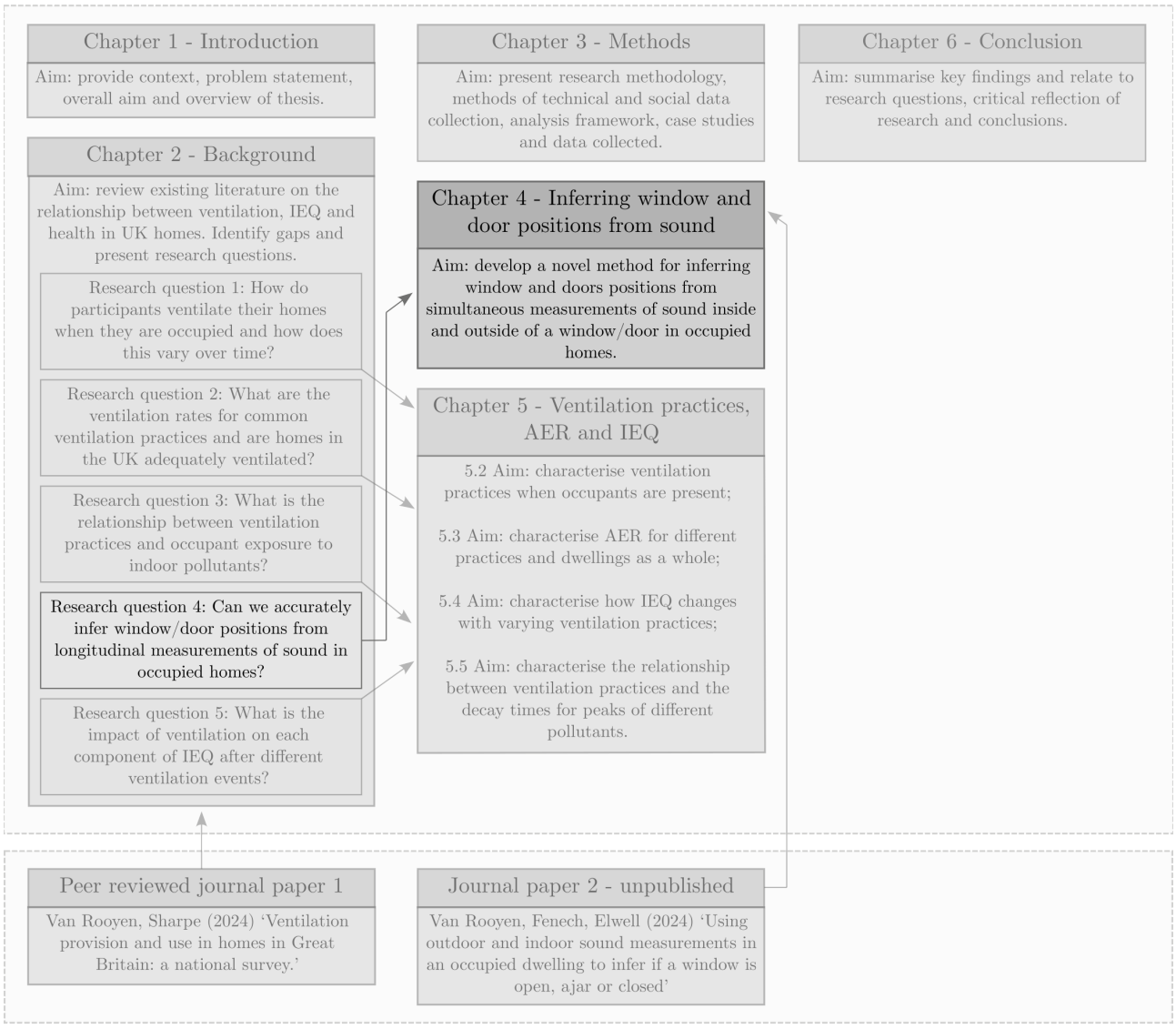


Figure 3.37: Conceptual causal diagram from Chapter 2 (2.8) updated to show methods of data collection.

4 | Inferring window and door positions from sound measurements



4.1 Introduction

This chapter has been prepared for submission to a journal, but has not yet been submitted. Please refer to the UCL Research Paper Declaration Form on page 5 for details.

Chapter (2) demonstrated that ventilation is an important modifier of indoor environmental quality (including indoor air quality, temperature, and noise) and also energy use in buildings. Occupants' use of windows and doors is one of the most common ways to ventilate buildings in the UK, Europe, and many other parts of the world (McKay and Ross, 2010; Litiu, 2012; Van Rooyen and Sharpe, 2024). Therefore, it is important to understand how people use them and what impact that has on ventilation rates, IEQ, and energy use.

Previously, in Section 3.2.2.4, two broad categories of methods for recording the status of windows/doors were discussed: (1) using people or (2) using equipment/technology.

Researchers or research participants can record window positions at different times of the day, however, this is time and labour intensive and can suffer from low temporal resolution, inaccuracies, and a lack of completeness (Kukadia and White, 2006; Fox, 2008).

From a technological perspective, electronic reed switch event loggers have been widely used in research since the late 1980's (e.g., Dubrul (1988); Sharpe et al. (2014); Balvedi et al. (2018); Wright et al. (2018)). These devices work by recording the time that a window/door opens and closes and can provide data over long periods of time with a low labour cost (installation, change of batteries, data download at regular intervals) and with ease of use. However, these devices are subject to a number of limitations. Dubrul (1988) noted that these devices were expensive and not always found to be acceptable to participants. The devices operate with a reed switch and magnet to record when the magnet is close enough (approximately 20mm) to the reed switch to either make or break a connection. Because of this, these sensors cannot accurately determine if a window is fully closed and sealed. Additionally, the installation of a single event sensor cannot distinguish an ajar from a fully open position (Few and Elwell, 2019; Few, 2021). This is an important limitation, as the position/angle of windows and doors can have a significant impact on noise, ventilation, IEQ and energy use (Locher et al., 2018; Liu et al., 2022). It is noted that a researcher can install two or more of these devices to infer how far a window or door has been opened (see Section 4.2.3.4), but this requires the careful installation of multiple event sensors. The installation of multiple sensors increases the cost and complexity of the monitoring, and also the intrusiveness of the measurements. For top and bottom hung windows, electronic accelerometer loggers (see for e.g., Andersen et al Andersen et al. (2013)) use the degree of tilt to infer how far the window has been opened. However, these can only be used for that specific type of window.

Previous studies have presented techniques for estimating air permeability and air infiltration of

building facade elements using sound measurements (Varshney et al., 2013; Iordache and Catalina, 2012; Berardi and Pouyan, 2019). However, such techniques relied on measurements under carefully controlled conditions, with a specific external sound source, optimised measurement locations, and low levels of indoor background noise. In contrast to this, in this chapter a novel method is presented for inferring the status of a facade window/door using longitudinal sound data captured in two different occupied homes. The main advantage of this method is that it outputs a three-state (closed/ajar/open) time history to inform IEQ and building energy use investigations, using a dataset that is of primary or secondary interest to such investigations.

There is an increasing body of evidence that noise is associated with adverse physical and mental health outcomes, including cardiovascular and metabolic health endpoints (CMO, 2017; WHO, 2018*a*; Gong et al., 2022; Jephcote et al., 2023). The proposed method provides quantified time series data of both outdoor and indoor sound levels which can also be used to quantify occupants' exposure to noise. However, from a health perspective, it's important to note that noise is a psycho-social stressor, rather than a toxicant, and the source of sound (and people's attitudes towards it) can act as a moderator and/or mediator of the exposure-health pathway. Therefore, it is important to distinguish between wanted (for example, TV audio, music) or unwanted sound. Outdoor sound is generally outside the control of the occupant, and in the case of sources such as transport, industry, and construction, it is often unwanted (Notley et al., 2014). Indoor sound is a combination of unwanted sound ingress from outside the dwelling, unwanted sound from inside the dwelling that the occupant may have control over (such as mechanical ventilation), and wanted sounds which the occupant has control over.

Figure 4.1 provides a graphical overview of the method used in this chapter. A statistical model is first trained using a small dataset of external and internal sound data, where the window position is known *a priori*. The model can then be used to predict the window status based on the outdoor and indoor recorded sound. The efficacy of this method has been explored in two occupied dwellings, one situated in a "noisy" urban environment and the other in a quieter rural location. The method has also been demonstrated to work with both an off-the-shelf state-of-the-art measurement system and a low-cost sound measurement platform which was developed by Dr. Benjamin Fenech and the researcher for this specific task (see Section 3.2.2.6 on page 124).

4.2 Materials and Methods

4.2.1 Theoretical principles

The four acoustics principles underpinning the proposed method are that:

1. The airborne sound insulation (resistance to sound) properties of a facade window or door are dependent on whether they are closed/ajar/open, resulting in measurable differences in outdoor

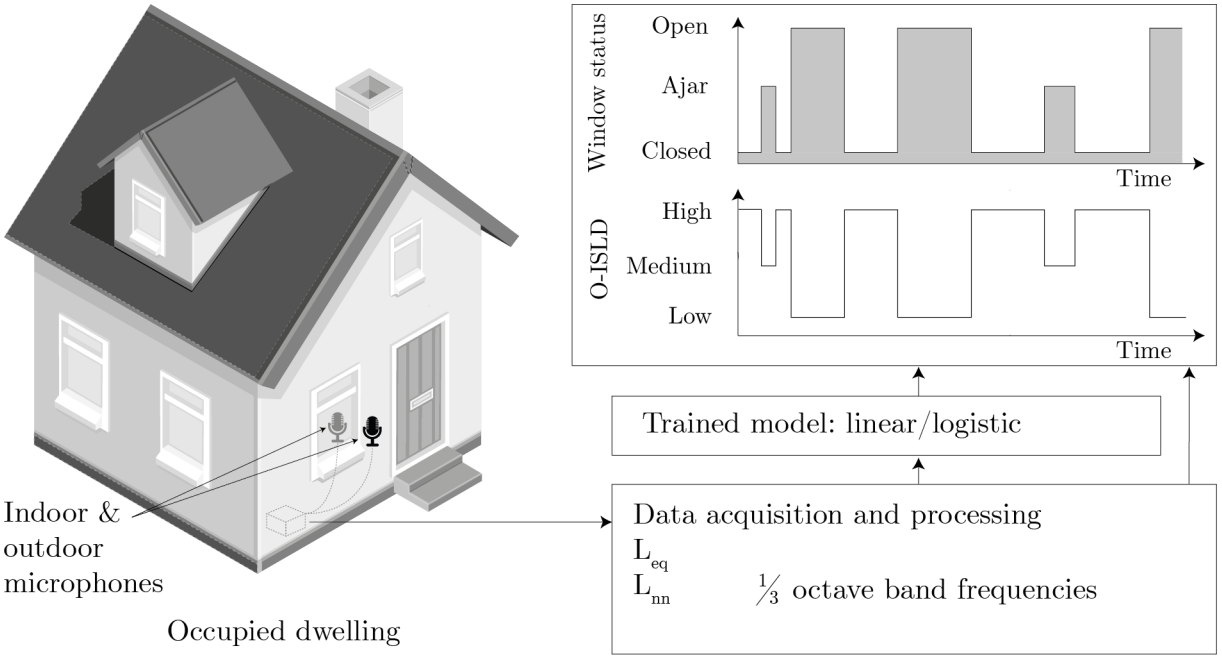


Figure 4.1: Graphical representation of method for inferring window/door positions from indoor and outdoor sound measurements. L_{eq} is the average level of sound pressure within a certain time period. L_{nn} is the sound pressure level exceeded for nn % of a certain time period (percentile).

to indoor sound levels in a typical domestic setting (The Building Performance Centre, 2007; Buratti, 2002; Locher et al., 2018).

2. The airborne sound insulation properties of a facade window or door are dependent on their construction, including the mass per unit area of the glazing and frame and the presence of any damping (such as the air gap in a double-glazed unit) (Quirt, 1982, 1983; Locher et al., 2018).

3. The airborne sound insulation properties are frequency-dependent, i.e., they vary with the frequency (pitch) of the sound.

4. Sounds from occupant activities within a dwelling are more likely to be intermittent in nature compared to outdoor sources of environmental sound.

The first principle implies that window positions can be inferred from the outdoor to indoor sound level difference (O-ISLD) at regular intervals. Therefore, absolute sound levels are not as important as the relative difference between indoors and outdoors. The second principle implies that there is no universal set of values that can be used to infer window status, and therefore, a "training" exercise is required to determine the correct parameters for a specific situation, i.e., for a given outdoor sound environment, facade and window construction, and location of outdoor and indoor microphones. The training data will remain valid as long as these three parameters remain unchanged. The amount of training data (length and number of features) required depends primarily on the sources of sound outside the dwelling, but is also likely to be dependant on indoor sources of sound. A minimum amount

of training data is needed where there is one or more dominant fixed sound source, e.g., a busy road with a fairly constant stream of traffic. Conversely a relatively quiet rural location with a variety of different and intermittent sound sources would likely require a larger training dataset. In very quiet locations the training data requirements may make this method unfeasible to implement in practice.

To be useful for long-term indoor environmental quality (IEQ) monitoring campaigns, the method needs to work in occupied buildings. In occupied buildings, the internal sound environment comprises sound ingress from outdoors/adjacent spaces and sound from internal sources, including occupants and their activities. There are likely to be frequent periods when the overall sound level indoors is comparable to or even higher than that outdoors. However, the frequency spectrum of indoor sound activities (such as from speech, music, or home appliances) is often different to that of outdoor noise sources such as transportation (Buratti, 2002). Therefore, the third acoustic principle set out above can be applied to address this situation. The temporal patterns of outdoor and indoor sources of sound can also vary - for example, the level of sound from a road or railway is likely to vary much less than sound from occupant activities inside their dwelling, however, this is likely to be very dependant on the dwelling and its outdoor sound environment (fourth principle). Statistical levels or percentiles (the level of sound exceeded for a percentage of time within a measurement period) can be used to distinguish between ambient sources of sound in a specific environment.

An overview of the method, as it might be applied in a future monitoring campaign, is shown in Figure 4.2.

4.2.2 Metrics and implementation

4.2.2.1 Metrics

The method requires continuous measurement of outdoor and indoor sound. Standardised acoustic metrics have been chosen to facilitate the method's implementation and deployment. The simplest acoustic parameter to measure is the overall instantaneous sound pressure level L_p; however, this is of no practical use as it can fluctuate substantially within a small period of time (sound in the human audible range is typically sampled tens of thousands of times per second). Therefore some form of time averaging is required within a defined time period t_{int}. The most common time averaged acoustic metric is the L_{eq}, however, as noted previously, it may be more advantageous to consider acoustic percentiles to minimise the influence of occupant-generated sound indoors: this was investigated in this chapter.

The next layer of information is obtained by breaking the sound down into its frequency components using the Fast Fourier Transform (FFT). Following this transformation, the audio recordings are deleted from the measurement platform, ensuring the privacy of the occupants. In acoustics, frequency information is often presented either as narrowband FFT spectra, or as octave or one-third octave band spectra. A narrowband spectrum consists of hundreds or thousands of sound data points for each

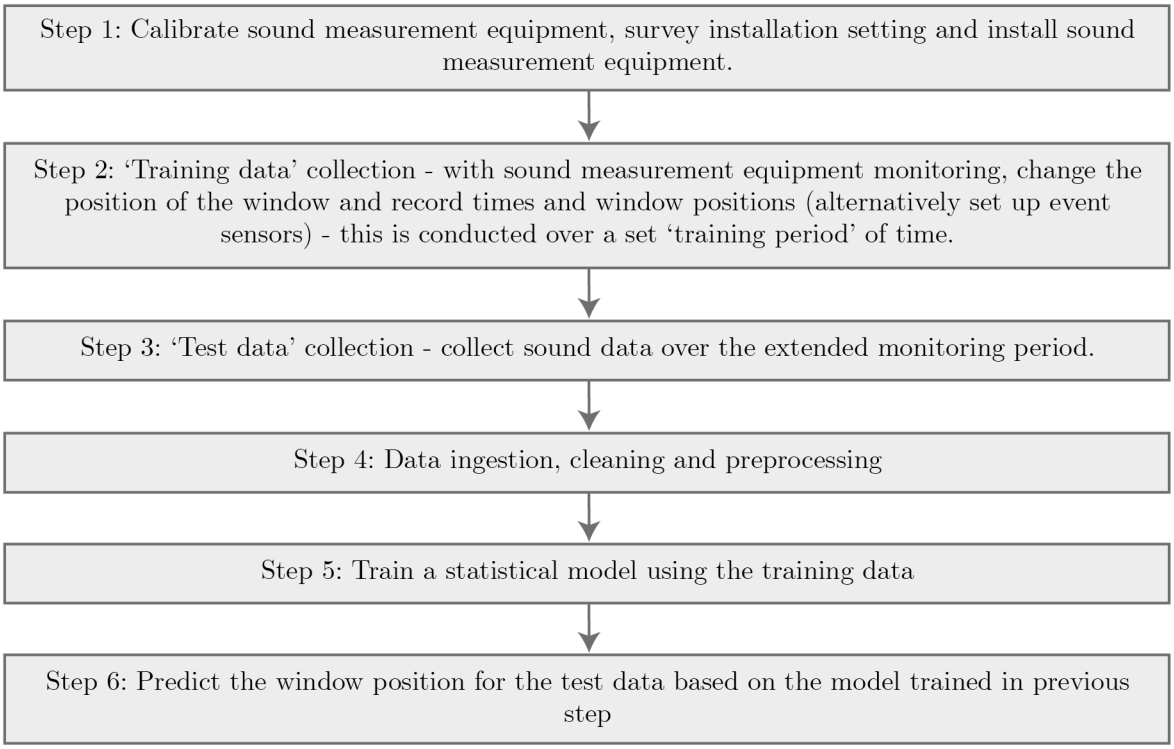


Figure 4.2: Overview of method, as it might be applied in a monitoring campaign for inferring window and door positions.

time interval, and whilst this would provide granular detail to a prediction model, it would come at large computational/processing and storage cost. Octave-band and fractional-octave-band spectra are a simplified version of narrowband spectra, generated by summing up the energy in frequency bands centered around specific "preferred" frequencies, which are standardised (BSI, 1996). For environmental noise applications centre frequencies between 25Hz and 10kHz are often of greatest interest. One-third octave band spectra were chosen for this method as they offer sufficient granularity at low frequencies whilst having a manageable computational and storage cost (28 values per time interval for frequencies between 20Hz and 10kHz). Most modern off-the-shelf professional acoustic meters are able to measure acoustic percentiles in one-third octave bands.

4.2.2.2 Measurements

From an equipment perspective, the data requirements are the simultaneous recording of indoor and outdoor one-third octave spectra, recorded at regular time intervals (e.g., every five minutes); most commercial professional sound level meters offer this functionality. Professional sound level meters are best suited when accuracy of the absolute levels is the top priority (e.g., legal meteorology). However the software and hardware of these systems cannot be easily changed by the user, which may introduce difficulties for deploying in a wide range of scenarios (e.g., mounting external microphones for dwellings not on the ground floor and without access to a balcony). Furthermore, equipment cost (typically several thousand pounds per unit) is an important limiting factor, particularly when considering monitoring at scale. An alternative to sound level meters, particularly for measurement campaigns targeting tens or hundreds of dwellings, is to use sound monitoring systems (SMSs). SMSs are distributed systems typically with a microphone, local processing unit, and some means of data transmission to a remote/cloud-based server (Institute of Acoustics, 2019). SMS can be more adaptable to specific applications and have a lower cost per unit; however, they often require a more in-depth knowledge of acoustics and more rigorous data validation protocols to ensure valid measured datasets (Noriega-Linares and Navarro Ruiz, 2016).

An important consideration for internal sound measurements in occupied buildings is privacy concerns. It is important that no audio information is stored on or transmitted from the device in case of tampering or hacking by a third party. Therefore, the raw sound data should be analysed and converted into a sequence of numbers in real or near real-time within the installed equipment. These datasets can then be uploaded to a central repository so that home visits to download the data are not required. A delay of 24 hours was implemented for the transmission of data to avoid the risk of inferring the current status of the door/window if the data transmission is compromised.

The next question was where to measure. Sound consists of longitudinal pressure waves that exhibit complex interference patterns in the presence of solid boundaries and objects such as facade elements, internal walls, and furniture - sound varies spatially in rooms. In environmental and building

acoustics, standards, and good practice guides stipulate that external sound measurements are carried out either well away from a facade or at the facade. Indoor sound measurements are typically carried out either at the normally-occupied position, or a spatial average obtained from using a moving microphone measurement, or from four or more fixed microphone positions (International Organization for Standardization, 2014; ANC, 2020*b*). These measurement procedures are not feasible for long-term campaigns in occupied dwellings and have a different purpose from identifying window position. For the purpose of this method, the measurement locations are dictated by practicality and minimising disruption to the occupants' use of their home, including the presence of children and pets. This often meant that the microphones and ancillary equipment were installed immediately outside and inside the window/door under investigation, and also in part dictated by the furniture present and the occupants' use of the space. Although this is suitable for identifying window position, it means that the indoor sound measurements are not likely to be representative of the occupants exposure. Because of this, it is recommended that indoor noise exposure is estimated from the outdoor noise measurement and the knowledge of the window status, together with the empirical relationships of typical, spatially-averaged outdoor to indoor level differences found in the literature (Locher et al., 2018). This together with other algorithms that can detect room occupancy from other pollutants (e.g., decay of CO_2) (Few et al., 2019) can allow researchers to estimate exposure within dwellings. Further research comparing the measured indoor sound data with optimum spatially averaged indoor sound measurements would enable a better understanding of the differences and to establish if the data is suitable for estimating occupant exposure.

4.2.2.3 Statistical modelling

Statistical machine learning models were applied to predict one of three states (open/ajar/closed) from a sequence of acoustic parameters for a time interval T_{int}. There are many statistical models available to use for this classification problem and the decision of which model to use is dependant on a number of different factors and model assumptions. Two models were shortlisted for this method based on the researchers knowledge of the models, model transparency and the ability to interpret the models (not 'blackbox') - these models were: multinomial linear regression and ordinal logistic regression models. Both are considered forms of 'unsupervised machine learning' and use labelled datasets for making predictions. Linear regression uses least squares to determine a straight line of best fit for the data and uses this to predict a continuous output variable (Arya, 2022). On the other hand, logistic regression uses maximum likelihood estimation and the sigmoid function to classify data into discrete ordered groups (Arya, 2022). In applying these models to this application using frequency-resolved sound data, certain model assumptions are unlikely to be complied with, such as the absence of multicollinearity, the absence of autocorrelation, and time-series independence (Ottenbacher et al., 2004; Long, 2008). However, as the models are being used for the sole purpose of predicting window positions for a specific

situation (i.e., model coefficients are generated for a specific installation setup and are not generalised), only the accuracy of the model in predicting window position was considered important, enabling a loosening of the application of the statistical techniques and their assumptions. Principal component analysis (PCA) could be used to analyse model coefficients and reduce possible non-compliance of model assumptions by reducing dimensionality and correlation of the model variables; however, this may have a detrimental impact on model accuracy and this impact was not investigated here.

Given the vast acoustic variations for different measurement setups, even for the same building (as noted in 4.2.1), it is not possible to generalise model parameters beyond a given setup, therefore, for every implementation of this method, there will be a need to train a model for that specific setup. In order to infer window positions, it is necessary to collect a small data set (termed the 'training data set') of both the acoustic parameters and the 'true' window/door positions and use this to train a statistical model. This step is particularly important, as the quality and quantity of the training data will be critical for the accuracy of the statistical model. Ideally, the training data set should contain a range of measurements for each of the three window positions; in practice this may be achieved by repeatedly changing the window position after a set period of time (for example, every 30 minutes) to one of the three window positions (randomly) over the 'training period' (for example, a day), with the investigator/occupant recording the time that the window position was changed and the position it was changed to. The timing of the training exercise is also important. If the measurements over this period are not 'typical' of the indoor and outdoor sound for this environment, the model will have a reduced accuracy. For example, if there is music being played indoors or temporary construction work outside the window of interest and the model is trained on this data, the accuracy of the model using measurements without music or construction noise may be adversely impacted. Furthermore, some environments might experience a wide range of different sounds and seasonal variation, which mean that care should be exercised when using this method over long-term campaigns. The magnitude of these effects on model accuracy is not known, as it is expected that this will be highly specific to the situation. It is hypothesised that longer training data sets would improve the accuracy of the model as they would account for a wider range of acoustic conditions, especially for situations where there is not a continuous and/or dominant external sound source.

4.2.3 Validation

4.2.3.1 Test cases

The method was tested in two distinctively different test cases in England: a dwelling in a semi-rural setting with relatively low levels of environmental noise (arithmetic mean = 46.7dB(A) st dev = 5.7dB(A)) and a dwelling in Central London exposed to relatively high environmental noise levels (arithmetic mean = 54.8dB(A) st dev = 6.2dB(A)). Both dwellings are in addition to the case studies

described in Section 3.2.6. The test cases were monitored during COVID-19 lockdown periods and both were occupied by two adults, working from home full-time. Therefore, both test cases include sound from internal activity throughout the measurement periods.

The first test case, henceforth referred to as the 'semi-rural dwelling', is located in Northchurch, Hertfordshire. The dwelling is a 1960s terraced dwelling with brick cavity wall construction and aluminium metal framed double glazed windows. The windows are split with a fixed lower pane and an outward opening top window light. The top window light is secured closed using two latches. The opening part of the window is sealed (when closed) by a small rubber gasket around the whole of the opening part of the window and a smoke strip. Sound measurements were taken in the master bedroom, which is located on the first floor of the dwelling. The window of the master bedroom is facing towards a single carriageway collector and distributor road (A-road) which is approximately 100m away and a main railway line approximately 500m away. Data was captured for approximately 9 days (2,591 5-minute observations). See Figure 4.3, showing a photograph of the window and sound measurement equipment for the semi-rural test case.

The second test case, henceforth referred to as the 'urban dwelling', is a flat located in Central London, near Camden Road overground railway station. The flat is located in a 4-storey pre-1900 terraced building with solid brick walls and single glazed wooden framed windows. The sound measurements were taken in the living room on the second floor of the building, both inside and outside the living room balcony door. The balcony door is directly overlooking a main overground railway route in central London, which carries both freight and passenger trains throughout the day and some freight trains overnight. Most of the freight and overnight trains are diesel and most of the passenger trains were electric. The door directly faces the railway tracks with a short wall partially obscuring direct sound from the tracks. The train tracks are approximately 25m from the balcony door. Data was captured for approximately 34 days (9,791 5-minute observations). See Figure 4.4, showing a photograph of the window and sound measurement equipment for the urban test case.

The measurement environment for each test case was surveyed to determine physical arrangements of the buildings, construction information of the buildings and a qualitative sound survey of noise sources. Table 4.1 provides a summary of key characteristics for both test case dwellings and the measurements collected during the campaign.

4.2.3.2 Sound measurements in the semi-rural test case.

For the semi-rural dwelling, sound measurements were taken inside the master bedroom and outside the master bedroom window simultaneously using a specialist multi-channel sound measurement platform, RIONOTE by RION. All equipment was supplied and calibrated by ANV systems. The

Table 4.1: Test case characteristics (* as measured by the event loggers).

	Semi-rural dwelling	Urban dwelling
Location:	Semi-rural location	Central London location
Environmental noise:	Low	High
Distance to major road:	100m	Road noise is not the dominant source.
Distance to major railway:	500m	25m
Room monitored:	Bedroom	Living room
Device monitored:	Window	Balcony door
Noise instrument:	RIONOTE class 1	RPi
Campaign start	12.05.2020	03.07.2020
Campaign end	21.05.2020	05.08.2020
Campaign duration	8d 23h 50min	33d 23h 55min
Total observations	2,591	9,791
Closed*	992 (38%)	6,827 (70%)
Ajar*	409 (16%)	129 (1%)
Open*	1,190 (46%)	2,835 (29%)

whole measurement platform was calibrated and successfully completed the class 1 periodic tests as per the International Electrotechnical Commission (IEC) 61672-3:2006.

The RIONOTE (SA-A1) was coupled with a 4 channel amplifier (SA-A1B4), connected to a preamplifier (NH-22A) and $\frac{1}{2}$ inch electret condenser microphone (UC-59) by BNC-BNC coaxial cable (EC-90 series). The indoor microphone was mounted on a tripod and placed 300mm away from the window, facing it.

The outdoor sound measurements were taken by a wireless dock (SA-A1WD), coupled with a 4 channel amplifier (SA-A1B4), connected to a preamplifier (NH-22A) and 1/2 inch electret condenser microphone (UC-59) by BNC-BNC coaxial cable (EC-90 series). The outdoor microphone was installed with a foam cover to protect from wind, weather, and pests. Figure 4.3 shows the RION noise equipment and event sensors installed in the semi-rural dwelling.

The RIONOTE one-third octave band analysis software (SX-A1RT) was used to carry out real time analysis of sound levels inside and outside of the bedroom by means of analysing one-third octave bands from 0.4 Hz up to and including 20 kHz (total of 48 one-third octave bands). The real time analysis is processed into 5 minute measurements of L_{eq} (average sound pressure level), L_{max} (maximum sound pressure level), L_{min} (minimum sound pressure level), L_5 (5th percentile), L_{10} (10th percentile), L_{50} (50th percentile), L_{90} (90th percentile), and L_{95} (95th percentile). Data was exported into csv format using RION AS-60 software to feed into the predictive model.

4.2.3.3 Sound measurements in the urban test case.

The data for the urban test case dwelling was acquired using a custom sound monitoring system designed and constructed by Dr Benjamin Fenech and the researcher. A technical and detailed

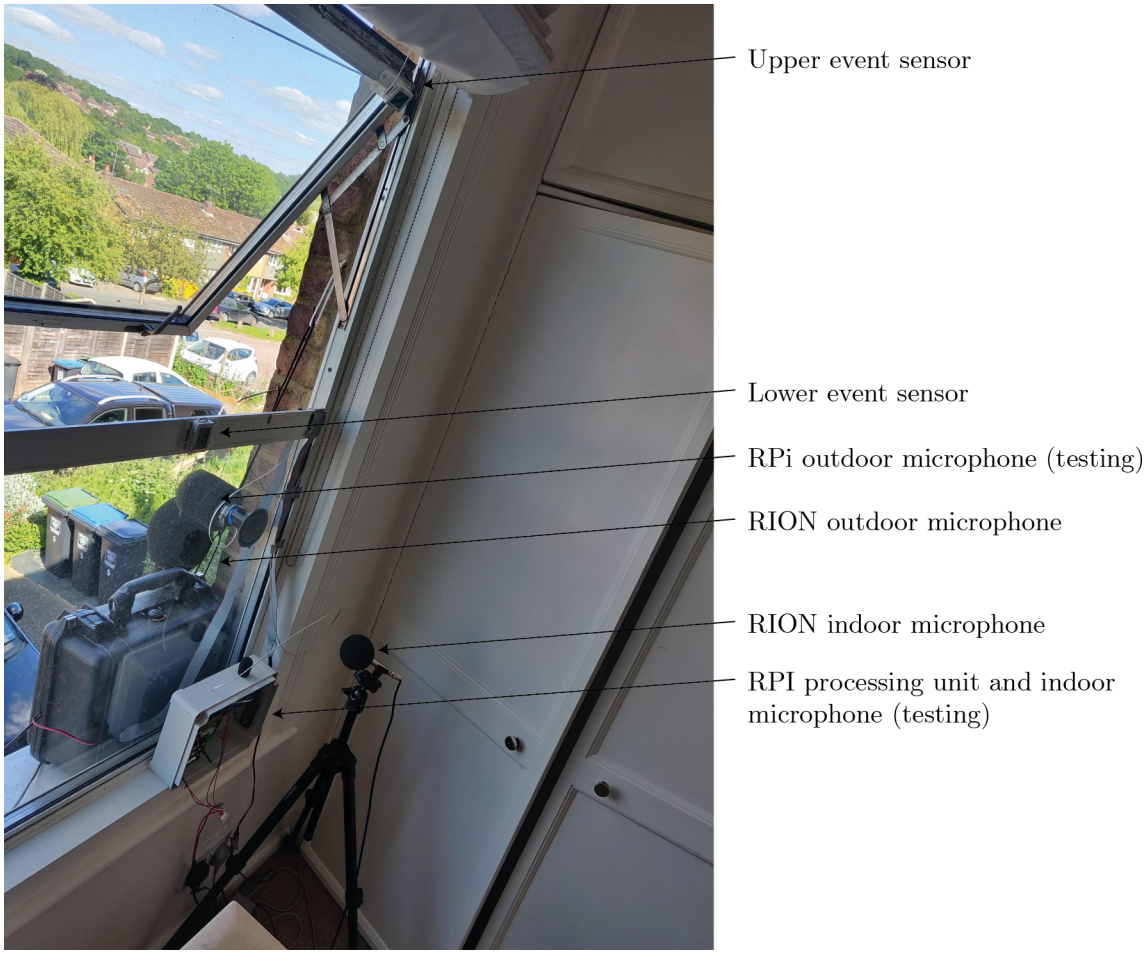


Figure 4.3: Photograph of the noise measurement equipment in the semi-rural dwelling (also showing the Raspberry Pi installed for testing and cross calibration purposes).



Figure 4.4: Photograph of the noise measurement equipment in the urban test case.

description of this system, along with details of the calibration and cross-checking process can be found in Section 3.2.2.6 on page 124.

Figure 4.4 shows the RPi noise equipment installed in the urban dwelling.

4.2.3.4 Window and door measurements for both test cases.

For both the window and door being measured in the respective test cases, two ONSET HOBO UX90-001M event sensors were used to record the window and door positions in each test case. These event sensors were positioned such that they could measure when the window and door was closed, ajar (specifically at a distance of 50mm), or fully open. For the purposes of this method, the window and door is defined according to three distinct 'positions': open, ajar, and closed. See Figure 4.3 for a photo of the noise equipment and event sensors for the semi-rural setting. Table 4.2 presents the window positions and the associated event sensor logic for the pair of event sensors.

Window and door positions in the training data were inferred and extrapolated for every 5-minute period, such that each 5-minute observation in the training data showed the window or door as either open, ajar, or closed. The logic applied to this extrapolation is that the last position of the window or

Table 4.2: Window positions and event sensor logic.

Window position	Lower event sensor	Upper event sensor
Closed	Closed	Closed
Open < 50mm	Open	Closed
Fully open	Open	Open

Table 4.3: Training data set properties.

	Semi-rural dwelling	Urban dwelling
Closed (0)	226	1,496
Ajar (1)	53	12
Open (2)	217	140
Total	496	1,648

door in each 5-minute period is what defines the position for that 5-minute period - for example, if the window or door closes towards the end of a 5-minute period, that 5-minute period is classified as closed. The need to classify window positions as a discrete variable for each 5-minute period is to align with the logging interval of the IEQ variables - see Section 3.2.2.1 (page 109). The 5-minute interval is widely used in IEQ research and selected as a balance between data storage, battery life, disruption to participants, and cost. Furthermore, shorter periods will be subject to higher error, as there is less averaging and so, the 5-minute interval offers a further balance of minimising this error.

4.2.3.5 Model implementation, training, and main analysis

Two predictive models were implemented in Python using the `sklearn.linear_model.LinearRegression` function (multinomial linear regression) and `sklearn.linear_model.LogisticRegression` function (ordinal logistic regression model). The models were trained using a training dataset consisting of the first 20% of the acquired data for both the semi-rural and urban dwellings. In the semi-rural dwelling, the window position was changed approximately every 30 minutes over a period of 8 hours a day, over two days. For the urban dwelling, the occupants used the balcony door exactly as they normally would and did not 'artificially' change the position of the door during the training data phase. Table 4.3 provides a summary of the training data sets for each test case and the number of observations (5-minute time periods) for each window and door position. It is notable that there is only a very small amount of ajar door positions for the urban test case.

The remaining 80% of the measurement campaign data constituted the "test" data, and the trained model used this training data to predict the corresponding window/door state for each 5-minute time interval. For the linear models, the output is a decimal number between 0 and 2. This number is

rounded to the nearest integer to infer the window position: 0, 1, or 2, representing closed, ajar, and open respectively. For ordinal logistic regression, the output is an integer (0, 1, or 2) representing the window position.

For the main analysis, the models used all one-third octave frequencies (n=48 for semi-rural and n=29 for urban) in the entire dataset (semi-rural = 0.4Hz to 20kHz; urban = 25Hz to 10kHz) - results discussed in Section 4.3.2. The following sensitivity analyses were also carried out:

1. only including data when the overall A-weighted averaged sound level $L_{eq,5min}$ was higher outdoors than indoors. This will exclude the impact of times when indoor sound levels were greater than outdoors (results in Section 4.3.6);

2. excluding frequencies higher than 1 kHz to focus on frequencies that road and rail transport dominate. Buratti (2006) reported that road and rail traffic sound levels peak at around 1kHz, and there is a greater frequency content below this from road and rail transport (10 one-third octave frequency bands below 1kHz vs 7 above) (results in Section 4.3.4);

3. for the semi-rural dwelling, omitting frequencies below 20Hz (equipment measures 0.4Hz to 20kHz) to investigate the contribution of these frequencies and directly compare with the researcher built platform, which measures between 25Hz and 10kHz. This also investigates the suitability of using low cost and DIY/researcher-built equipment with this method (results in Section 4.3.5).

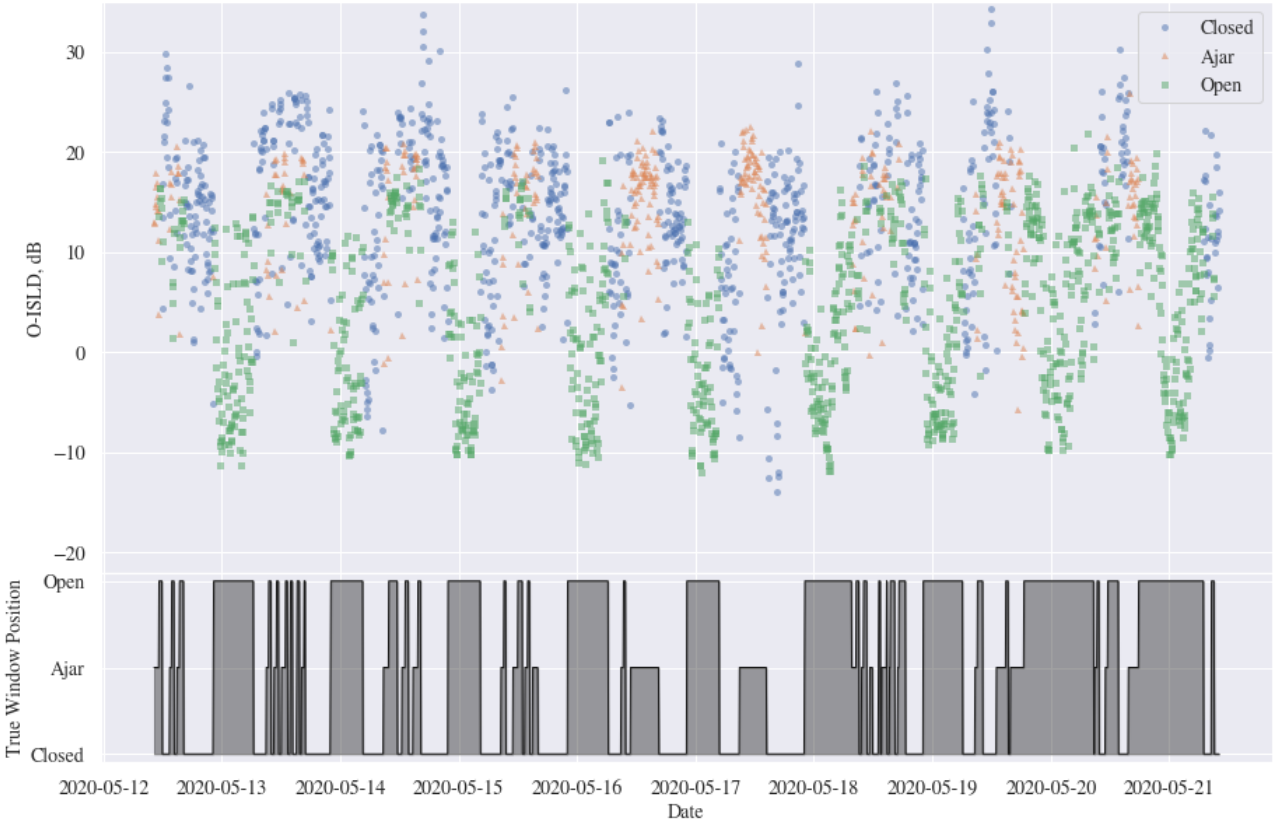
Additional analysis was carried out using sequential forward feature selection (SFS) to investigate which features (one-third octave bands) were contributing to the model's accuracy most, based on the cross-validation score of a number of different 'prediction evaluation metrics'. SFS (`SequentialFeatureSelector` from `mlxtend.feature_selection`) was used with both linear and logistic regression models. These results are discussed in Section 4.3.3.

The accuracy of the prediction models was obtained by comparing the predicted state with the 'true' state as determined by the dual event sensor setup mentioned in 4.2.3.4. The accuracy of each model is the ratio of correctly predicted window/door states (in 5-minute periods) to the total number of predictions (using only the test data).

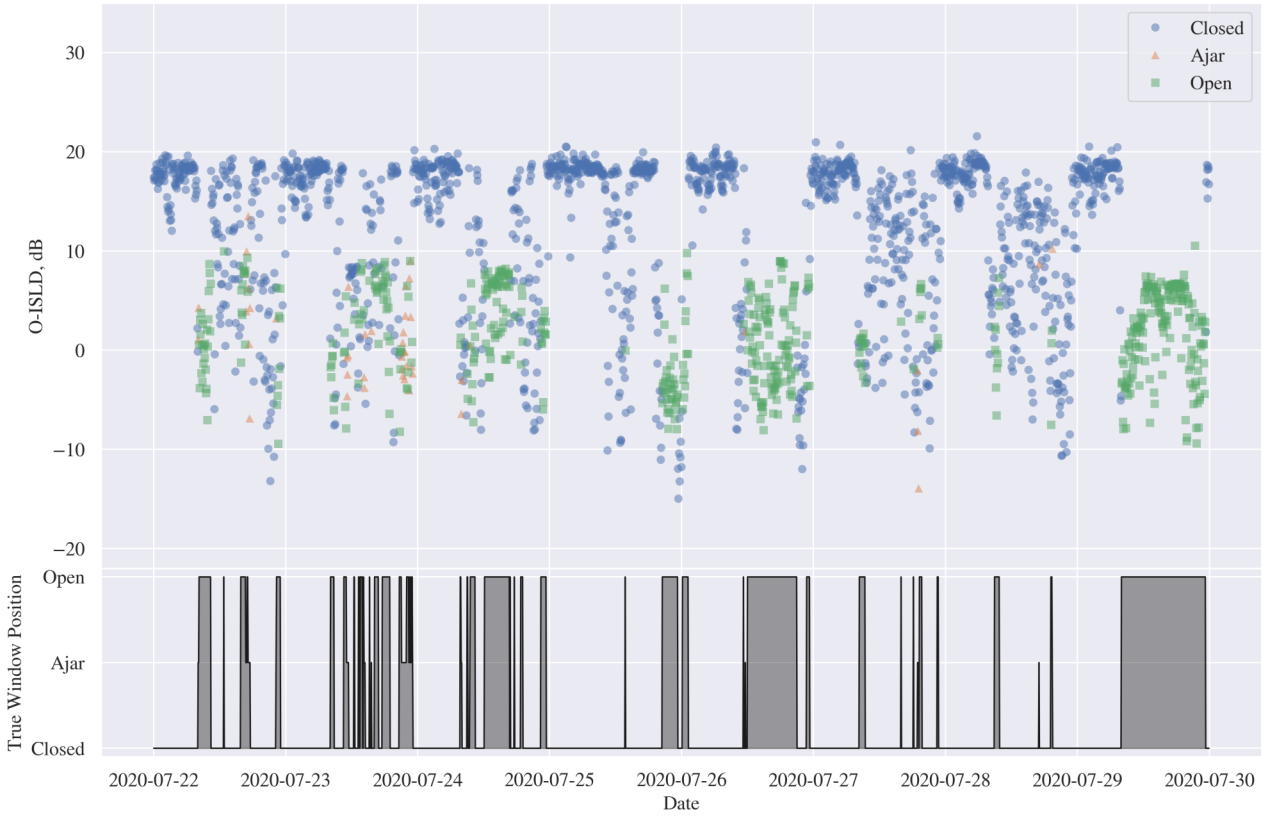
4.3 Results

4.3.1 Results overview

Figure 4.5 shows the O-ISLD using the energy averaged noise metric ($L_{eq,5minute}$) for the two validation test cases. Each measurement represents the $L_{eq,5minute}$ for a 5-minute period, and the measurements were taken over a period of 9 days in the semi-rural test case and 34 days in the urban



(a) Semi-rural dwelling.



(b) Urban dwelling (graph reduced to a week for clarity).

Figure 4.5: Scatter plots showing the outdoor to indoor sound level difference (O-ISLD) using the energy averaged noise metric ($L_{eq,5minute}$), and the graph below showing the window positions for the two validation test cases. Both graphs show the 'true' window positions, as determined by the event sensors. Blue dots represent measurements when windows were closed, orange triangles when in the ajar position, and green squares when open.

Table 4.4: Descriptive statistics for O-ISLD - L_{95} dB(A).

	Semi-rural test case		Urban test case	
	Arithmetic mean	Standard deviation	Arithmetic mean	Standard deviation
Closed	14.5	3.5	13.8	8.0
Ajar	14.2	2.4	3.7	7.5
Open	7.8	4.3	2.3	5.0

test case. Data points where O-ISLD is negative are shown. The lower panel for each of these plots show the 'true' window and door positions, as measured from the event sensors (see Section 4.2.3.4).

The O-ISLD metric was chosen on the basis of the acoustics principles described in Section 4.2.1, specifically seeking to identify different window positions where the absolute sound levels are not important but the difference between indoors and outdoors is. As expected, the results shown in Figure 4.5 show that higher O-ISLD are associated with the window and door in the closed position, lower differences with the ajar position, and the lowest differences with the open window and door position. However, both sub-figures also show that the O-ISLD were not constant for each of the three states, that the O-ISLD for the three states (open/ajar/closed) are not clearly delineated, and that there is significant overlap between the three states, particularly between the closed and ajar states. A model for predicting the window status using overall frequency averaged noise metrics is not likely to be accurate. Instead, the hypothesis (proposed in Section 4.2.2.1) that the O-ISLD for different window positions is more pronounced in certain one-third octave bands and using percentile metrics is tested below.

Table 4.4 shows the O-ISLD for the 95th percentile of the $L_{Aeq,5minute}$. This data contrasts with the much higher O-ISLD measurements from 102 Swiss dwellings exposed to high road traffic noise (Locher et al., 2018). Locher et al. (2018) reported the mean O-ISLD in 102 Swiss dwellings exposed to high road traffic noise and found the mean O-ISLD to be 10dB(A) for open windows, 16dB(A) for tilted windows, and 28dB(A) for closed windows. There are a number of possible reasons for the differences between the O-ISLD measured by Locher et al. (2018) and this research: (1) In the study by Locher et al. (2018), the sound measurements indoors were taken either at the position of the pillow or the centre of the living space at a height of 1.5m; however, in both test cases presented here, measurements of indoor noise were taken in the window reveal or very close to the window - reasons for this microphone positioning are because the main objective was to infer window positions and minimise inconvenience to occupants rather than to capture the occupant's experienced sound level during the long monitoring campaign. Furthermore, in the semi-rural test case, the microphone was placed in the corner of the room, where sound levels are typically the highest due to the influence of the wall

boundaries. (2) The measurements by Locher et al. (2018) spanned only 3 minutes and all internal noise was minimised as much as possible. In contrast, the measurements taken for this chapter spanned weeks, and the dwellings were constantly occupied during the national COVID-19 lockdowns. Therefore, the O-ISLD is likely to be much smaller, as there is a source of noise indoors throughout the monitoring, effectively reducing the O-ISLD, and in certain cases (when the indoor level is higher than the outdoor level), it becomes negative. (3) The short duration measurements by Locher et al. (2018) were taken in dwellings that were subject to high road traffic noise, which is typically a more constant source of noise (higher L_{95}) compared with long-term measurements in the semi-rural dwelling, which was in a quiet location and the urban test case, which had more intermittent noise from rail. Furthermore, the short duration measurements by Locher et al. (2018) were typically taken during the 'evening' and this could have been during periods of busy traffic, thereby increasing the L_{95}. (4) The construction methods and particularly the properties of the windows are expected to be different. Both test cases were over 40 years old and the doors in the urban test case were timber framed and single glazed, whereas its expected (not reported by Locher et al. (2018)) that the construction methods in the Swiss homes will have higher acoustic insulation properties.

As described in Section 4.2.1, one of the principles underpinning the proposed method is that the airborne sound insulation properties of a facade element are frequency dependent. This has the result of filtering out some frequencies more than others (O-ISLD will vary by frequency), such that the whole whole frequency spectrum changes depending on the sound insulation properties of the facade element. Furthermore for a specific scenario and outdoor sound environment it's expected that certain one-third octave bands will exhibit larger differences between the closed - ajar - open cases. Before conducting the predictive modelling, an initial analysis was carried out using a range of statistical calculations to better understand the statistical relationships in the dataset. This analysis included calculating the Cohens D value (effect size of the difference between two means) for each pair of window and door positions (open vs ajar, open vs closed, and ajar vs closed); the one-way ANOVA F value (variation between sample means / variation within the samples), and Pearson's correlation between O-ISLD and window and door positions. These statistical calculations were conducted for each test case and for each percentile.

Table 4.5 provides a summary of the aforementioned statistical calculations for all data (training and test data). This table shows the one-third octave band that scored the highest for each of the calculations and also provides the result of the calculation in brackets. For the semi-rural test case, as the percentile increases, there is a corresponding increase in Cohens D, ANOVA and Correlation for each window position. On the other hand, for the urban dwelling, there is a less conclusive relationship. This suggests that the higher percentiles in the semi-rural dwelling and potentially the lower percentiles in the urban dwelling will yield the highest statistical power.

Table 4.5: Summary of statistical calculations for both test cases. The results show the one-third octave band that scored the highest for each of the calculation methods and the calculation result in brackets.

	Semi-rural test case				
	Cohens D			ANOVA (F)	Correlation [1]
	Closed vs open	Closed vs ajar	Ajar vs open		
L_{eq}	200Hz (1.75)	0.4Hz (0.80)	250Hz (2.01)	200Hz (1031)	800Hz (0.59)
L_5	200Hz (1.55)	0.4Hz (0.69)	250Hz (1.98)	200Hz (848)	100Hz (0.57)
L_{10}	200Hz (1.92)	0.4Hz (0.95)	250Hz (1.94)	200Hz (1225)	200Hz (0.68)
L_{50}	200Hz (2.90)	200Hz (1.24)	400Hz (2.29)	200Hz (2426)	250Hz (0.72)
L_{90}	200Hz (3.19)	200Hz (1.50)	400Hz (2.73)	200Hz (2961)	20Hz (0.80)
L_{95}	200Hz (3.24)	200Hz (1.52)	400Hz (2.72)	200Hz (3049)	200Hz (0.84)
	Urban test case				
	Cohens D			ANOVA (F)	Correlation [1]
	Closed vs open	Closed vs ajar	Ajar vs open		
L_{eq}	31.5Hz (4.15)	31.5Hz (2.39)	40Hz (2.58)	31.5Hz (17364)	31.5Hz (0.88)
L_5	31.5Hz (4.58)	31.5Hz (2.19)	63Hz (2.86)	31.5Hz (20925)	31.5Hz (0.90)
L_{10}	31.5Hz (4.77)	31.5Hz (2.28)	63Hz (2.88)	31.5Hz (22666)	31.5Hz (0.91)
L_{50}	31.5Hz (4.52)	31.5Hz (2.12)	40Hz (2.83)	31.5Hz (20490)	31.5Hz (0.90)
L_{90}	63Hz (4.35)	63Hz (2.13)	40Hz (2.63)	63Hz (18926)	50Hz (0.84)
L_{95}	63Hz (4.45)	63Hz (2.19)	63Hz (2.59)	63Hz (19751)	50Hz (0.85)

[1] Pearson's R

Generally, from Table 4.5 it can be seen that for the semi-rural test case, 200Hz in the 95th percentile provides the highest correlation, ANOVA, and Cohens D results. For the urban test case, this is 31.5Hz in the 10th percentile. Figure 4.6 and 4.7 show the distribution of O-ISLD for each third octave frequency and each window position for the two test cases for the 95th and 10th percentile for the semi-rural and urban test cases respectively. Both of these figures illustrate the 200Hz and 31.5Hz one-third octave bands as having the largest ANOVA F value (variation between sample means / variation within the samples) for the semi-rural and urban test cases respectively.

Following the above analysis, Figures 4.8a and 4.8b provide detailed normalised histograms of the distribution of O-ISLD measurements for each window position in the semi-rural and urban test cases for the 95th percentile, 200Hz one-third octave band and the 10th percentile, 31.5Hz one-third octave band respectively. These figures generally illustrate a separation between the open and closed positions from each other, but also show the large overlap of the ajar on both the open and closed distributions.

The analysis above confirms the initial hypotheses that:

1. the O-ISLD in the three states (closed-ajar-open) are more pronounced in certain frequency bands, which vary by setting (type of outdoor and indoor sound source, facade construction, etc.);

2. the percentile used has a noticeable effect on the statistical difference between standardised means of groups of data for each window/door state in the two test cases.

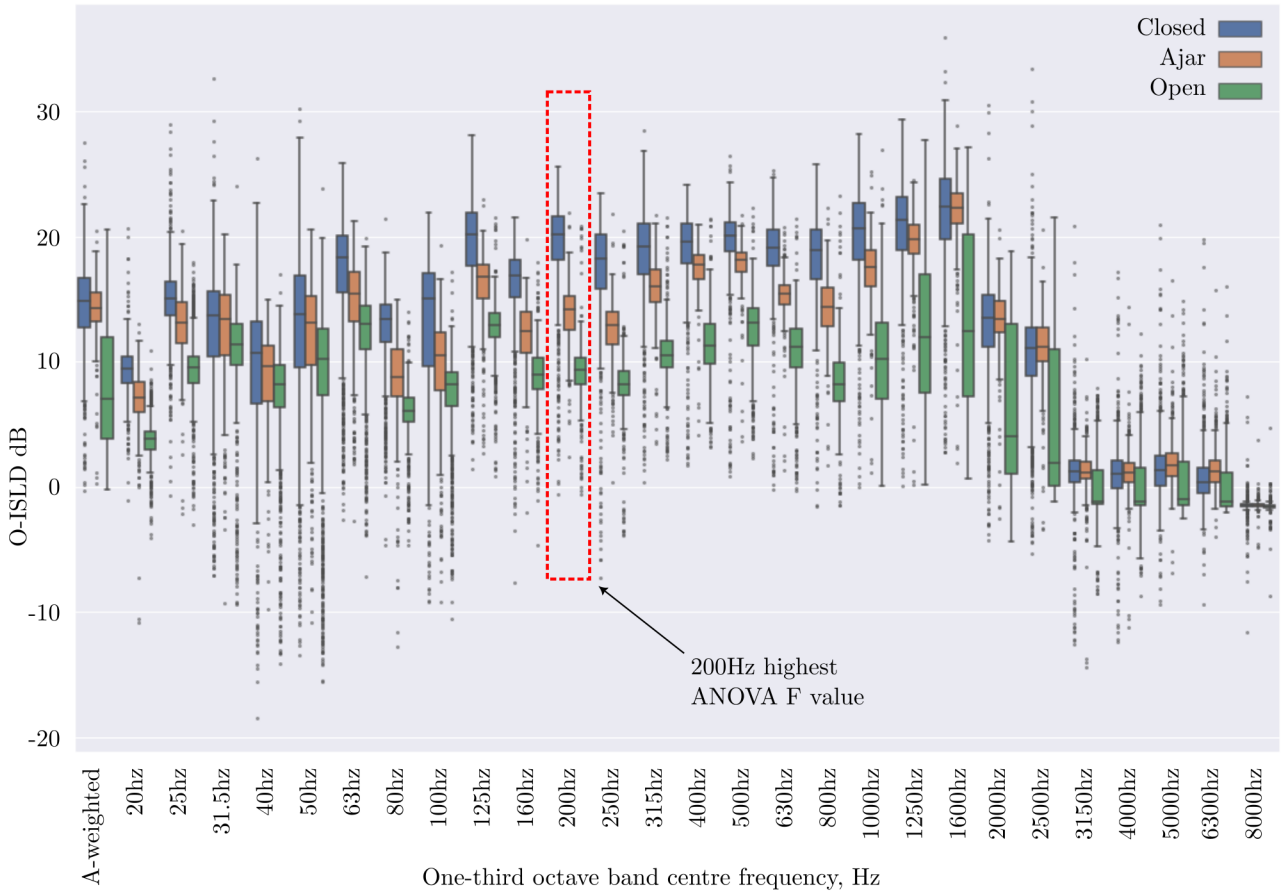


Figure 4.6: Boxplots of the distribution of data for L_{95} O-ISLD for each one third octave frequency and each window position for the semi-rural test case. Blue boxes are for closed window, orange is ajar, and green is open window. The y-axis is the noise difference in dB, and the x-axis represents groups of each one-third octave frequency. The red dashed boxes highlight the one-third octave frequencies with the highest ANOVA-F values.

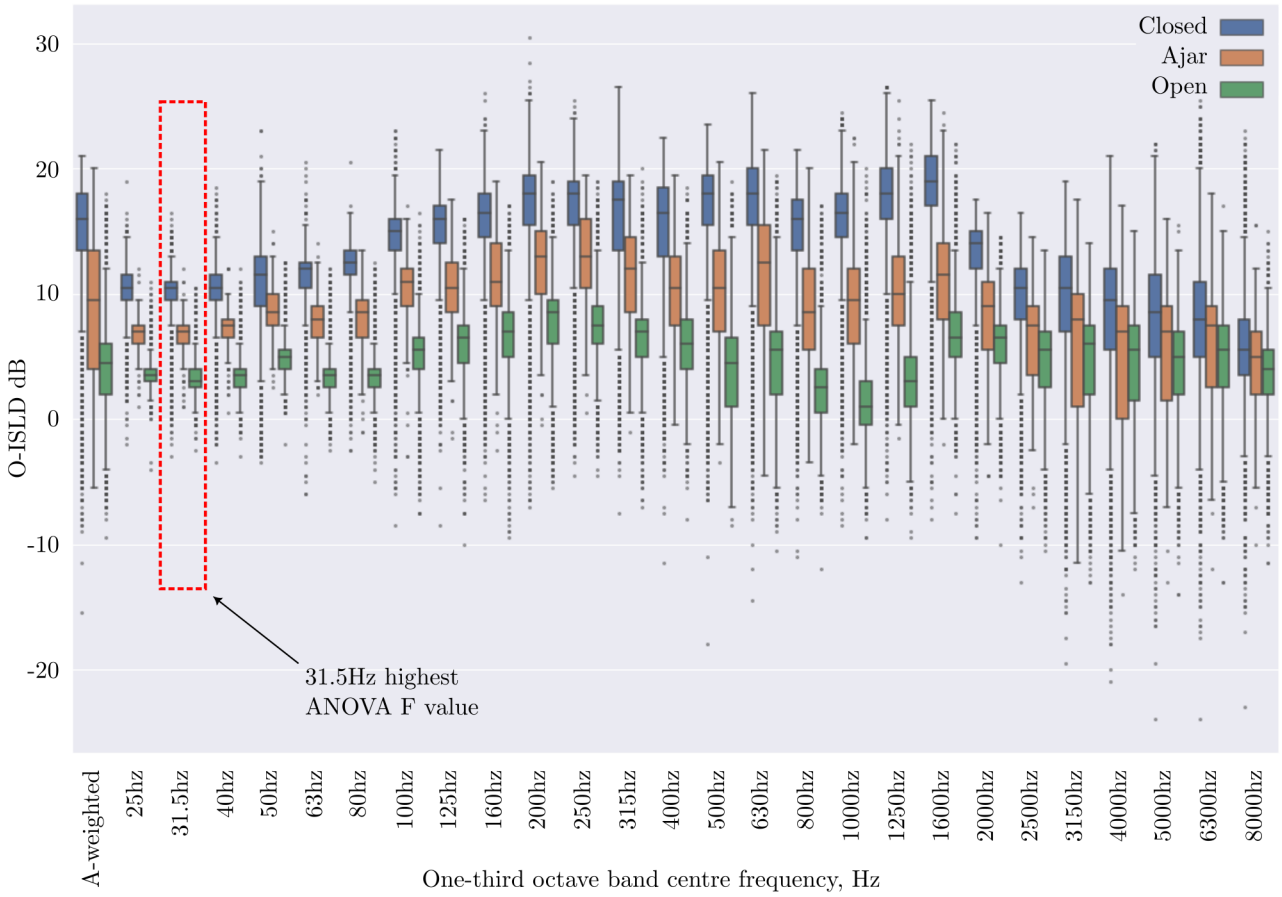
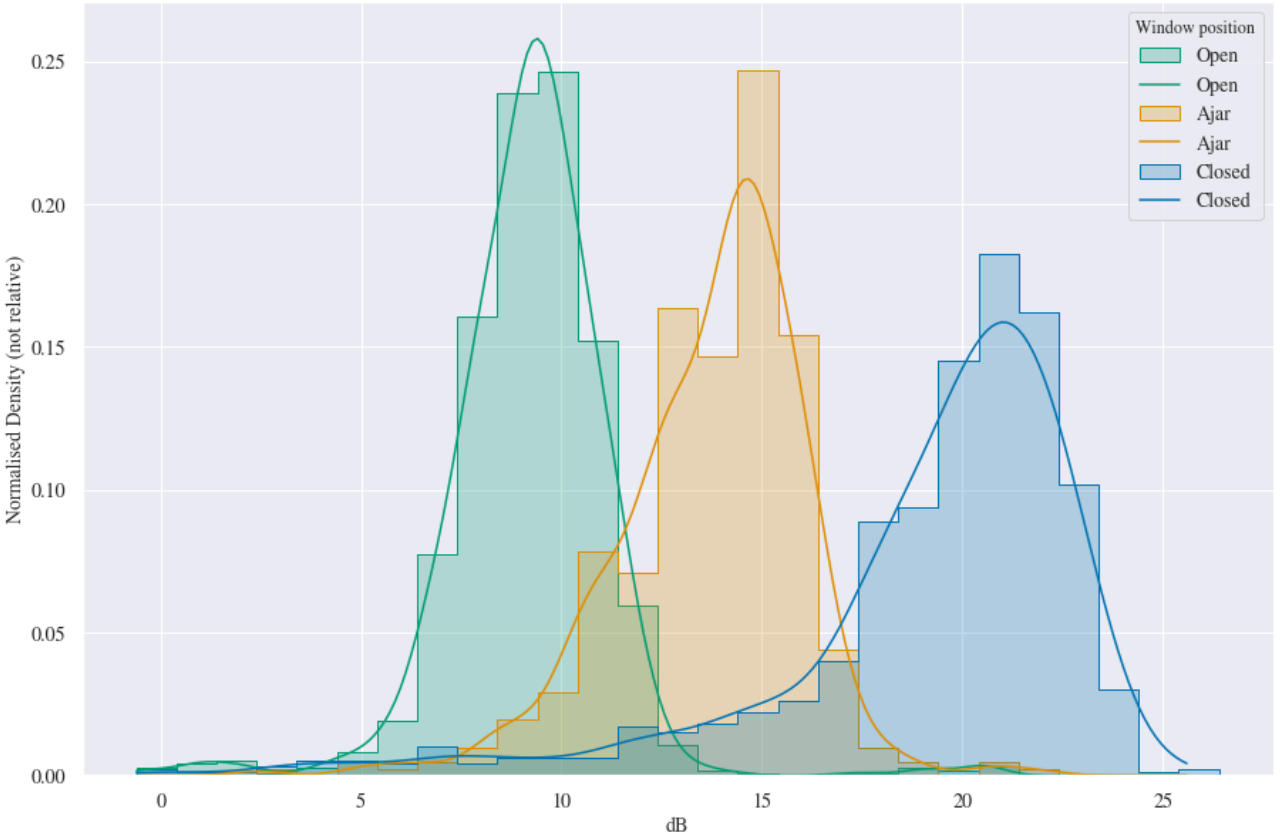
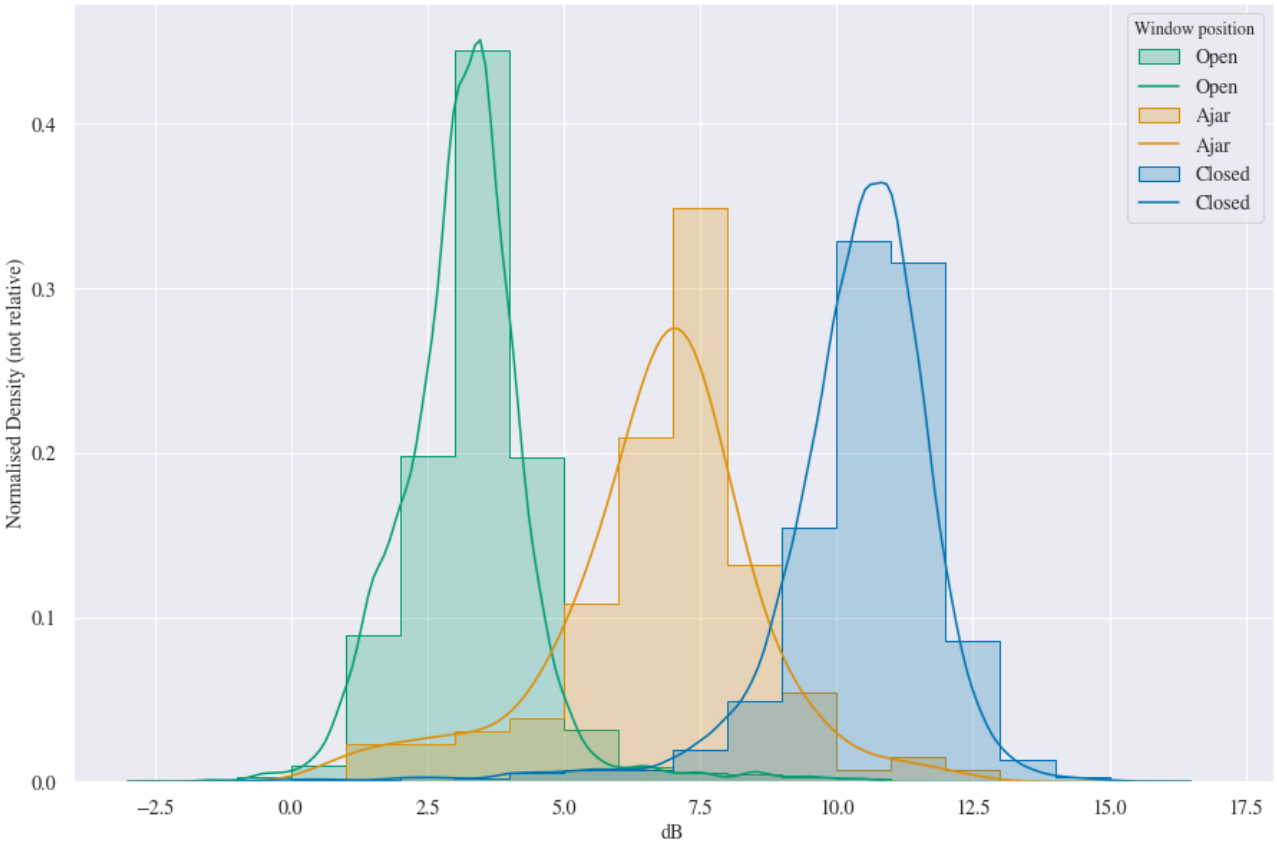


Figure 4.7: Boxplots of the distribution of data for L_{10} O-ISLD for each one third octave frequency and each window position for the urban test case. Blue boxes are for closed window, orange is ajar, and green is open window. The y-axis is the noise difference in dB, and the x-axis represents groups of each one-third octave frequency. The red dashed boxes highlight the one-third octave frequencies with the highest ANOVA-F values.



(a) Semi-rural dwelling - L_{95} 200Hz.



(b) Urban dwelling - L_{10} 31.5Hz.

Figure 4.8: Normalised histograms showing the distribution of O-ISLD measurements for each window position in the semi-rural and urban test cases for the 95th percentile 200Hz one-third octave band and 10th percentile 31.5Hz one-third octave band respectively.

The data therefore suggests that there is no universal noise metric or specific one-third octave bands that are suited for a predictive model to determine window/door status, and confirms that a statistical model which has been trained for a specific setting is required.

In the next sections the results of the performance of two model types (linear and logistic) are presented which have been trained using the following different subsets of the data:

1. All data and all one-third octave bands for the semi-rural test case (48 one-third octave bands 0.4Hz to 20kHz) and the urban test case (29 one-third octave bands 25Hz to 10kHz);

2. Using all data and sequential forward feature selection (SFS) to select the top 10 one-third octave bands which perform the highest when measured using a range of SFS performance metrics. These top 10 one-third octave bands are then used to predict window/door positions. This also allows the relationship between the number of features (one-third octave bands) and model performance to be objectively evaluated against each SFS performance metric;

3. Subset of the data, modelling only one-third octave bands below 1kHz. This was designed to test the hypothesis/assumption that environmental sounds from transport (which have a greater frequency content below 1kHz) would be contributing more towards the models predictive power than sounds above this frequency threshold;

4. Subset of the data, modelling only one-third octave bands above 20Hz for the semi-rural test case. The professional RION equipment used for the semi-rural test case measured sound with frequencies as low as 0.4Hz, which is not typical for most commercially available SLMs. This data subset was designed to closely match the typical frequency measurement range of commercially available sound level meters and low cost sound level meters, which typically measure between 20Hz and 10kHz;

5. Subset of the data, modelling only where the overall A-weighted averaged level $L_{Aeq,5min}$ was higher outdoors than indoors. This was designed to investigate the impact of internal activity on model performance, with the hypothesis that the model would be more accurate when noise is higher outdoors than indoors;

4.3.2 Results part 1 - model using all data

The first set of models used all data from both test cases, including all one-third octave bands and no filtering. In terms of post measurement processing, using all the data in this way is the least time consuming, as there is no requirement for implementing any filters or sub setting of the data in any way after measurement.

Table 4.6 provides a summary of all model accuracies using all data for both test cases across a range of different metrics, including percentiles for linear and logistic models. This table shows that

Table 4.6: Model accuracy using all data and all one-third octave bands for both test cases, linear and logistic models and all percentiles.

Percentile	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
Model	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
Semi-rural	75%	79%	66%	73%	75%	79%	84%	82%	**88%**	84%	**88%**	83%
Urban	85%	95%	75%	**96%**	78%	95%	87%	92%	78%	91%	75%	85%

for the semi-rural test case, the linear models using the highest (L_{90} and L_{95}) percentiles yielded the highest accuracies at 88%. Interestingly, the urban dwelling is quite different and a logistic model using the lowest (L_5) percentile yields the highest accuracy at 96%.

These differences are likely to arise from a number of possible effects which are discussed here. Firstly, addressing the difference in model type might be explained by the difference in content of different window positions in the training data. Notably, Table 4.3 shows that for the urban test case, there were a very small amount of ajar positions (0.7%), so for this case, models that are efficient at differentiating between the dichotomous open and closed positions would perform best. The results suggest that logistic models are best suited to this task. On the other hand, the semi-rural test case has a much larger percentage of ajar positions in the training data (11%). Next, addressing the difference in low and high percentiles might be explained by the outdoor acoustic environment. The urban test case has regular loud train passings, which are likely to be best characterised using a lower percentile (L_5 = noise level exceeded 5% of the time). On the other hand, the semi-rural test case does not have regular loud sounds outdoors, and the highest accuracy models used higher percentiles, which are commonly referred to as 'background sound level' (L_{90} = noise level exceeded 90% of the time) (BSI, 2019*b*). The background sound for the semi-rural test case is likely characterised by the constant sound from the road and less by the much quieter railway in the distance. Indoor sources of sound could have also played a role in the performance of the models; however, the nature of indoor sounds are unknown. Section 4.3.6 explores model performance whilst only using data where outdoor sound levels were higher than indoors.

Greater insights can be drawn from analysing the prediction accuracy according to state (open/ajar/closed) - this is shown in tables 4.7 and 4.8. These tables show the results for the top performing models using all data for each test case. Both of these tables illustrate that the models were least accurate at predicting the ajar positions, with 25% and 98% of the ajar positions incorrectly predicted for the semi-rural and urban test cases respectively. For the semi-rural test case, almost half of the incorrect predictions for the ajar position are predicted as closed and the other half as open. Whereas, for the urban dwelling, 28% of the predictions are incorrectly classified as closed and the remaining 70% are incorrectly classified as open. It must be noted that for the urban dwelling, less than 1% of the training

Table 4.7: Table showing a cross tabulation of the relationship between actual window position and predicted window position for the semi-rural test case L_{90} linear model trained with all data. Bold results are where the model has correctly predicted the window position.

Actual Position	Predicted Position			
	Open (2)	Ajar (1)	Closed (0)	Total
Open (2)	901 (**94%**)	59 (6%)	1 (<1%)	961
Ajar (1)	43 (12%)	266 (**75%**)	45 (13%)	354
Closed (0)	4 (1%)	98 (13%)	656 (**87%**)	758
Total				2,073

dataset has the ajar position, and therefore, there is very little data to determine an effective boundary between the ajar and the other positions, whereas there is more data for determining a boundary between the open and closed positions.

In addition to the lack of data for the ajar position, Figures 4.6, 4.7, and 4.8 show that there are overlapping distributions for the open and closed groups on the ajar group. This overlapping of the distributions make it challenging for the models to determine an effective boundary for differentiating between the different positions. A potential explanation for the long tails of the distribution for a specific state could be that the dominant external sound source that has a peak at that specific one-third octave band (e.g., railway for the 31.5Hz band for the urban case study) is not present for every 5-minute observation, and the tails represent all the 5-minute periods where this sound source is not present (e.g., no train passbys), and hence the O-ISLD is less pronounced. The lack of data for ajar positions and this overlapping of the distributions provides some possible explanations into why the models have the lowest accuracy for the ajar window positions.

It is notable, however, that it appears possible to make improvements to the accuracy of the models if there was a need to prioritise a single position over the others. For example, it might be possible to improve the accuracy of predicting the ajar position, but this might be at the expense of accuracy to the other positions (see Figures 4.6, 4.7, and 4.8). The models used here are optimised for overall performance, and as there are many more observations for open and closed than for the ajar position, the models are likely to be optimised for differentiating between the open and closed positions.

Next, the application of sequential forward feature selection is explored as a method of (1) further understanding the contribution of different one-third octave bands towards the linear and logistic models; (2) improving model performance.

Table 4.8: Table showing a cross tabulation of the relationship between actual door position and predicted position for the urban test case L_5 logistic model trained with all data. Bold results are where the model has correctly predicted the door position.

Actual Position	Predicted Position			
	Open (2)	Ajar (1)	Closed (0)	Total
Open (2)	2,594 (**98%**)	8 (0%)	47 (2%)	2,649
Ajar (1)	68 (70%)	2 (**2%**)	27 (28%)	97
Closed (0)	112 (2%)	67 (1%)	4,908 (**96%**)	5,087
Total				7,833

4.3.3 Results part 2 - sequential forward feature selection

Table 4.5 suggests that certain one-third octave bands may have better predicting power for determining window position; however, the results suggest that it is specific to each test case. Figures 4.8a and 4.8b show the normalised histograms for 200Hz (L_{95}) and 31.5Hz (L_{10}) for the semi-rural and urban test cases respectively. The three peaks for closed-ajar-open states are clearly separated; however, there is still a substantial overlap of the three distributions on each other, demonstrating that a model trained with a single one-third octave band is unlikely to predict window or door position with high accuracy on its own.

The research explored the application of sequential forward feature selection (SFS) to investigate (1) which single one-third octave band contributed the most to the logistic and linear models, (2) which are the top 10 one-third octave bands that contribute the most towards the linear and logistic models, how much model performance is influenced by the quantity of one-third octave bands in the linear and logistic models, and (3) if the models perform better with all data or only the top 10 one-third octave bands.

Model performance for SFS was measured using all available 'prediction evaluation metrics' (explained variance regression score, maximum residual error, mean absolute error regression loss, mean squared error regression loss, root mean squared error regression loss, and R^2 (coefficient of determination) regression score functions . In this chapter, for brevity, only the results for R^2 (coefficient of determination) and root mean square error (RMSE) regression loss metrics are presented and only for the highest performing models.

4.3.3.1 SFS Top single one-third octave bands

Which one-third octave bands contribute most to the models performance?

Table 4.9 shows the single one-third octave bands selected by SFS which provided the highest performance for the corresponding metric, for linear and logistic models, each percentile, and each test case. It is interesting to see that for both test cases, the most common single one-third octave bands selected by SFS across all percentiles align with the expectations in Section 4.3.1 - that is the 200Hz

Table 4.9: Table showing the single one-third octave bands selected by SFS, which provided the highest performance for the corresponding prediction evaluation metrics (R^2 and RMSE), for linear and logistic models, each percentile (L_{eq}, L_5, L_{10}, L_{50}, L_{90}, L_{95}), and each test case.

Percentile	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
Model type	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
Evaluation metric	Semi-rural											
R^2	200	0.4	200	200	200	200	200	160	16	200	16	16
RMSE	200	0.4	200	200	200	200	200	160	160	8	16	16
Evaluation metric	Urban											
R^2	31.5	31.5	31.5	25	31.5	25	31.5	25	63	31.5	63	40
RMSE	31.5	31.5	31.5	25	31.5	25	31.5	25	63	31.5	63	31.5

and 31.5Hz one-third octave bands. However, it is also interesting to note that when considering the L_{90} linear model for the semi-rural and L_{10} logistic model for the urban test case, which were the highest performing models using all data (and multiple one-third octave bands - Table 4.6), there are slightly different one-third octave bands used by SFS to that which was expected from the earlier statistical analysis in Section 4.3.1. These are, namely, 16Hz (R^2) and 160Hz (RMSE) for the semi-rural, where 200Hz was expected. And for the urban dwelling the single frequencies are both 25Hz (R^2 and RMSE), where 31.5Hz was expected. The reason for these slightly different frequencies are that the model performance is evaluated using only the test data and the ANOVA calculations in Section 4.3.1, which provide an overview of the dataset, includes both test and training data.

The single one-third octave bands selected by SFS for the urban test case are within a narrow band of 25Hz to 63Hz, and most are 31.5Hz. This narrow selection and the frequency range are likely driven by the fact that the outdoor acoustic environment is dominated by sounds from the nearby overland railway. In contrast to the urban test case, for the semi-rural test case, there is a wider range (8Hz to 200Hz) and a pattern of selecting lower one-third octave bands for higher percentiles, which is likely driven by the quieter outdoor environment, with a range of different sounds.

4.3.3.2 SFS Top 10 one-third octave bands

Which are the top 10 one-third octave bands that contribute the most towards the models, and what impact does the quantity of one-third octave bands in the models have on model performance?

Using SFS, the top 10 one-third octave bands that provided the highest performance according to the prediction evaluation metrics were calculated and collated into sub-sets of the complete dataset - this was calculated for each test case, each percentile, and six different prediction evaluation metrics. For brevity, only the results for the highest performing models and for two evaluation metrics (R^2 and root mean square error) are discussed here. With the exception of maximum residual error, the

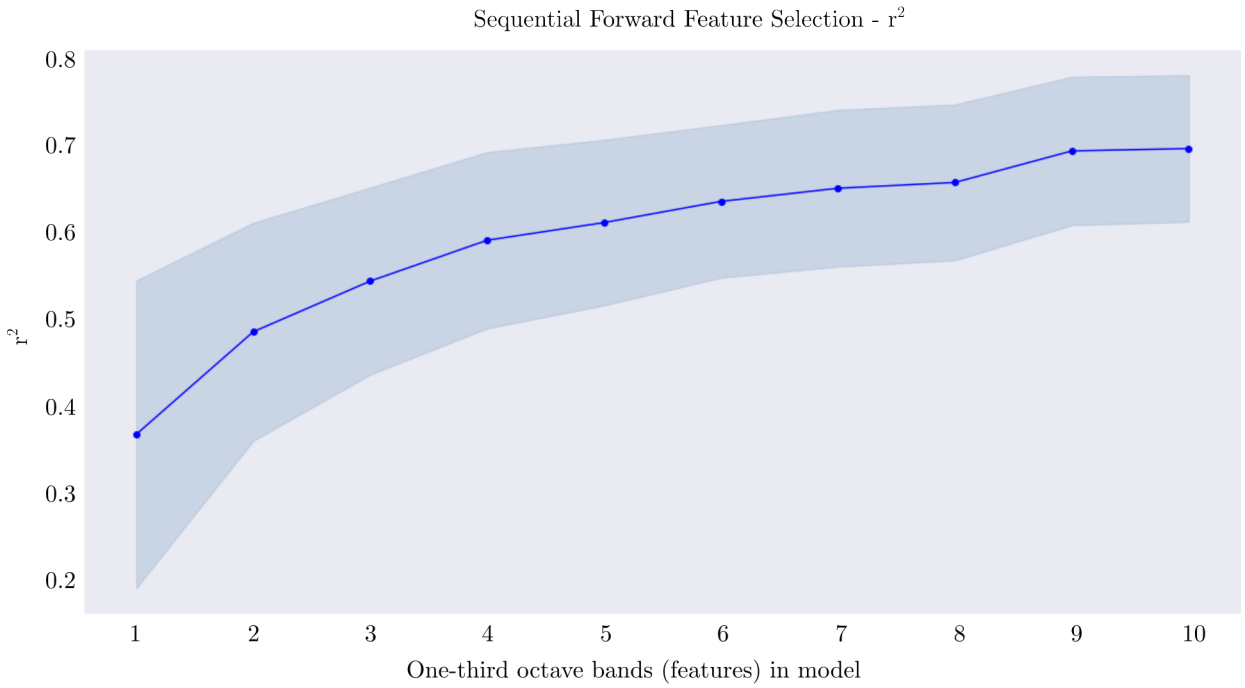


Figure 4.9: Plot showing the results of SFS and illustrating the effect of adding one-third octave bands into the semi-rural test case L_{50} linear model on model performance (measured using R^2)

accuracy of models using the different prediction evaluation metrics are broadly similar.

Using the R^2 and root mean square error prediction evaluation metrics, the L_{50} linear models had the highest accuracies for the semi-rural test case at 86% and 85% respectively. The top 10 one-third octave bands selected by SFS using the R^2 prediction evaluation metric were 6.3Hz, 8Hz, 10Hz, 20Hz, 125Hz, 160Hz, 200Hz, 250Hz, 800Hz and 10kHz, and for the RMSE prediction evaluation metric, the top 10 selected bands were 6.3Hz, 8Hz, 20Hz, 125Hz, 160Hz, 200Hz, 250Hz, 400Hz, 800Hz, 10kHz. Figures 4.9 and 4.10 show the results of SFS and illustrate the monotonic improvement in model performance (measured using R^2 and RMSE) with the addition of one-third octave bands (features) up to 10 one-third octave bands.

The same analysis above was completed for the urban test case. Using the R^2 prediction evaluation metric, the L_5, L_{10}, and L_{90} logistic models all had the same accuracies at 95% and using RMSE, the L_{10} logistic models had the highest accuracy at 96%. The top 10 one-third octave bands selected by SFS using the R^2 prediction evaluation metric and L_{10} were L_{eq}, 31.5Hz, 80Hz, 100Hz, 630Hz, 1kHz, 1,250Hz, 1,600Hz, 3,150Hz, and 6,300Hz, and for the RMSE prediction evaluation metric, the top 10 selected bands were L_{eq}, 31.5Hz, 80Hz, 250Hz, 800Hz, 1kHz, 1,250Hz, 1,600Hz, 3,150Hz, and 8kHz.

Figure 4.11 shows the results of SFS and illustrates a monotonic improvement in model performance (measured using R^2) with the addition of one-third octave bands up to 6 one-third octave bands, at which the performance plateaus. Figure 4.12 shows the same but for RMSE and this illustrates more variation in performance as one-third octave bands are added into the model.

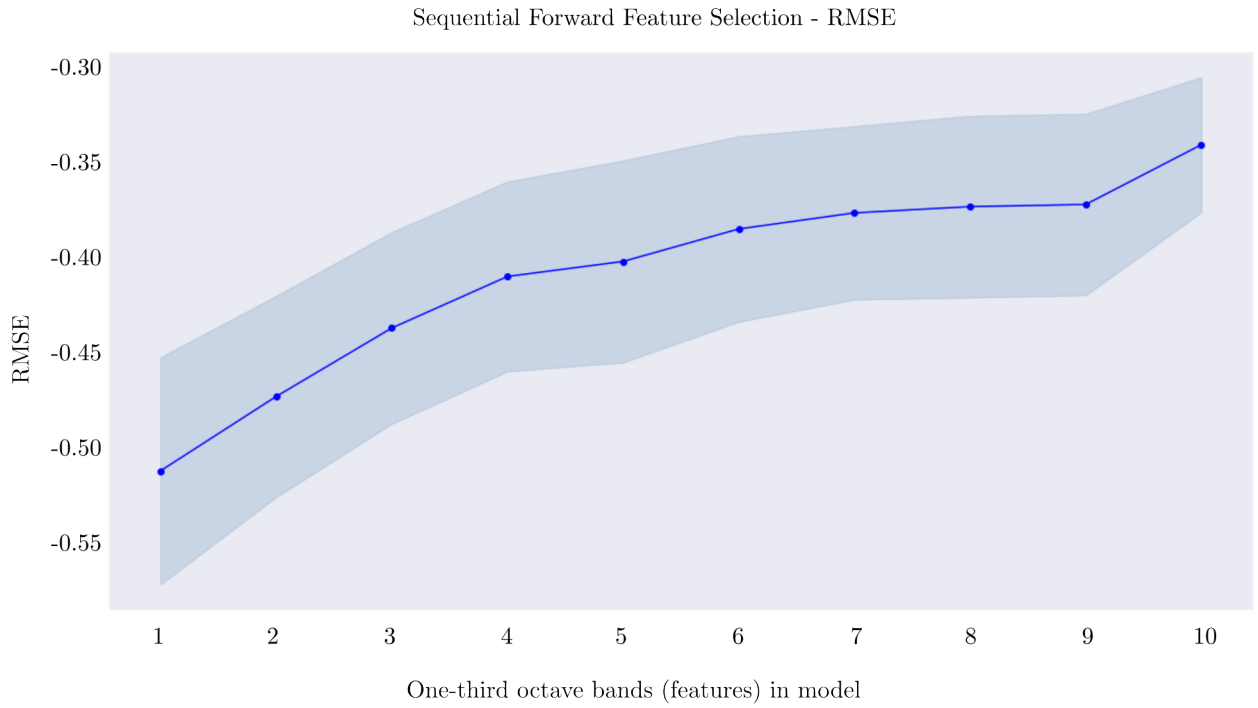


Figure 4.10: Plot showing the results of SFS and illustrating the effect of adding one-third octave bands into the semi-rural test case L_{50} linear model on model performance (measured using RMSE)

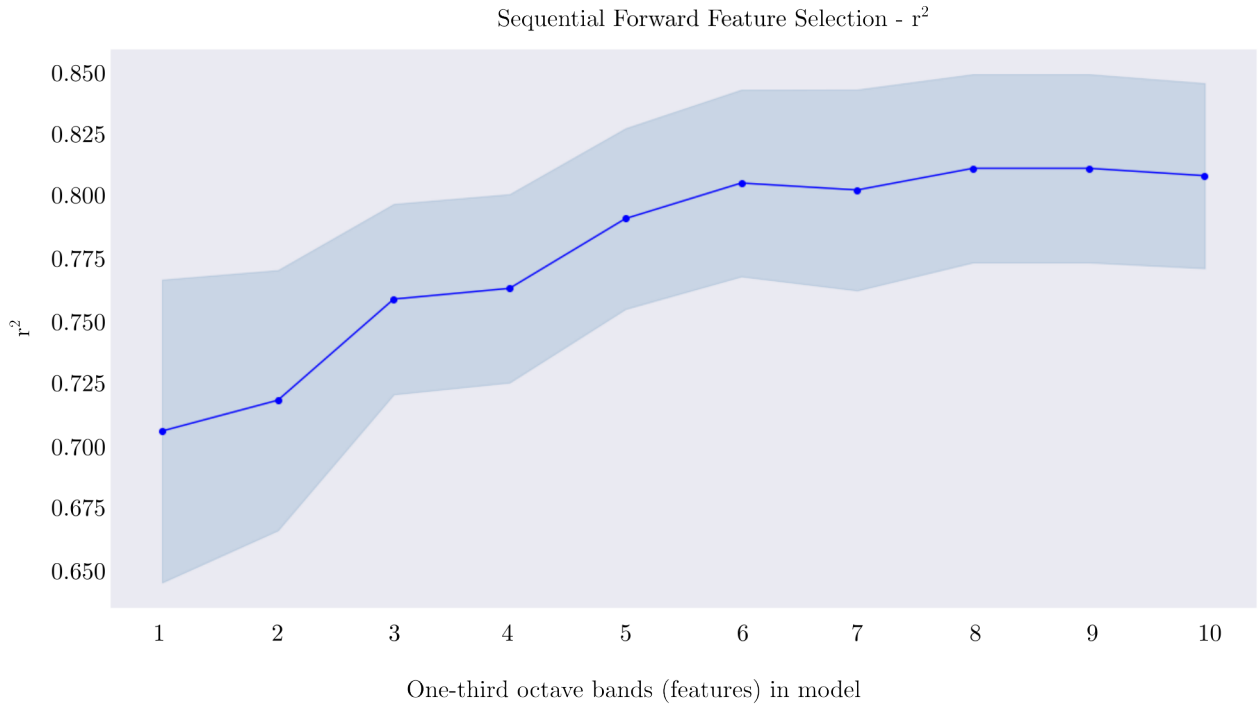


Figure 4.11: Plot showing the results of SFS and illustrating the effect of adding one-third octave bands into the urban test case L_{10} logistic model on model performance (measured using R^2)

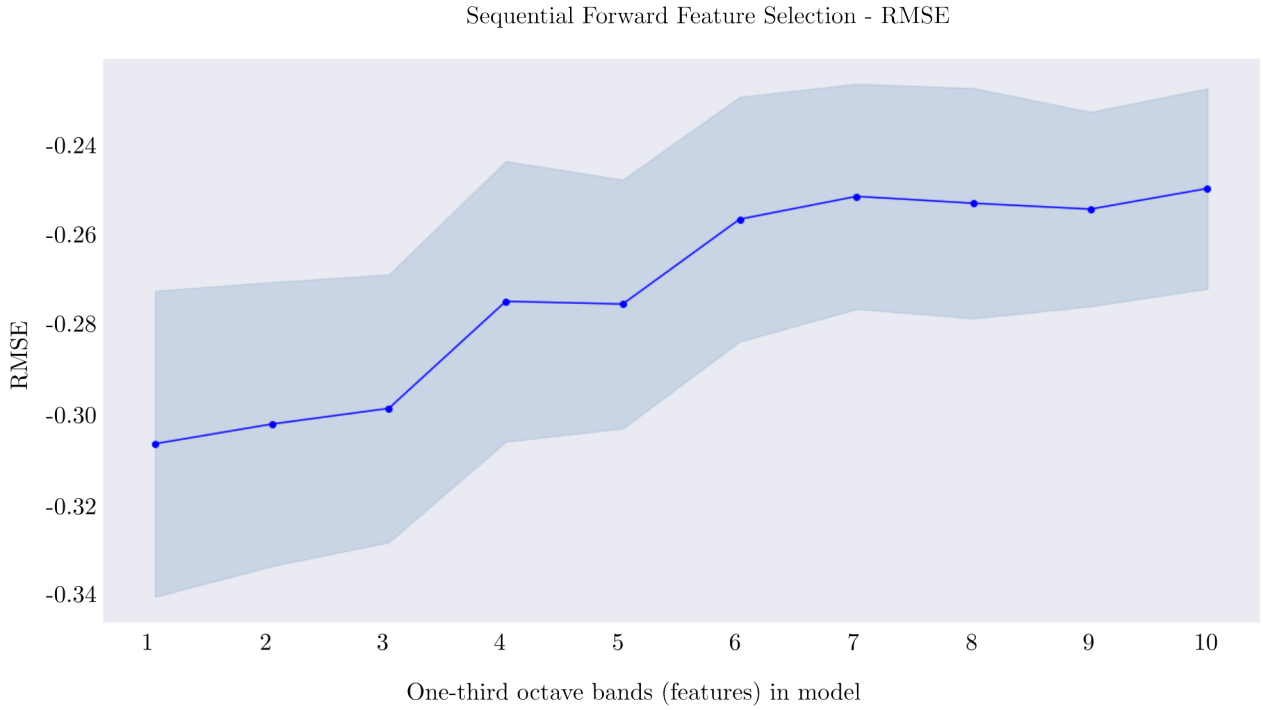


Figure 4.12: Plot showing the results of SFS and illustrating the effect of adding one-third octave bands into the urban test case L_{10} logistic model on model performance (measured using RMSE)

The above four figures illustrate an important difference in model performance for the two different test cases. For the semi-rural test case, Figures 4.9 and 4.10 show that model performance is positively impacted by the number of features, although, each additional feature does not have the same impact as the previous feature - diminishing returns. On the other hand, for the urban test case, performance of the models shown in Figures 4.11 and 4.12 appear to reach a maximum and plateau with around 5 or 6 features.

This may be caused by differences in the outdoor sound environments; where there is dominant, regular sound outdoors, the predictive performance of the models are highest and most affected by the one-third octave bands that are produced by that dominant sound. So, in the urban test case, where there are regular train pass-bys, the model performance will be highest when the one-third octave bands that are produced by the train are added into the model and frequencies that are more intermittent, will have less impact on the performance of the models.

However, when using SFS, additional features require a substantial amount of additional computational processing power, and therefore, for each additional feature, the improvement in model performance needs to be evaluated against the additional computational needs or additional time to complete the calculations/analysis.

4.3.3.3 SFS Top 10 VS all data

Do the models perform better with all data or only the top 10 one-third octave bands?

The data sub-set from SFS described in the previous section, which contained the top 10 one-third octave bands, was used to train linear and logistic models and predict window and door positions for each test case. The aim was to test the hypothesis that models containing only the top 10 one-third octave bands selected by SFS would be more accurate than models containing all the data.

Tables 4.10 and 4.11 show the accuracies of the linear and logistic models for each percentile and for the two prediction evaluation metrics (R^2 and RMSE) for each test case. These tables also show the difference between the model accuracy of the models using the top 10 one-third octave bands and the accuracy of the models that used all the data (from Section 4.3.2). Using the top 10 one-third octave bands for R^2 and RMSE for the semi-rural test case has a mixed impact when compared with the models that used all the data. Some of the models have a small improvement, but across all models, using the top 10 one-third octave bands selected by SFS has a detrimental impact on overall model accuracy. As explained above, for this test case, where there is no dominant regular outdoor sounds, the models rely on a greater number of features to predict the window position and by limiting the number of features to 10, this appears to limit the accuracy of the models. Using the top 10 one-third octave bands selected by SFS, the highest accuracy model (linear L_{50}) for the semi-rural test case had an accuracy of 86%, which is 2% lower than the highest accuracy model using all the data (L_{90} linear = 88%).

Similar to the semi-rural test case, the results for the urban dwelling of using the top 10 one-third octave bands have a mixed effect, but with a smaller impact. Again, this is expected, following the analysis in Section 4.3.3.2, where the accuracy of the models for the urban dwelling are determined largely by the first 6 one-third octave bands and less by the additional one-third octave bands. Interestingly, for the urban test case, using the top 10 one-third octave bands selected by SFS for R^2 and RMSE has a large impact on improving the accuracy of the logistic L_{95} models - an improvement of 9 and 10%. This large positive improvement suggests that using the top 10 one-third octave bands selected by SFS might be worth further investigation for other different test cases, since this improvement might be dependant on construction, indoor and outdoor sound, but there is potential that using SFS could be valuable in some cases. Overall, the model with the highest accuracy using SFS for the urban test case is the same as the model with the highest accuracy using all the data.

4.3.3.4 SFS summary

In the context of these results and the method presented here, SFS can be used for investigating the contribution of different one-third octave bands towards model performance, when using a range of different possible performance evaluation metrics. However, SFS is computationally expensive and can be time consuming to implement. In light of this and given the fact that the models do not have a higher accuracy when using the top 10 frequency bands selected by SFS in these test cases, the results

Table 4.10: Semi-rural dwelling model accuracies for SFS top 10 one-third octave bands and comparison with models containing all one-third octave bands.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
SFS r2	65	79	65	71	77	82	**86**	82	80	78	82	85
Difference [1]	-10	0	-1	-2	+2	+3	+2	0	-8	-6	-6	+2
SFS RMSE	76	78	66	69	77	77	**85**	82	79	**85**	81	83
Difference [1]	+1	-1	0	-4	+2	-2	+1	0	-9	+1	-7	0

[1] Difference when comparing each model accuracy with the corresponding model accuracy when using all data.

Table 4.11: Urban dwelling model accuracies for SFS top 10 one-third octave bands and comparison with models containing all one-third octave bands.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
SFS r2	82	94	77	**95**	80	**95**	88	93	75	**95**	69	94
Difference	-3	-1	+2	-1	+2	0	+1	+1	-3	+4	-6	+9
SFS RMSE	82	94	76	95	77	**96**	87	95	77	91	77	95
Difference	-3	-1	+1	-1	-1	+1	0	+3	-1	0	+2	+10

[1] Difference when comparing each model accuracy with the corresponding model accuracy when using all data.

suggest that using all the data in the models is more accurate and easier to implement.

4.3.4 Results part 3 - excluding frequencies greater than 1kHz

Next, it was hypothesised that the models might have improved accuracy, if only those frequencies which were typical of rail and road transport in the UK were included in the models. To test this hypothesis, a subset of the full data set was created, which included only one-third octave bands up to and including 1kHz and no one-third octave bands higher than this.

Table 4.12 summarises the results of the accuracies of these models and the difference in accuracy of these models compared with each models' accuracy when using all data (from Section 4.3.2).

For the semi-rural test case, omitting the one-third octave bands above 1kHz generally resulted in a very small improvement in the performance of lower percentile logistic models. Overall, filtering frequencies above 1kHz reduced the performance of the best performing models for the semi-urban test case from 88% to 84%. This could be explained by the presence of sounds that contain higher frequencies in the outdoor sound environment for this test case, which contribute towards the predictive power of the higher percentile models. It also shows that these higher frequencies are less important in the lower percentile models, which might be because there are no dominant, regular loud sound sources that have frequencies above 1kHz that contribute towards the predictive power of these models.

Table 4.12: Summary of model accuracies using one-third octave bands less than 1kHz (bold = highest accuracy model for each test case).

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
Semi-rural	73	78	66	75	75	80	83	82	**84**	83	**84**	**84**
Difference	-2	-1	0	+2	0	+1	-1	0	-4	-1	-4	+1
Urban	70	**96**	89	**96**	90	**96**	84	**96**	72	**96**	73	**96**
Difference	-15	+1	+14	0	+12	+1	-3	+4	-6	+5	-2	+11

[1] Difference when comparing each model accuracy with the corresponding model accuracy when using all data.

For the urban test case, filtering frequencies above 1kHz has improved the accuracy of almost every logistic model. The filtering has improved the accuracy of the lower percentile linear models. Possible reasons that the models for the urban dwelling have improved when only including one-third octave bands below 1kHz are that there could be other sources of sound in the higher frequency range indoors and/or outdoors, which are confounding the models that used the higher one-third octave bands and adversely impacted the predictive power of those models. Overall, the highest performing model for the urban dwelling and the filtered data is the same as with all data at 96%.

For these test cases, filtering has reduced the accuracy of the highest performing model for the semi-rural dwelling (from using all data) and not made any improvements to the accuracy of the highest performing model for the urban test case. Furthermore, this filtering requires additional processing of the data, so using all data in the models is more accurate and easier to implement.

4.3.5 Results part 4 - semi-rural excluding frequencies below 20Hz

The models in this section used only one-third octave frequency bands equal to and greater than 20Hz to enable comparison between the monitoring equipment (see Sections 4.2.3.2, 4.2.3.3, and 4.2.3.5). Similar to the analysis described in sections 4.3.2, 4.3.3, and 4.3.4, this smaller dataset (20Hz to 20Khz) for the semi-rural test case was passed through a series of linear and logistic models. A further sub-set for frequencies between 20Hz and less than 1kHz (similar to Section 4.3.4) was created - SFS was conducted on this smaller dataset to select the top 10 one-third octave bands, and models were run using the top 10 SFS one-third octave bands (similar to Section 4.3.3).

A summary of the model accuracies can be seen in Table 4.13. Table 4.14 compares the results of all models (f>20Hz) with the model accuracy from previous analysis using (1) all data (Table 4.6), (2) SFS (tables 4.10 and 4.11) and one-third octave bands less than 1kHz (Table 4.12).

These two tables together show an interesting result, which is that for most of the models and percentiles, omitting one-third octave bands below 20Hz has a negative impact on the accuracy, except for a number of logistic models that contain the top 10 one-third octave bands (selected by SFS for R^2

Table 4.13: Semi-rural dwelling model accuracies for various data sub-sets that include one-third octave bands equal to and greater than 20Hz.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
20Hz to 20Khz	62	72	57	67	67	75	77	81	71	84	73	84
20Hz to 1Khz	59	71	55	66	64	77	77	84	72	83	74	83
SFS R2	58	73	55	65	64	75	83	73	69	84	72	87
SFS RMSE	58	74	56	65	66	74	82	76	69	**89**	67	85

Table 4.14: Comparison of the model accuracies for the semi-rural test case, shown in Table 4.13 with the model accuracies from previous analysis using (1) all data (Table 4.6), (2) SFS (tables 4.10 and 4.11) and one-third octave bands less than 1kHz (Table 4.12).

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
20Hz to 20Khz	-13	-7	-9	-6	-8	-4	-7	-1	-17	0	-15	1
20Hz to 1Khz	-16	-8	-11	-7	-11	-2	-7	2	-16	-1	-14	0
SFS R2	-17	-6	-11	-8	-11	-4	-1	-9	-19	0	-16	4
SFS RMSE	-17	-5	-10	-8	-9	-5	-2	-6	-19	5	-21	2

and RMSE) for the highest percentiles (L_{90} and L_{95}).

Based on this one test case, this analysis suggests that if the optimum percentile and model type is selected (L_{90} logistic model in this case), it is not important to measure sound below 20Hz. However, if equipment has the facility to measure below 20Hz, this additional data can reduce potential error and miss-classification, particularly if the optimum model type and percentile is unknown.

4.3.6 Results part 5 - outdoor noise greater than indoor noise

Finally, it was hypothesised that model accuracy would be highest if models contained only data, where the noise (dB(A)) outdoors was higher than the noise indoors. This hypothesis was derived from the assumption that models would largely be predicting the window and door positions from noise ingress from outside.

A subset of all data for both test cases was created, in which all observations where the indoor A-weighted sound pressure level (dB(A)) was greater than outdoors were omitted from the dataset. The analysis follows the previous sections, where linear and logistic models for all percentiles were calculated using (1) all one-third octave bands, (2) one-third octave bands equal to and greater than 1kHz, and the top 10 one-third octave bands selected by SFS for (3) the co-efficient of determination (R^2), and (4) root mean square error (RMSE).

Table 4.15: Semi-rural dwelling model accuracies data where dB(A) outdoors > dB(A) indoors.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
All frequencies	71	74	62	66	74	78	84	82	**88**	84	**88**	83
=< 1Khz	70	74	62	67	72	78	83	82	84	83	84	84
SFS R2	53	76	63	68	74	75	86	86	75	78	82	85
SFS RMSE	71	75	63	71	74	77	84	86	80	85	81	83

Table 4.16: Semi-rural dwelling model accuracies data where dB(A) outdoors > dB(A) indoors - comparison with all data.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
All frequencies	-4	-5	-4	-7	-1	-1	0	0	0	0	0	0
=< 1Khz	-3	-4	-4	-8	-3	-2	0	0	0	0	0	0
SFS R2	-12	-3	-2	-3	-3	-7	0	4	-5	0	0	0
SFS RMSE	-5	-3	-3	2	-3	0	-1	4	1	0	0	-1

Results of model accuracy for the semi-rural dwelling are shown in Table 4.15. Table 4.16 compares the results in Table 4.15 with the model accuracy for all data, as shown in previous tables. These tables together illustrate that for the semi-rural test case, omitting observations where the dB(A) indoors is greater than outdoors, generally has a negative impact on model accuracy across the different percentiles. Higher percentiles were not impacted by removing observations where dB(A) indoors > outdoors, indicating that there were no sounds from indoors that were 'constant' to form part of the background noise, and which contributed towards the predictive power of the models. However, the lower percentiles were most affected by removing observations where dB(A) indoors > outdoors, indicating that there were short-duration loud (indoors > outdoors) sounds that contributed positively towards model performance. Overall the highest accuracy model for this subset was 88%, which is the same as the highest accuracy model using all the data.

Results of model accuracy for the urban test case are shown in Table 4.17. Table 4.18 compares the accuracy of the models in Table 4.17 with the accuracy of the models containing all data from earlier in this chapter. Together these tables show a mixed set of results and illustrate that omitting observations, where dB(A) indoors > outdoors, can have a variable impact on the accuracy of the models, but with a pattern of improving the accuracy of the higher percentile models. Overall, filtering out this data has produced a number of models that have an accuracy of 97%, which is a small (1%) improvement on the models that use all the data, but this required additional processing. Using this filtering technique

Table 4.17: Urban dwelling model accuracies data where dB(A) outdoors > dB(A) indoors.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
All frequencies	89	96	76	96	75	96	87	83	80	95	84	91
=< 1Khz	76	**97**	90	**97**	91	**97**	84	**97**	77	**97**	81	**97**
SFS R2	76	96	86	96	84	94	73	94	76	89	83	95
SFS RMSE	89	**97**	76	95	72	95	88	94	77	**97**	87	95

Table 4.18: Urban dwelling model accuracies data where dB(A) outdoors > dB(A) indoors - comparison with all data.

	L_{eq}		L_5		L_{10}		L_{50}		L_{90}		L_{95}	
	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log	Lin	Log
All frequencies	4	1	1	0	-3	1	0	-9	2	4	9	6
=< 1Khz	6	1	1	1	1	1	0	1	5	1	8	1
SFS R2	-6	2	9	1	4	-1	-15	1	1	-6	14	1
SFS RMSE	7	3	0	0	-5	-1	1	-1	0	6	10	0

might be less appropriate in very quiet outdoor settings or in cases with high indoor sources of sound - effectively this could reduce the dataset.

4.4 Summary and discussion

The aim of this chapter was to test the feasibility of determining the open/ajar/closed status of a facade door/window from indoor and outdoor sound measurements. This is simple in principle for unoccupied dwellings with a defined external sound source, controlled indoor noise, high background noise levels, and optimum microphone positions; these factors ensure that the outdoor sound level is distinctly higher than the indoor sound level. In real occupied homes with real occupants, the outdoor and indoor sound environments are unpredictable, and optimum microphone locations are not possible for long-term monitoring campaigns in occupied dwellings. Validation data was captured from two different scenarios, confirmed that the outdoor to indoor sound level difference using a simple time and frequency averaged noise metric (LA_{eq}) would not be an effective predictor of window status (Figure 4.5). However, by decomposing the sound data into frequency bins and looking at statistical percentiles within relatively short-time intervals (e.g., 5 minutes), a statistical model can be trained to predict window status with a high degree of accuracy.

This is the first known method developed to infer window positions using simultaneous outdoor and indoor sound measurements specifically from occupied dwellings, which are subject to unpredictable

occupant-related sounds. The method can yield high predictive accuracies, not just in urban noisy environments, but also in quieter semi-rural environments. Given the focus here on long-term monitoring campaigns, the microphone locations are determined by convenience (close to the window/door), rather than optimisation from an acoustics perspective. A comprehensive analysis was presented on the influence of different noise metrics as well as one-third octave bands, and the impact of data filters on method accuracy. The method relies on industry-standard noise metrics, thereby enabling the use of off-the-shelf professional noise instrumentation. Alternatively, low-cost, smart sensor monitors can be developed specifically for this method to facilitate medium-scale deployment for a modest budget, with data transmitted to a centralised server on a regular basis.

For the urban test case, overall accuracies of up to 96% were achieved using a logistic regression model based on L_5 metric and all available one-third octave frequency bands with no data filters. The high accuracies are likely due to the relatively noisy outdoor sound environment with two distinct and regular sound sources (a busy urban road and railway). Slightly higher accuracies (97%) were achieved with a data filter: excluding data where the overall averaged level indoors was higher than outdoors. However, this data filter has implications for the number of predictions available: in the urban case, 16% of the data was excluded based on this condition. Similar accuracies were also obtained using sequential forward feature selection (SFS) to select the top ten one-third octave bands; however, this came at a substantial computational cost. When looking at the prediction accuracies for the three states (closed/ajar/open), the highest accuracies were for open (98%) and closed (96%). The model failed to predict almost all of the ajar positions correctly (98%), with the majority of the predictions miss classified as open (70%). The urban test case was looking at the status of an outward-opening balcony door. The indoor microphone was installed at mid-level in the corner of the balcony door reveal. This was not an ideal choice for capturing small differences in noise ingress with the balcony door ajar. Whilst some guidance on installation was provided to the participant, the final choice for microphone placement was largely driven by participant preference and convenience - a key requirement for this method to be feasible and scalable. The second issue was availability of sufficient ajar data for training the model: less than 1% of the data corresponded to the ajar position. The reason for the low number of ajar positions was simply that the participants did not leave their balcony door in the ajar position frequently during the training or test phases of data collection.

For the semi-rural test case, overall accuracies were lower: 88% was achieved using a linear regression model based on L_{90} & L_{95} metrics and all available one-third octave frequency bands. The lower accuracies are likely due to the relatively quieter outdoor sound environment with no clearly defined regular sound sources. Applying the same data filters as before (excluding frequencies above 1 kHz) did not result in higher accuracies. Similarly, SFS did not result in an improvement in predictive accuracy. Excluding very low frequencies (below 20Hz, typically considered as inaudible) resulted in a marginal increase (1%) in accuracies. When looking at the prediction accuracies for the three states

(closed/ajar/open), the highest accuracies were once again for open (94%) and closed (87%). However this time the accuracy for ajar position was much higher (75%) than for the urban test case. This is believed to be due to the simpler installation setup: there was only one window in the room, and the microphone was closer and directly below the gap formed when the window is ajar. Furthermore, there was also much more data corresponding to the ajar status in the training dataset (16%) compared to the urban test case.

This method has been shown to predict window positions with variable accuracy - up to 88% and 96% for two different test cases. Although this method has been shown to have a high accuracy, the lower accuracies might not be acceptable for research which requires a very high level of accuracy.

It was not possible to determine a single optimum noise metric for a predictive model based on the two different test scenarios. For the urban test case the lower percentiles (L_5, L_{10}) performed best, whereas for the semi-rural case the higher percentiles (L_{90}, L_{95}) performed best. This may be caused by the distinctively different outdoor sound environments. The urban test case was characterised by frequent rail traffic and the time period associated with the L_5 or L_{10} metrics (15-30 s for a 5-minute measurement interval) corresponds well with a typical train passby. Conversely, there were no distinct noise sources for the semi-rural case, and the L_{90} and L_{95}, often associated with background noise, were more appropriate to separate out intermittent occupant sounds within the dwelling. Based on the limited observations, it is proposed that for outdoor environments where there are regular loud events, a lower percentile may increase predictive accuracy. Where the outdoor sound environment is relatively quiet with no dominant sounds, a higher percentile is expected to perform better. These proposals are based on a measurement interval of five minutes, and may not be valid for shorter or longer intervals.

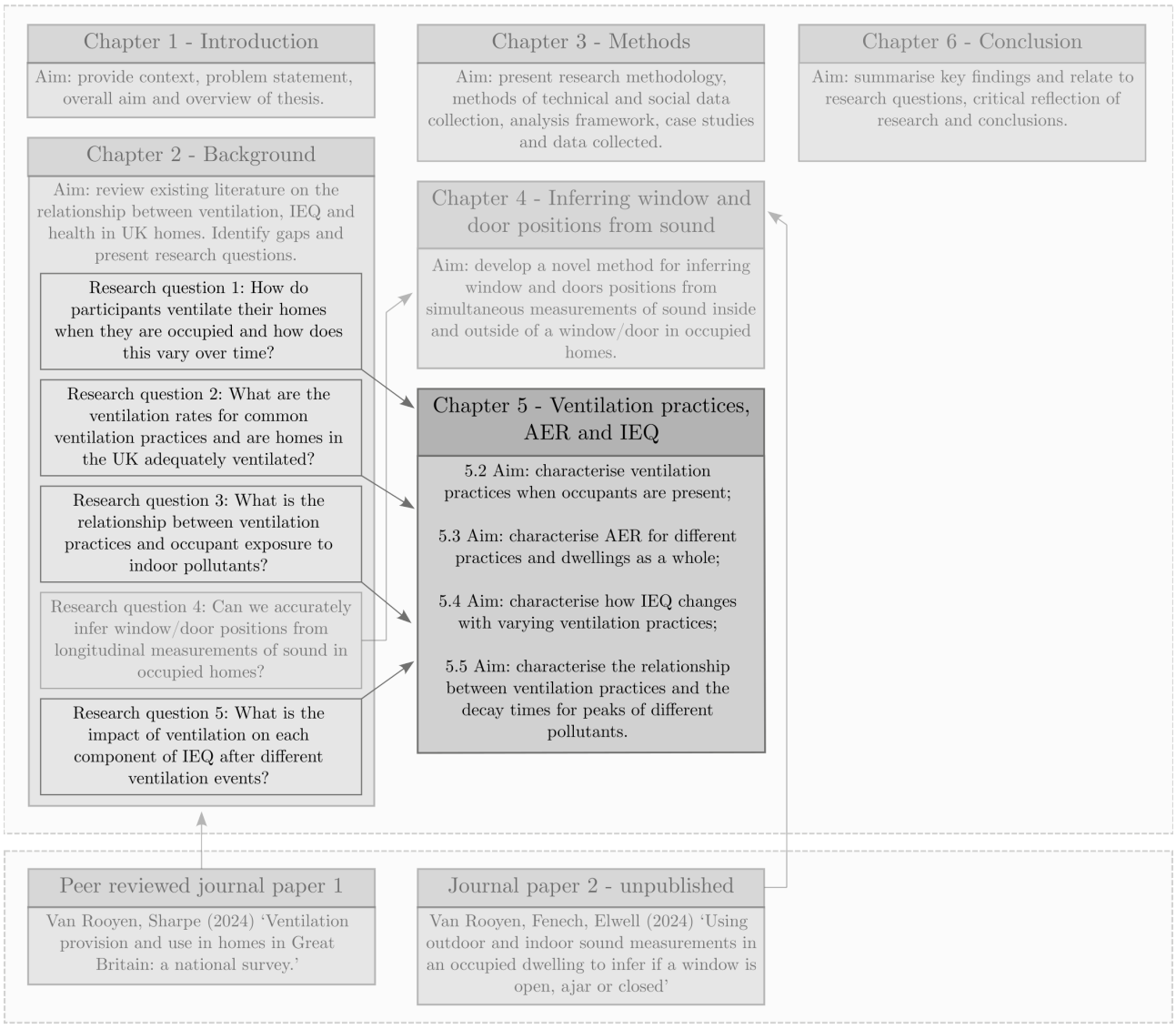
It was not possible to determine an optimum model (linear or logistic) for both test cases for generalising this method to other settings. One explanation could be that the logistic model gave higher predictive accuracies for the urban case because the data was largely dichotomous (open/closed) with very few ajar positions. The semi-rural test case had a more uniform distribution of the three states, and therefore, a linear model was more appropriate. An alternative hypothesis is that a logistic regression model is more effective when there are loud, distinct sources of outdoor sound (e.g., train, or heavy good vehicle passbys, or aircraft flyovers). Further work is required to test these hypotheses.

Whilst the aim was to choose two very different test cases (in terms of outdoor sound environment, facade construction, occupants' behaviours, and instrumentation), further validation is required before the findings can be generalised. The prediction accuracy for the ajar position in the urban test case was poor. Whilst this was attributed to the specific installation conditions and poor availability of training data for this status, further investigation is required, particularly on the sensitivity of prediction accuracy to the microphone positioning and presence of other facade openings. The data collected and the method tested in this chapter only considered three window/door positions: open/ajar and closed, where the ajar position was a gap of approximately 50mm. Future research could consider different

definitions of ajar and determine if the method can be used for inferring more than one ajar position. However, given the challenges experienced here, it is likely that this will come at a loss of predictive power but may deliver alternative valuable insights. In both test cases the method was tested with 20% of the available data (163hrs for the urban test case; 43hrs for the semi-rural test case); further research could be carried out to determine the sensitivity of the models accuracy to lower amounts of training data. The time interval for each observation was set to five minutes to align with other IEQ measurements during the validation campaigns. Shorter or longer time frames could be chosen to suit the objectives a specific study - this could impact on the suitability of noise metrics. Finally, there are many other potential statistical and machine learning models that can be applied instead of the models (linear/logistic) investigated here, which could potentially give even better prediction accuracies.

This method was considered a success in terms of the wider research and it was intended that this would be implemented in all case studies to determine window positions of key windows. However, as discussed in Section 3.2.6, the COVID-19 pandemic in the UK and national lockdowns coincided with the start of the monitoring campaigns (see Figure 3.25 on page 151), and it was not possible for the researcher to attend the participants homes to implement this method. Therefore, this method was not deployed for the main monitoring campaign and does not form part of the results in this thesis.

5 | Ventilation practices, air exchange rates and indoor environmental quality



This chapter focuses on the three themes that emerged from the literature review, that the limited evidence suggests: (1) a lack of ventilation provision, (2) a lack of knowledge of ventilation, and (3) ventilation rates are often lower than recommended in occupied homes. The overall aim of this chapter is to understand how the case study occupants ventilated their homes when they were occupied (ventilation practices and ventilation configurations) and the air exchange rates (AER) during different ventilation configurations, to characterise how different components of IEQ changed in response to a change in ventilation state, and finally, to investigate the relationship between ventilation configuration and the time for peaks of pollutants to decay to safe levels. This chapter responds to four research questions, each contained within their own section in this chapter.

The first section of this chapter (5.1) characterises ventilation practices and ventilation configurations of the different case studies and explores the spatial and seasonal variation of those practices and configurations - the analysis methods were described in Section 3.2.4.2 (page 133). The results are filtered for when the case studies are occupied, as this is most relevant for what occupants experience and their exposure to the different components of IEQ. This first section of this chapter also considers how occupant's ventilation practices are related to their questionnaire responses. See Section 3.2.3 (page 129) for the rationale of the questionnaire and Appendix D (page 368) for the questionnaire and justification of questions. This first section (5.1) of this chapter aims to respond to the following research question:

Research question 1: How do participants ventilate their homes when they are occupied, and how does this vary over time?

The second section (5.2) of this chapter is focused on estimating whole house air exchange rates (AER), individual room AER (using CO_2 decay), and relating this to the ventilation practices from the first section of this chapter - the analysis methods were described in Section 3.2.4.3 on page 135. The AER results are discussed in context of a new construct ('experienced AER'), AER from the literature, whole house vs individual room AER, and background ventilation. This section (5.2) of this chapter aims to respond to the following research question:

Research question 2: What are the ventilation rates for common ventilation configurations/practices, and are homes in the UK adequately ventilated?

The third section (5.3) of this chapter aims to characterise the direction and magnitude of change of all IEQ components upon a change in state of different ventilation devices - the analysis methods were described in Section 3.2.4.4 on page 140. This Section 5.3 aims to respond to the following research question:

Research question 5: What is the impact of ventilation on each component of IEQ after different ventilation events?

The fourth section (5.4) of this chapter calculates the time for peaks of all pollutants above their respective health threshold to decay back to the health threshold. The analysis uses the measured IEQ data from the case studies, using the same configurations reported in the previous sections, and so the insights from the previous sections are directly transferable. Section 3.2.4.5 on page 142 describes the method used in this chapter. This chapter aims to respond to the following specific research question:

Research question 3: What is the relationship between ventilation practices and occupant's exposure to peaks of pollutants?

Together, the four sections of this chapter aim to give a thorough description of how participants ventilated their homes, the AER arising from this, and the relationship between those ventilation practices and IEQ. The fifth section (5.5) of this chapter describes key limitations from the previous four sections and discusses opportunities for future work. The final section (5.6) contains a summary and global discussion of the chapter.

5.1 Participant's ventilation practices when at home

The discussion throughout this section refers to results which have been summarised in seven tables (F.1, F.2, F.3, F.4, F.5, F.6 and F.7) located in Appendix F.1 (page 394), which provide summaries of the top ventilation configurations (external windows and doors) for each case study, while the dwellings were occupied. The occupancy detection algorithm developed by Few and Elwell (2019) was adapted for determining periods when the case studies were occupied, this is detailed in Section 3.2.4.2. The configurations comprise of the most common combinations of windows and doors, specific to each dwelling. These tables present the counts (5-minute periods) and percentage of occupied time that each case study was in each of these configurations during the whole monitoring campaign and separates this for the summer and winter seasons. These results are distinct from most research concerned with ventilation and IEQ, as these results include only the times when occupants were present in their homes, where much of the research on ventilation and IEQ does not differentiate between occupied and unoccupied periods. Research concerned with ventilation and IEQ, which does not differentiate between occupied and unoccupied periods, can be challenging to relate to conditions that occupants experience and are exposed to, as unoccupied periods can represent large amounts of data from longitudinal monitoring campaigns. Furthermore, research which reports IEQ averaged over periods including occupied and unoccupied data is not representative of experienced IEQ and importantly might not be representative of occupant's exposure (Nazaroff, 2021; Stamp et al., 2022).

The results highlight that it is challenging to generalise ventilation practices because each case study has its own unique set of ventilation configurations and that ventilation behaviours are different between the case studies. Research often reports that ventilation practices across households are very different (Dick J.B and Thomas D.A, 1951; Dubrul, 1988; Van Dongen and Phaff, 1989; Iwashita and Akasaka, 1997; Kukadia and White, 2006; Andersen et al., 2013; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015); and the literature review of occupant's ventilation behaviour by Roetzel et al. (2010) concluded that even in similar conditions, most field studies of occupant's control of natural ventilation observe a wide range of different behaviours. The observed differences could be due to many internal and external factors, including those previously discussed in Section 2.2.2. Van Dongen and Phaff (1989) categorised these factors as: climatological (temperature, orientation, and wind), human (patterns of activity, thermal comfort, energy, perceived indoor pollutants, IAQ preferences, health. and health conditions), environmental (condensation, mould, moisture in dwelling, noise/odours from outside), and architectural (room type, ventilation and heating provision, infiltration, geometry of rooms). These factors all come into effect for the case studies and contribute to how and why ventilation practices vary across the different case studies. The measurements and survey information presented in this chapter provide insights into this.

5.1.1 Windows and doors closed most of the time when occupied

For all case studies, apart from P2, while they were occupied, the most common configuration the dwellings were in during the monitoring was with all external windows and doors closed - for P1-7 this was 63%, 29%, 57%, 74%, 83%, 67%, and 65% respectively. This agrees with research by Wang et al. (2022), who monitored ventilation and IEQ in 17 flats in the UK and reported that windows were open for only 30% of the summer period and mostly closed during the winter. Similarly, Morgan et al. (2017) measured ventilation practices in 26 Scottish homes constructed after 2009 and reported that 42% of the homes had either trickle vents or windows or both closed at all times during a one year monitoring campaign. However, in both cases it is not clear if the results include unoccupied periods.

Regular opening of external windows and doors may not be required for many homes, but this will be dependant on their installed ventilation provision, ventilation strategy and indoor pollutants. Table 5.1 provides an overview of the ventilation provision for each case study and shows that only three of seven had functional background ventilation provision compliant with current standards. Out of the seven case studies, only four have trickle vents for background ventilation in all habitable rooms, and the remaining have limited or no fixed provision for background ventilation. P1 has a background ventilation strategy which relies on continuous dMEV in combination with the trickle vents; however, the dMEV system was not operational, thus the background ventilation system was not adequate. Given the fact that four case studies (P1, P2, P6, and P7) did not have adequate or operational background ventilation provision, it might be expected that the participants would need to regularly open external windows and doors to provide background ventilation and control indoor air quality. However, of the four case studies without background ventilation provision, P2 is the only one that regularly opened windows - 71% of all occupied time with one or more windows open. The remaining three case studies (P1, P6, and P7) without adequate and operational background ventilation provision had all windows and doors closed for substantial amounts of the time that the homes were occupied - between 63% and 67% of all occupied times and up to 82% of the winter season.

Ventilation practices are a result of the occupants' interaction with the building fabric, and therefore, it is important to consider the results above in the context of the qualitative data collected from the participants. Ventilation practices will be determined by occupants balancing their perceived need to ventilate and their perceived barriers to ventilation (Few, 2021). Occupants responded that the single main reason for opening the windows and doors was for cooling the house (P1), fresh air (P2, P5, P6, P7), connection/contact with outdoors (P3), and to remove moisture/damp (P4). This agrees with a large scale survey, where the desire for fresh air (57%) and to cool the home (28%) were the top reasons for opening windows (Van Rooyen and Sharpe, 2024).

Three participants reported that they felt ventilation was 'fairly important' for health, and the remaining four felt that it was 'very important'. However, despite this stated importance, windows

in most homes remained closed for most of the time when occupied and barriers to ventilation are explored below as possible reasons for this.

The case studies were chosen with the potential for high outdoor air pollution and noise (see Section 3.2.6.1), where both of these factors were identified in the literature review as key barriers to opening windows. However, only one case study (P2) reported that outdoor air pollution was a barrier to opening windows, and four of the seven case studies (P2, P5, P6 & P7) reported that outdoor noise was a barrier to opening windows. In addition to noise and air pollution, the participants reported security (three of seven), draughts (two of seven), cooling room too much, and insects, among many other barriers to opening windows for ventilation.

The number of questions in the questionnaire was restricted in order to minimise survey fatigue (Heinzerling et al., 2013). Because of this, the questionnaire did not collect data on barriers and drivers for ventilation for the different seasons and is therefore unable to explain seasonal differences from the questionnaire.

Despite being located in the noisiest location and reporting that both outdoor air pollution and noise were barriers to opening windows, P2 opened their windows for more of the occupied time than any other case study. This participant reported that they felt IAQ and noise were both 'very important' for health, but ventilation was 'fairly important' for health. This participant opened the windows facing the road much more infrequently and for shorter periods of time when compared with the windows on the opposite facade. This suggests that this participant considered the outdoor environment and adapted their ventilation behaviour accordingly. This participant might have consciously or subconsciously balanced these factors and decided that the best action was to ventilate the way they did. Interviews with this participant following the monitoring could bring about a deeper understanding of this observed behaviour.

Table 5.1: Table showing the ventilation provision in each case study dwelling.

	Passive			Active			Notes
	Windows	Trickle vents	Other passive	Cooker hood	Bathroom Extract	Other active	
P1	Yes	Yes (open)	NA	Extract atmosphere	dMEV*	dMEV*	* not working
P2	Yes	No	Airbrick bathroom	Recirc	No	NA	
P3	Yes	Yes (open)	NA	Recirc	Yes	NA	
P4	Yes	Yes (open)	NA	Recirc	Yes	NA	
P5	Yes	Yes (open)	NA	Recirc	dMEV	dMEV	
P6	Yes	Bathroom	NA	Recirc	No	NA	
P7	Yes	Some	NA	Recirc	Yes*	NA	* not working

5.1.2 Seasonal and spatial differences in ventilation practices

Tables F.1, F.2, F.3, F.4, F.5, F.6 and F.7 highlight a strong relationship between the amount of occupied time that all windows were closed and the season, where during the summer, the occupied time that one or more window was open was much greater than during the winter.

Table 5.2 shows the number of times, the median duration, and the percentage of occupied time that windows and doors were opened in each room during the summer and winter. This table shows that windows and doors were opened for much longer and for a much greater proportion of the occupied time in the summer than in the winter. It is interesting to note that in some cases the number of times a window was opened (referred to as 'frequency' in this thesis) was less in summer than in winter, but for significantly longer (referred to as 'duration' in this thesis).

Section 2.2.2 highlighted the many internal and external factors that influence ventilation behaviour and their complex interactions. However, of the many factors, indoor and outdoor temperatures and season are described as one of the main drivers for window opening and a key reason for the variation in ventilation practices (see Section 2.2.2.3). In this research, five of seven participants reported that one reason for opening windows was due to high internal temperatures (cool down the house) and one participant reported it was the single main reason for opening windows. In addition to this, four of seven participants felt that their homes got uncomfortably hot in the summer and three did not. The questionnaires were completed by the participants during the summer, which could bias the results towards responses relating to the summer ('time of observation bias') and also possibly reduce the accuracy of the results pertaining to the prior winter ('recall bias'). These biases could be reduced by conducting separate questionnaires during each season; however, only a single questionnaire was issued to participants to minimise the burden of the overall research, particularly in view of the intensive technical monitoring. Section 5.5 explores this limitation and opportunities for future research to address this. In addition to these heat related responses, there are other drivers and also barriers to opening windows that could be contributing or driving the observed seasonal variation. For example, draughts (P2 & P3), pollen/allergies (P2 & P7), insects/pests (P2), heat loss/cost of heating (P3), cools the room too much (P5), outdoor noise (P2, P5, P6 & P7), and outdoor pollution (P2 & P7) are barriers reported by the participants that could be driving or contributing factors to the observed seasonal differences.

In Appendix F.2 (398), Tables F.8, F.9, F.10, and F.11 provide summaries of the participants questionnaire responses on ventilation practices during different times of day and seasons, where they reported that they opened windows a lower number of times during the winter than the summer, which aligns with the recent national survey of ventilation in the UK (Van Rooyen and Sharpe, 2024). However, Table 5.2 shows a mixed set of results, where some windows were opened a greater number of times (frequency) during the summer and others more during the winter. The difference between

occupants' self reported perceptions of their ventilation practices and actual practices are explored further in Section 5.1.3.

Room type and room use is described by Dubrul (1988) and Van Dongen and Phaff (1989) as an important factor influencing ventilation behaviour. Dubrul (1988) characterised ventilation behaviour according to three 'zones': 'lived in', 'functional', and 'sleeping zones'. They report that lived in spaces had low and constant background ventilation, with windows opened the least in these spaces. Functional zones such as kitchens and bathrooms have higher rates of infrequent (purge) ventilation, occurring when internal pollutants are generated. Sleeping zones are described as the main ventilation zones, and windows are opened up to four times more than in other zones. Bedrooms have the highest variation in behaviour between households. The results discussed below highlight that this simplified model does not always apply and that it is not always possible to generalise ventilation behaviour, which is found to be complex and highly variable.

The results shown in Table 5.2 show that on average, across all case studies during winter and summer, the windows and doors are open for the greatest percentage of occupied times in bathrooms (32%), then in kitchens (16%), bedrooms (15%), and least in living rooms (9%). Table 5.2 shows that each time a window and door was opened, they were typically opened the longest (duration) in bedrooms, closely followed by bathrooms, and least in kitchens and living rooms. Finally, windows and doors are opened the greatest number of times in living rooms, then in kitchens, bedrooms, and least in bathrooms. This table highlights that there are substantial differences in the frequency with which, duration of and amount of occupied time that windows and doors are opened during different seasons in the different rooms. In addition to this, there are differences between case studies, both spatially and seasonally.

The result that windows are open for longer during occupied periods in bathrooms than other rooms does not agree with the characterisation above by Dubrul (1988) and also does not agree with other studies in Europe (Brundrett, 1977; Van Dongen, 2007; MHCLG, 2019) and in America (Morrison et al., 2021), who most often reported that windows were opened more frequently and for longer in bedrooms than in other rooms. However, as previously mentioned, other research does not differentiate between occupied and unoccupied periods, which might contribute towards this difference. Furthermore, other regions have different ventilation systems in homes and might not rely on opening windows in bathrooms for ventilation. In addition to this, much literature does not report on window opening in bathrooms, which is problematic as bathrooms are a major source of moisture in homes, and therefore, ventilation behaviour is important for these spaces. In the UK, most of the housing stock is old, and many older homes do not have mechanical ventilation in bathrooms and may therefore rely on opening windows for controlling moisture in these spaces (Van Rooyen and Sharpe, 2024).

Dubrul (1988) and Van Dongen and Phaff (1989) both reported that window opening in bedrooms were independent of season, however, the results presented in Table 5.2 do not directly agree with this.

Despite the large amount of variation across case studies, Table 5.2 shows that for three of the seven case studies, the amount of time that a window is open in the bedrooms is significantly lower during the winter than during the summer, which suggests that the amount of time that a window is open in the bedroom is dependant on season. In addition to this, participants self-reported behaviour (Table F.8) also shows that, in most cases, they perceive to open bedroom windows less in the winter than in the summer, supporting the measured data that bedroom windows are not opened independently of season. The literature review found that outdoor temperature is likely to be an important factor for the frequency and duration that windows and doors are open, but the review also highlighted that many other factors are also likely to influence this relationship.

MHCLG (2019) both reported that windows were opened more frequently in bedrooms than in other rooms, which does not agree with the results presented here, where windows and doors in living rooms were opened most frequently. This research, however, does include sliding doors and balcony doors in living rooms in this analysis, which could be a reason for this difference. Van Dongen (2007) reported that windows were open for longer amounts of time in bedrooms than other rooms, which agrees with the findings of this research.

All case studies had a combined open plan living and kitchen space and also had a door in the living space to outside. These large and complex spaces have multiple uses and no distinguished boundaries, where it is not clear if ventilation behaviour in these spaces was attributed to one or the other space. In addition to this, the doors in living spaces also serve many different functions, and the reasons for using the doors over time are not clear, particularly at the high temporal resolution of the event data. Informal discussions with the participants offer some potential explanations and highlight the value of interviews/walk-throughs; however, further research is required to ensure this anecdotal evidence is robust. Further semi-structured walk-throughs would have benefited this study, as planned, but were not possible due to the ongoing COVID pandemic. P2 and P6 had pets and regularly used their living room doors to allow their pets access to the garden. P3 was occupied by participants who smoked outside their living room door and also used this door as normal access to their home as well as the main source of ventilation for their living/kitchen space. Table F.11 shows the percentage of occupied day and night periods that sliding and balcony doors were opened in the case studies, and this shows that for P2 and P6 (with pets) during the summer, the sliding doors were opened at least once every day and night. During the winter, the amount of days when the sliding door was opened reduced, but not as much as for other windows in the case studies. Interestingly, the percentage of night periods that the sliding door was opened, reduced substantially, which might be due to the lower temperatures in the night. To contrast this, P1, P5, and P7 did not have pets, and were not smokers, and opened their living room doors less.

The reason for each individual door opening is not known, and it is therefore not known if this was to ventilate the home or for other reasons. This makes interpretation of the results challenging and

highlights the need to collect information from the participants on reasons for using doors that can be resolved at a spatial and temporal resolution that is compatible with the event data - this would address the so called 'spatio-temporal problem' (Love and Cooper, 2015). However, the practicalities associated with collecting and resolving this social data at a high spatial and temporal resolution for longitudinal campaigns remain unresolved. Additional information about ventilation practices, such as that obtained from informal discussions, can be collected more formally through structured or semi-structured interviews and/or walk-throughs.

Possible reasons for differences between this research and other research could arise because the results presented in this research are for occupied times only, whereas other research often includes times when the homes were unoccupied. Differences can be due to geographic differences and differences in ventilation provision. Differences could also arise from different definitions of summer and winter periods, particularly as this research uses half of the shoulder seasons in the summer and winter definitions, which might include ventilation behaviours that are not fully representative of the peak winter/summer. Finally, COVID will have had an exceptional impact on this research, as participants were present in their homes (during the national lockdowns) for much longer than in other research, altering the occupancy times and also the way that participants used their homes and their ventilation behaviours. For example, some rooms are likely to have had multiple uses as many people were working from home during the pandemic. Additionally, the UK Government and media issued advice to the public on ventilation, specifically that ventilation was an important factor for infection prevention, and this advice could have altered occupants' behaviours, giving rise to differences between this research and other research.

The results presented above show that the frequency of opening, duration that windows and doors were open, and percentage of the occupied time they were open are highly variable: (1) within the same room of each case study, (2) across different rooms in the same case study, and (3) also across different case studies. That is to say, ventilation is highly variable both within individual households and across different households.

Table 5.2: Table showing the number of times each window is opened (frequency), the median duration it is opened for (mins), and the amount of the occupied period that each window was opened for the main bedroom, living room, kitchen, and bathroom during the summer (S) and winter (W) for all case studies. For durations, bold results indicate where the difference between summer and winter is statistically significant (Kruskal–Wallis test $p > 0.05$).

	Bedroom						Living					
	Frequency		Duration		Occupied		Frequency		Duration		Occupied	
	S	W	S	W	S	W	S	W	S	W	S	W
P1	74	34	**203**	**64**	35%	3%	94	52	71	118	57%	17%
P1 [a]	-	-	-	-	-	-	76	32	**24**	**5**	3%	1%
P2	23	165	**1436**	**443**	94%	39%	59	15	**429**	**296**	10%	1%
P2 [b]	-	-	-	-	-	-	-	-	-	-	-	-
P3	393	389	30	11	9%	1%	551	472	88	81	1%	1%
P4	5	6	276	210	4%	1%	-	-	-	-	2%	0%
P5	62	50	**43**	**7**	14%	4%	2	1	176	1	1%	0%
P5 [a]	-	-	-	-	-	-	195	157	2	2	15%	6%
P6	3	51	189	136	15%	3%	19	498	**76**	**2**	31%	4%
P7	11	40	93	94	3%	2%	84	186	2	3	3%	1%
P7	16	25	138	102	7%	1%	-	-	-	-	-	-
	Kitchen						Bathroom					
	Frequency		Duration		Occupied		Frequency		Duration		Occupied	
	S	W	S	W	S	W	S	W	S	W	S	W
P1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
P1 [a]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
P2	11	2	389	155	2%	13%	87	248	**604**	**450**	72%	27%
P2 [b]	427	1008	**104**	**10**	37%	12%	-	-	-	-	-	-
P3	NA	NA	NA	NA	NA	NA	182	134	**170**	**78**	41%	14%
P4	21	12	**335**	**29**	9%	1%	79	108	**184**	**81**	27%	14%
P5	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
P5 [a]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
P6	NA	NA	NA	NA	NA	NA	5	87	958	310	81%	12%
P7	4	6	**535**	**77**	28%	25%	28	83	**137**	**75**	33%	3%
P7	-	-	-	-	-	-	-	-	-	-	-	-

[a] Balcony door
[b] Sliding door

5.1.3 Comparison of questionnaire responses and measurements with respect to ventilation practices

In the questionnaire that was issued to participants (see Appendix D on page 368), a series of questions were asked about how often they open windows in the main bedroom, living room, and kitchen. The qualitative questionnaire scales (e.g., 'Once a month', 'Once every couple of weeks', 'Once a week', 'A few times a week') were transformed into days, and from this, into percentages for each season. Tables F.8, F.9, and F.10 (see Appendix F.2 on page 398) compare measured data from ventilation practices with these questionnaire responses.

These tables show that there is a poor level of agreement between questionnaire responses and actual measurements. Across all case studies, in bedrooms, only 29% of the questionnaire responses across the seasons and time of day agree with the measurements; in living rooms this is 46%; and in kitchens 42%. Gauthier and Shipworth (2014) also reported major differences between occupants' self reported behaviour (semi-structured interviews) and observations. Both the results presented here and that of Gauthier and Shipworth (2014) conflict with Dubrul (1988) and Rijal et al. (2007), who reported less differences between questionnaire responses and actual behaviours. However, the research by Gauthier and Shipworth (2014) and Dubrul (1988) were in different subject areas (thermal comfort and ventilation) and used different methods (interviews and questionnaires).

It is interesting that participants were most accurate at recalling their ventilation behaviours for living rooms, where this was also the room which had the most frequent window and door openings. It is possible that this was the space where participants spent most of their time when they were awake during the pandemic, and window opening might be associated with specific practices in living rooms, enabling participants to more accurately recall their ventilation behaviours for this space. However, this research cannot determine the cause of this difference, and further research is necessary to disentangle the reasons why participants cannot recall their ventilation practices accurately and the reasons for spatial differences.

Possible reasons for the difference between the questionnaire responses and the measurements are: assumptions around what constitutes an occupied period (>40% of a day), interpretation of scales in the questionnaire (e.g., 'a few times a week'), the Hawthorne effect, lack of motivation to record questionnaire responses accurately, and finally that the questionnaire happened at a single specific time whereas the measurements span months and seasons (recall error/bias). A possible reason for recall error associated with ventilation is that these practices might be carried out less consciously (automatic/habitual) than other behaviours, and so participants may be less aware of their ventilation practices. Another potential source of the difference between questionnaires and measurements is that the questionnaires were answered only by a single occupant; however, many of the case studies were occupied by more than a single person, and the measurements include the actions of all occupants. Despite this potential error, the questionnaires responded to by single occupancy case studies still have poor agreement with measurements. Future research could determine if there are differences in ventilation behaviour between different people living in the same dwelling, quantify the differences, and explore the reasons for any differences.

Although this research has a small sample and cannot be generalised with confidence, the finding that there are substantial differences between reported and actual ventilation behaviours is noteworthy. This suggests that surveys issued once during longitudinal monitoring campaigns might not be able to adequately capture the real variation of ventilation behaviours - multiple surveys may be necessary. This difference might also suggest that participants are unable to accurately report on their ventilation

practices. If both of these possibilities reflect a wider trend, this may affect the conclusions drawn from such research. This is particularly important in the context of the large body of literature on ventilation behaviour, where much of that body of literature is derived from questionnaire responses and not directly from measurements of ventilation practices.

No other studies were found that compared measured ventilation practices with participant reported practices over extended monitoring campaigns in occupied homes. Future research could carry out measurements of ventilation and self-reported perceptions of ventilation to investigate in more detail if respondents are able to accurately recall and report on their ventilation behaviours. This finding highlights the importance of actual measurements of ventilation practices in lieu of only using self-reported measurements of ventilation practices.

5.2 Relationship between ventilation practices and air exchange rates

This section presents the results of the AER calculations for all case studies and the relationship with ventilation practices and configurations from the previous section. The method developed by Few and Elwell (2019); Few (2021) was adapted to suit this research, and a detailed description of this can be found in Section 3.2.4.3 on page 135. The CO_2 tracer gas decay model fundamentally assumes a single zone, which does not represent real homes, which typically contain multiple connected spaces (previously discussed in Section 3.2.4.3) (Nazaroff, 2021). Acknowledging this assumption, this research attempted to characterise both the individual room AER and whole house AER across multiple zones, with the aim of identifying how this varies with different ventilation practices. Section 3.2.4.3 describes that the single zone model assumption is not upheld in the case studies and CO_2 will migrate between internal spaces - therefore, the calculated individual room AER is not representative of the real indoor-outdoor AER but instead is indicative of the experienced change of air for occupants in that particular space.

As expected, based on the reports of previous research, the distributions of AER are typically log normal, and therefore, throughout this section, results are discussed in terms of the median and interquartile range (IQR), which are appropriate descriptors for the log normal distributions (Nazaroff, 2021).

Table 5.4 shows the top ventilation configurations for each case study and the corresponding number of whole dwelling AER results, the median AER, and the interquartile range. As well as whole dwelling AER, AER were calculated for each room, and Table 5.5 shows the same measures as the previous table but for individual room AER. There are limitations when estimating AER from the decay of CO_2, particularly around inter-zonal flows - these limitations were discussed earlier in Section 3.2.4.3 and are also discussed in Section 5.2.4 of this chapter, in context of the results.

Note: no whole house AER calculation results for P5 are presented because this dwelling had a short campaign which took place shortly after the second national lockdown in the UK, during which restrictions were in place for non-essential travel. From the data, it was inferred that the participants left their home unoccupied only on a few occasions, and when they did, they closed all external windows and doors.

5.2.1 Higher AER with more windows open

As expected, tables 5.4 and 5.5 plus Figure 5.1 and Figure 5.2 show that for most case studies, the median whole dwelling and individual room air exchange rates were lowest when all windows and doors were closed, and higher AER were estimated when one of more window was open. Both of these tables show where the estimated AER are statistically significantly higher (bold results) than when all

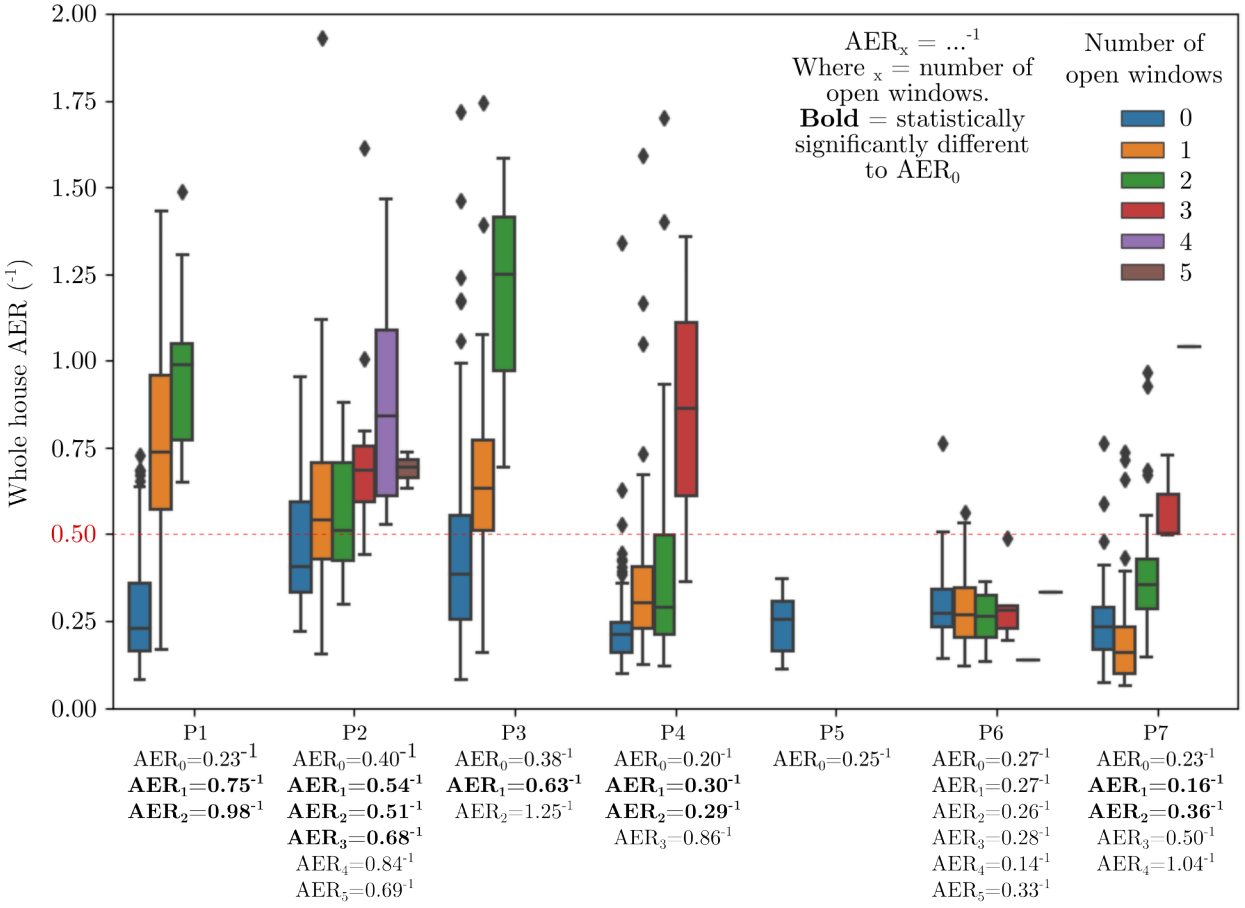


Figure 5.1: Box plots showing the distribution of whole house AER with varying numbers of open windows for each case study. Figure also shows the median whole house AER ($^{-1}$) for varying amounts of open windows for each case study. Bold results indicate where the AER is statistically significantly higher (Kruskal Wallis $p < 0.05$) than when windows are all closed (AER$_0$).

windows and doors were closed. Statistical significance appears to be strongly affected by the number of observations and in many cases there are limited numbers of estimated AER for when windows were open, particularly larger numbers of windows. Therefore, even in cases where there is a large difference and we might expect to see a statistically significant difference, there is not.

The CO_2 decay method requires a decay that has a duration long enough relative to the measurement interval (5 minutes) such that a model can be fitted to the data. In this research, 40 minutes was chosen - see Section 3.2.4.3. This minimum duration limits the number of observations and could also result in a systematic bias towards low AER, as observations with high ventilation rates and/or low starting concentrations of CO_2 are more likely to be excluded. This limitation can be problematic when trying to estimate AER when windows are left in the open position, as ventilation rates can be high and the concentrations at the start of the decay can also be low, and so the decay durations could be less than 40 minutes. However, at low concentrations, monotonic decays are less likely to occur, and the error in estimating the AER increases.

After estimating the AER for each decay event, for each case study, the individual estimated AER

were combined into a single dataset. Across all case studies, the median whole house AER when windows were closed was 0.25 h^{-1} (IQR = 0.19 h^{-1}), and with one window, this rose to 0.35h^{-1} (IQR = 0.34 h^{-1}), two windows 0.41h^{-1} (IQR = 0.46 h^{-1}), three windows 0.60h^{-1} (IQR = 0.25 h^{-1}), and with four windows open 0.84h^{-1} (IQR = 0.46 h^{-1}). As expected, these results show that whole house AER increase with increasing numbers of open windows. This agrees with ventilation theory (Dick J.B and Thomas D.A, 1951) and empirical measurements of AER by Roulet and Scartezzini (1987); Howard-Reed et al. (2002), and Few (2021). However the results also show a high coefficient of variation (IQR divided by the median), and Figure 5.1 shows that there is a large amount of variation between the different case studies. This large amount of variation across the different case studies is reported in other research and is expected, as there will be variations in the geometry of rooms and windows, the amount windows were opened, internal door use and the fact that indoor and outdoor conditions vary across the case studies and with time - these differences are summarised in Section 5.6 (Dimitroulopoulou, 2012; Few, 2021; Nazaroff, 2021).

The variation of background AER (all windows and doors closed) across the case studies is discussed in detail in Section 5.2.5. Figure 5.1 clearly shows that different homes experienced very different AER with varying numbers of windows that were open and this highlights the challenge of generalising AER. This figure also shows that some homes experienced large changes in AER when windows were opened (e.g., P1 and P3), but others experienced very little change in AER when windows were opened (e.g., P6) - this variation across case studies is further discussed in Section 5.2.6 with regards to the widely adopted 'health threshold' for AER. Those homes with lower internal volume and internal geometry that is closer to a single zone appear to have experienced higher changes in AER when windows were opened. However, the whole house AER are dependant on internal flows, where internal doors can play an important role, and in many cases there were very limited measurements of internal doors to evaluate this. Table 5.5 avoids this specific limitation by examining AER in each room when windows were open and closed in that room.

The literature review highlighted that outdoor temperature and season were common factors influencing window operation. Figure 5.2 develops this issue compared to Figure 5.1 and displays boxplots of AER within the different case studies, for when different numbers of windows were opened for the summer and winter seasons. These boxplots show a large amount of variation between AER in summer and winter for the different case studies and numbers of windows that were open. In some cases, the median AER were higher in summer than winter, but in others the median AER were higher in winter than summer. The difference in AER for summer and winter was statistically significantly different in only two cases, when all windows and doors were closed. However, as mentioned previously, there was limited observations of whole house AER, particularly with windows open, which would impact these statistical calculations. One limitation of the event sensor measurements (and window open/closed status) discussed in Chapter 4 is that we do not know how far windows were open and so

caution is required when interpreting these results, as the amount a window was opened could have an impact on AER.

Multivariate linear regression models were created for each case study to investigate the relationship between different environmental variables and whole house AER. The multi-variate models included terms for the median outdoor temperature, median wind speed, and the number of windows that were open during each decay ($\text{AER} = \text{constant} + \alpha \times \text{temperature}_{\text{outdoor}} + \beta \times \text{wind}_{\text{speed}} + \gamma \times \text{openwindows}$). Wind direction in combination with wind speed is important, but wind direction is not considered here, as this requires constructing component vectors of wind speed and direction. The results show that in six of seven case studies, outdoor temperature was a significant factor, and of these, four of the co-efficients were negative. These results indicate that higher AER were experienced during periods when the outdoor temperature was lower - this could be driven by a higher indoor to outdoor temperature difference and/or higher wind speeds during winter. Wind speed was a significant factor for three of the seven case studies. Finally, the numbers of windows that were open was a significant factor in five of the case studies, with positive co-efficients for all five.

Table 5.3 summarises the maximum AER for each case study during the summer and winter seasons, with the outdoor temperature and the number of windows that were open during the decay used for calculating the AER.

Table 5.3: Table showing the maximum AER for each case study, for summer and winter, along with the outdoor temperature and number of windows that were open for that AER.

Participant	Winter			Summer		
	Maximum AER ($^{-1}$)	Windows open	Outdoor temperature (°C)	Maximum AER ($^{-1}$)	Windows open	Outdoor temperature (°C)
P1	0.67	0	14.3	2.24	1	20.0
P2	1.93	1	10.0	1.13	4	21.2
P3	1.46	0	7.3	1.74	1	11.8
P4	1.59	1	16.8	1.7	2	24.4
P5	NA	NA	NA	0.37	0	12.0
P6	0.76	0	4.7	0.33	5	18.4
P7	1.04	4	16.5	0.72	1	18.2

Table 5.5 shows that for individual rooms, AER in the room can double when a window is open, which is comparable with Hill et al. (2001), who also found AER almost doubled when windows were open relative to when they were closed. However, this figure also illustrates the limited number of results for when windows were open and the large variability between case studies - see previous paragraph for possible reasons for this variability. The differences between whole house and individual room AER are discussed in Section 5.2.4.

An extensive review and meta-analysis of AER from approximately 10,000 homes reported wide variation in the change in AER with the number of windows that were opened, which agrees with the

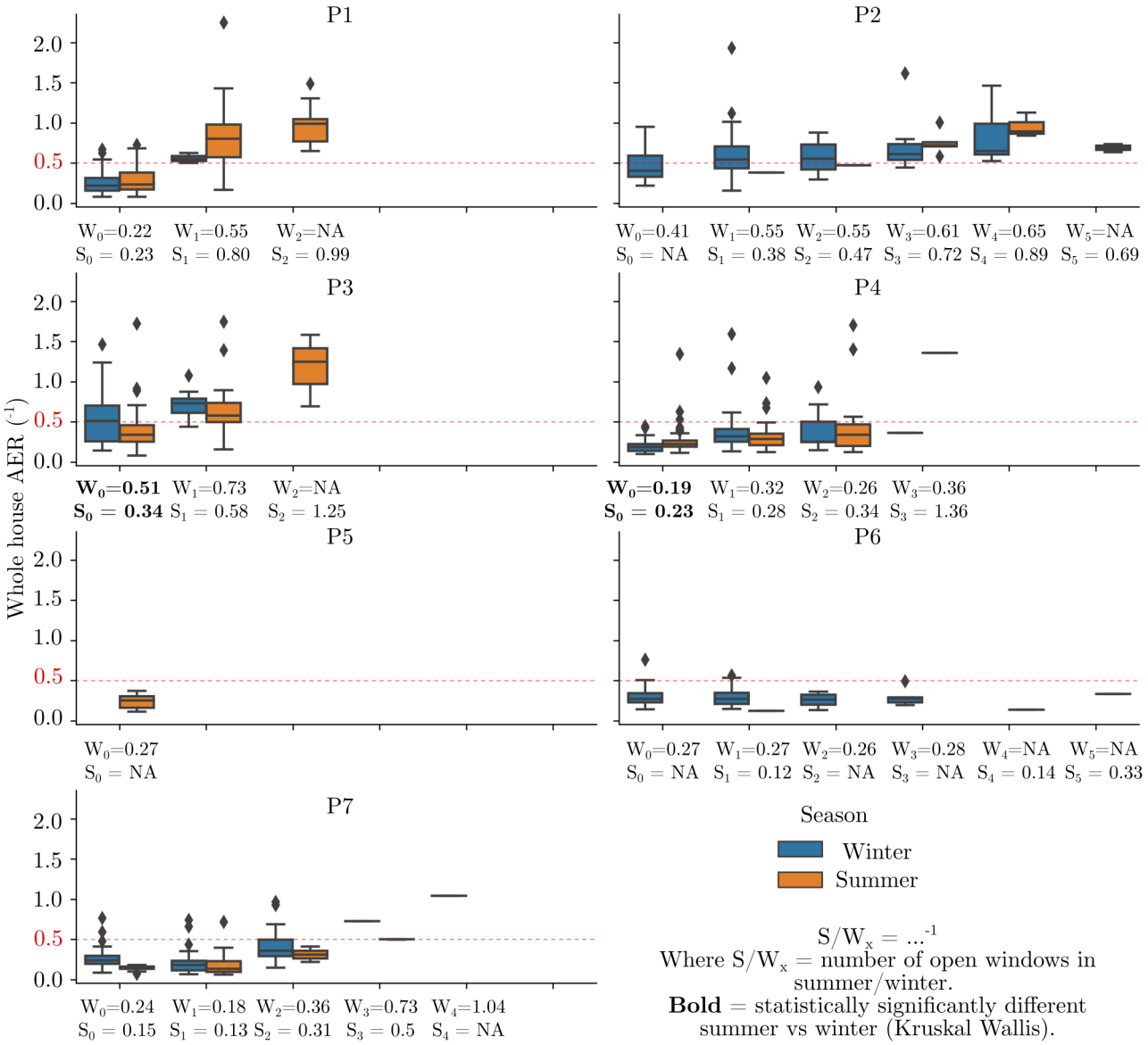


Figure 5.2: Box plots showing the distribution of whole house AER with varying numbers of open windows for each case study for the summer and winter seasons. This figure also shows the median whole house AER ($^{-1}$) for the summer and winter seasons with varying numbers of open windows for each case study. Bold results indicate where the AER is statistically significantly different for the seasons (Kruskal Wallis $p < 0.05$).

results presented here (Nazaroff, 2021). For example, for P3, the AER rises from $0.39h^{-1}$ with windows closed to $0.58h^{-1}$ with the bathroom room window open, an increase of $0.19h^{-1}$, but for P4, P6, & P7, this increase is much lower at $0.09h^{-1}$, $0.02h^{-1}$ & $0.01h^{-1}$ respectively.

Table 5.4: Table showing the most common ventilation configurations for each case study and the number, median, and interquartile range of whole dwelling air exchange rates (h^{-1}). Bold results indicate where the air exchange rate for the configuration is significantly higher than the AER with all windows/doors closed (Kruskal–Wallis test $p > 0.05$). Note: significance is strongly affected by the number of observations, of which there are very few in some cases.

P1			
Vent config	n	$A\tilde{E}R$	IQR
All closed	263	0.23	0.20
Balcony door only	0	-	-
Living window only	**35**	**0.75**	**0.39**
Bed & living window	**11**	**0.98**	**0.25**
Bed window only	1		-

P3			
Vent config	n	$A\tilde{E}R$	IQR
All closed	132	0.39	0.31
Bathroom window	**29**	**0.58**	**0.25**
Bed2 & bathroom	1	1.25	0.00
Bed2 only	**4**	**0.75**	**0.15**
Living door	1	0.31	0.00
Bed1 & bathroom	1	0.69	0.00
Bathroom & living sliding door			
Other	3	1.58	0.70

P5			
Vent config	n	$A\tilde{E}R$	IQR
All closed	11	0.29	0.15

P7			
Vent config	n	$A\tilde{E}R$	IQR
All closed	84	0.23	0.12
Kitchen window	-	-	-
Bathroom window	17	0.24	0.14
Living sliding door	0	-	-
Bed3 and kitchen window	**7**	**0.36**	**0.12**
Bed2 and bath window	1	0.67	0.00
Bed1 and bath window	0	-	-
Other	**22**	**0.42**	**0.42**

P2			
Vent config	n	$A\tilde{E}R$	IQR
All closed	32	0.40	0.23
Bed1 window	10	0.46	0.33
Bed1 & bathroom window	**18**	**0.55**	**0.29**
Kitchen window	**5**	**0.82**	**0.14**
Bed1, bathroom, bed3, bed2 & sliding	**3**	**1.09**	**0.12**
Bed1, bathroom & bed3	**6**	**0.57**	**0.20**
Bed1, bathroom, bed3 and kitchen	**4**	**0.79**	**0.15**
Other	**35**	**0.61**	**0.15**

P4			
Vent config	n	$A\tilde{E}R$	IQR
All closed	225	0.23	0.13
Bathroom 1 only	**31**	**0.32**	**0.15**
Bedroom 2 only	0	-	-
Bathroom 2 only	6	0.24	0.03
Kitchen window	1	1.59	0.00
Kitchen and bathroom 1 only	1	1.70	0.00
Bathroom 1&2 and kitchen	-	-	-
Other	**2**	**0.86**	**0.50**

P6			
Vent config	n	$A\tilde{E}R$	IQR
All closed	37	0.27	0.11
FF bathroom window	13	0.29	0.12
GF bathroom window	14	0.25	0.13
FF&GF bathroom & bedroom 2	3	0.23	0.04
FF&GF bathroom	4	0.23	0.15
Bedroom 1 window	4	0.52	0.13
Bedroom 4 window	2	0.25	0.05
Other	10	0.28	0.11

[a] Balcony door
[b] Sliding door
[c] Internal door

Table 5.5: Table showing the number, median, and interquartile range of individual room air exchange rates for different rooms in the case study dwellings when the window/door is open and closed. Bold results indicate that the AER is significantly higher when open (Kruskal–Wallis test $p > 0.05$).

	Bedroom						Living					
	Open			Closed			Open			Closed		
	n	$\tilde{x}$	IQR	n	$\tilde{x}$	IQR	n	$\tilde{x}$	IQR	n	$\tilde{x}$	IQR
P1 [a]	1	-	-	109	0.29	0.33	**17**	**0.67**	**0.23**	**173**	**0.22**	**0.18**
P2 [a]	**53**	**0.66**	**0.32**	**44**	**0.49**	**0.28**	0	-	-	34	0.47	0.45
P3 [a]	1	-	-	107	0.53	0.29	0		-	105	0.52	0.36
P4 [a]	1	-	-	115	0.36	0.16	0	-	-	61	0.31	0.18
P4 [d]							**11**	**0.5**	**0.26**	**121**	**0.26**	**0.14**
P5 [a]	0	-	-	12	0.38	0.18	0	-	-	4	0.28	0.23
P6 [a]	5	0.46	0.03	71	0.39	0.18	0	-	-	78	0.39	0.21
P7 [a1]	**4**	**1.29**	**0.1**	**125**	**0.27**	**0.19**	0	-	-	85	0.25	0.16
P7 [a2]	**5**	**0.87**	**0.34**	**124**	**0.27**	**0.2**						
Mean		0.82			0.37			0.59			0.32	

	Kitchen					
	Open			Closed		
	n	$\tilde{x}$	IQR	n	$\tilde{x}$	IQR
P1 [b]	0	-	-	190	0.24	0.25
P2 [a]	3	0.69	0	57	0.57	0.33
P2 [c]	3	1.19	0.39	57	0.58	0.32
P4 [a]	0	-	-	133	0.26	0.18
Mean		0.83			0.38	

[a] Window
[b] Balcony door
[c] Sliding door
[d] Internal door

5.2.2 Experienced AER

This research inferred occupancy, measured ventilation configurations, and calculated whole house AER over time. This section presents a new construct which attempts to combine this data to form an expression of the whole house AER that is experienced by occupants; this is termed 'experienced AER'. This analysis aims to estimate the AER experienced by the occupants by estimating the AER during occupied times. The use of only occupied periods means that this analysis is relevant for occupants' health and exposure.

The 'experienced AER' was calculated by first calculating the median AER for each ventilation configuration for each case study (Table 5.4). This median AER was then matched to each of the 5-minute observations (per case study) based on the ventilation configuration for that observation. This information was then used to estimate the AER during all occupied periods in each case study.

The results of this analysis are shown in Table 5.6 and Figure 5.3. The previous section of this chapter reported a strong relationship between season, ventilation practices, and AER, and so, as

expected there is a statistically significant difference between 'experienced AER' and season for most case studies. The results also show large variation in the experienced AER across different case studies. Table 5.6 shows no difference between the summer and winter median experienced AER for P3, P4, and P7; however, the Kruskal Wallis calculation shows a statistically significant difference. The reason for this is due to the positively skewed distributions for the summer seasons for these case studies (see Figure 5.3) and that the Kruskal Wallis calculation uses rank sums and not medians to determine statistical differences between seasons.

P1 and P2 had substantially higher experienced AER during the summer relative to the winter. P3 and P4 had similar median experienced AER in summer and winter, but during the summer both had positively skewed distributions, showing that both experienced periods of much higher AER during the summer. P5 had very limited AER results to use for this analysis, P6 and P7 had very little monitoring covering the summer period, making comparisons of experienced AER across the seasons challenging for P5, P6, and P7. The reason that experienced AER was significantly higher in summer relative to winter is likely due to higher levels of ventilation arising from windows and doors being opened for longer amounts of occupied time during summer than in winter (see Table 5.2), particularly for P1 and P2. These results suggest that occupants' ventilation behaviour can have a significant impact on their experienced AER, which could in turn impact their exposure to other components of IEQ.

During the winter, P2 and P3 had higher experienced AER than the other case studies. There are a number of possible contributing factors for this: firstly, P2 and P3 have higher AER when all windows are closed (see Figure 5.1), and therefore they experience higher levels of background ventilation when windows are closed relative to other case studies - this is discussed in more detail in Section 5.2.5. Secondly, P2 and P3 generally had windows and doors open for longer (P2) and more frequently (P3) than other case studies during the winter, which would result in higher levels of AER. This aligns with research by Kukadia and White (2006), who reported that the home with the highest permeability and longest time with windows opened also experienced the highest average whole house ventilation rates. During winter, the median experienced AER for P2 and P3 is near the widely accepted health level of $0.5h^{-1}$ (previously identified in 2.2.3). On the other hand, P1, P4, P6 & P7 had low levels of background ventilation and also kept windows closed for most of the winter period, which explains why these case studies have a low experienced AER during the winter, which is further below the recognised health level of $0.5h^{-1}$ than P2 and P3.

Further research could improve the 'experienced AER' by conducting additional monitoring to determine the temporal and spatial variation of occupancy, the configuration of both internal doors and external windows and doors, and also estimate the temporal and spatial variation of AER for all possible ventilation configurations, possibly using different techniques. Additionally, the concept of experienced AER could be expanded by estimating individual occupants' experienced AER in multi-occupancy households by capturing the movement of individual occupants throughout the home. However, this

would entail a costly, intensive, and intrusive monitoring campaign.

Table 5.6: Table showing the inferred median whole house AER for occupied times only - 'experienced AER'.

Participant	Summer AER (h^{-1})		Winter AER (h^{-1})		Summer vs Winter
	Median	IQR	Median	IQR	Kruskal Wallis
P1	0.75	0.52	0.23	0.00	Significant differences (p=0.00)
P2	0.61	0.24	0.46	0.21	Significant differences (p=0.00)
P3	0.39	0.36	0.39	0.00	Significant differences (p=0.00)
P4	0.23	0.09	0.23	0.00	Significant differences (p=0.00)
P5 [a]	0.29	0.00	0.29	0.00	Insufficient summer to calculate
P6	0.28	0.04	0.27 [b]	0.00 [b]	Significant differences (p=0.00)
P7	0.23	0.01	0.23 [b]	0.00 [b]	Significant differences (p=0.00)

[a] Limited AER results
[b] Very short amount of summer in monitoring campaign.

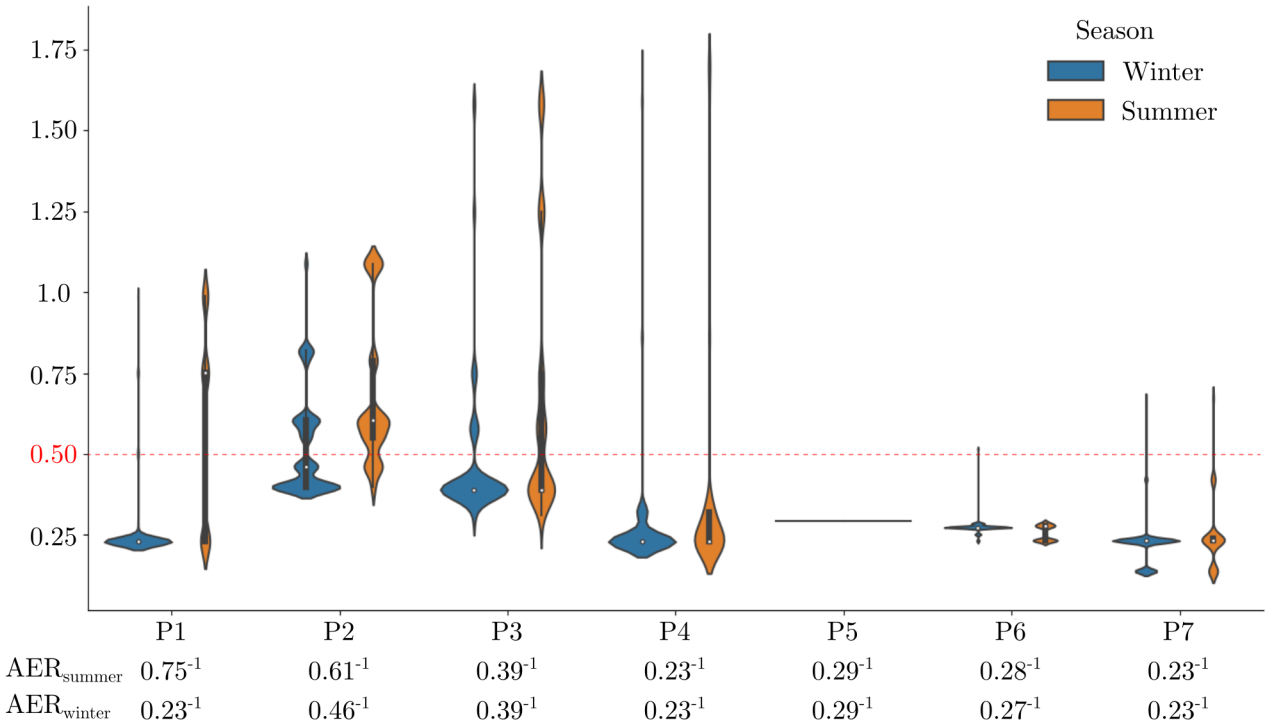


Figure 5.3: Violin plots showing the distribution of experienced AER during the summer and winter for each case study. The white dot indicates the median, and the black bar indicates the IQR. Figure also shows the calculated median AER during summer and winter.

5.2.3 Comparing AER with literature

The results presented in this section show a wide variation of AER across the case studies - this is also commonly reported in the literature. This large amount of variation is expected, as AER are dependant on the drivers of air exchange, which are highly variable within and across homes. Despite

the variation, comparing the AER calculated in this research with the literature shows a reasonable level of agreement for both background levels and when windows were open. This research, however, has a small sample, and AER in other research are often measured using different methods, which makes direct comparisons challenging. Furthermore, there are differences in metrics (e.g., mean vs median), monitoring timescales, and outdoor conditions.

Kvisgaard et al. (1985) reported average AER for sealed dwellings in Denmark of 0.19. Dimitroulopoulou et al. (2005) found the minimum AER in UK dwellings to be 0.19; similarly, Kukadia and White (2006) found the lowest AER of 0.29 in UK homes built before 1995. These minimum values in the research are assumed to represent homes when windows and doors are closed and compare well with the background AER in this research ($0.23h^{-1}$).

Dimitroulopoulou et al. (2005) used the PFT method to measure AER in dwellings and reported that the mean winter AER was $0.44h^{-1}$ (SD $0.11h^{-1}$ range 0.19-$0.68h^{-1}$) and the mean summer AER was $0.62h^{-1}$ (SD $0.23h^{-1}$ range 0.19-$1.06h^{-1}$).

Fan et al. (2022) calculated mean bedroom AER (CO_2 decay) to be $0.34h^{-1}$ (SD=$0.31h^{-1}$) when windows were closed and significantly higher at $1.21h^{-1}$(SD=$1.14h^{-1}$) when open. The high SD relative to the mean shows the high variability in the results for both window states, but nonetheless shows a reasonable level of agreement with the bedroom ventilation rates shown in Table 5.5. Nazaroff (2021) summarises AER from other research from which it might be possible to compare with the results of this research; however, much of the AER in that paper are from international studies, where the climate and construction techniques are substantially different from those in the UK, which makes direct comparison challenging. In addition to this, it is likely that there exists many more differences in the internal and external factors between UK homes and those located in other locations in the world.

Kukadia and White (2006) measured AER in 5 UK dwellings built before 1995 of between 0.29 and $0.55h^{-1}$, Kvisgaard et al. (1985) found the average AER in 25 Danish dwellings of $0.68h^{-1}$, Wallace et al. (2002) measured AER in a US home for a year and found an average AER of 0.65, and finally, Dimitroulopoulou et al. (2005) measured AER in up to 36 homes in the UK and found AER ranging from 0.19 to 1.06, with a summer and winter mean of 0.62 and $0.44h^{-1}$ respectively. These studies show a wide variation of AER, but are broadly comparable with the AER calculated in this research. The methods used to estimate AER in the aforementioned research differ, but all attempt to quantify the exchange of air between indoors and outdoors.

The literature review (2.2.3) discussed different techniques for quantifying ventilation rates and that each method has its own characteristics and nuances. For example, PFT is often undertaken over two weeks and represents the average AER over that period, which includes occupied and unoccupied periods. On the other hand, the CO_2 decay method normally represents much shorter periods of time, and these are typically for unoccupied periods of time. There is a lack of agreement of whether ventilation measurements should include occupied times or not. Both PFT and decay methods attempt

to estimate AER; however, the results describe this phenomena for different timescales and different conditions. Given the differences, it is challenging to directly compare the results from different research, and this must be done with caution. This highlights an important issue with research into ventilation in buildings generally, that there is no universally agreed and universally recognised standardised method for measuring AER in buildings (ODPM, 2006). However, reaching an agreement and developing a standardised method for measuring ventilation in homes is likely to be challenging, due in part to the high variation in costs, invasiveness, complexity, and suitability of the methods. Furthermore, there is a practical barrier to reaching this agreement.

5.2.4 Whole house AER VS individual room AER

This section considers the differences in ventilation rate measured at different spatial scales, addressing a particular gap in the literature (Few et al., 2019; Few, 2021).

Having estimated the whole house and individual room AER, it is useful to compare and contrast these for two different case studies. P1 is a one bedroom flat and has a median whole house background AER of $0.23h^{-1}$, rising to $0.75h^{-1}$ with the living room window open. The whole house AER are similar to the individual AER for the living room with the window closed, at $0.22h^{-1}$, rising to $0.67h^{-1}$ with the window open. On the other hand, P2 is a large 2-storey 3 bedroom semi-detached home with a median whole house background AER of $0.40h^{-1}$ when all windows and doors are closed, rising to $0.46h^{-1}$ with the bedroom window open. The individual room AER for the bedroom is $0.49h^{-1}$ with windows closed rising to $0.66h^{-1}$ when open.

These results suggest that whole house and individual room AER are comparable for smaller, lower volume dwellings, which act similar to a single zone. This in part agrees with the finding that room volume was one of the most important variables explaining the variation in AER in modelling AER in 500 Danish bedrooms (Bekö et al., 2011). However, in the example given above, it is not possible to fully account for the way that internal doors were used and the variation of CO_2 sources, and therefore, care is needed for interpretation. The AER in the examples above indicate how quickly IEQ might return to 'normal' after a pollution event for varying ventilation conditions in two different homes. This can inform exposure analysis and also form the basis of providing information on ventilation to occupants (see Section 5.6.2). In a similar vain to the lack of standards for ventilation measurements, there is a lack of universally accepted guidance and standards around the purposes for which individual room or whole house AER are to be used.

There is a lack of consensus in the literature about which room types achieve the highest AER in homes - this is expected, as AER will be influenced by different internal and external factors, which vary with home and season. For example, Kvisgaard B (1990) reported higher AER in bedrooms than living rooms, but MHCLG (2019) and Dimitroulopoulou (2012) (winter) reported lower in bedrooms than living and kitchen spaces. In this research, due to limited results (see Table 5.5), it is not possible

to compare differences in AER across the different room types for when windows were open. However, this table indicates very small variation of AER across the different room types when windows and doors were closed, which suggests that conditions were well mixed (Wallace et al., 2002).

The single zone model assumes perfectly mixed air, which is not likely to be upheld in homes where internal doors are closed. Internal doors have been shown to have a large impact on AER in other research (Hill et al., 2001; Few et al., 2019; Few, 2021; Almeida et al., 2020), and when internal doors are regularly closed, it is expected that the whole house AER will not be representative of the AER in individual room(s). In this research, 3 of 7 participants reported keeping the internal doors to their bedrooms closed at night, potentially limiting AER in their bedrooms and the whole house. Similarly, 41% of 1,861 British respondents reported keeping their bedroom doors closed at night (Van Rooyen and Sharpe, 2024).

This research is not able to provide any evidence for the differences between whole house and individual rooms with internal doors open vs closed, as most participants left their homes unoccupied with the internal doors and windows in the same configuration, so it was not possible to compare AER for different combinations of internal doors and external windows. This highlights the limits of empirical studies to provide insights beyond what the occupants did in reality. In order to study the impact of internal doors on AER, controlled experiments could be conducted.

5.2.5 Background ventilation and infiltration

The combination of infiltration and planned background ventilation rates were estimated by calculating the AER when all windows and doors were closed. Table 5.7 provides a summary of the AER when all windows and doors are closed, alongside other key characteristics of the dwellings, which together explore potential reasons for the variation in background ventilation rates across the case studies. This table shows that the range of background ventilation rates is similar for P1, 4, 5, 6 & 7 (0.23 - 0.29h^{-1}), but higher for P2 & 3 (0.39 - 0.40h^{-1}). It is noteworthy that these background ventilation rates are below the widely accepted health threshold of 0.5^{-1}, which is explored in more detail in Section 5.2.6. Discussing the higher background ventilation rates first, P2 is a large, old dwelling with a large ratio of floor area to exposed surface area, a permanently open and large airbrick in the first floor bathroom, a loosely fitted cat-flap and an old pitched roof with a loosely fitted loft hatch. P3 has old, latched, timber framed windows with routed trickle vents (permanently open) in addition to a large airbrick in bedroom 2 and the possibility for air to flow through the extract fan in the bathroom when not in operation. These factors combined could explain the higher background ventilation rates for P2 and P3.

Despite having one of the highest background ventilation rates, permanently open trickle vents, a fully operational mechanical ventilation system in their bathroom and regularly opening their bathroom windows, P3 had mould in their bathroom - this was both reported in their questionnaire responses

and observed during the building survey. Given that this participant had ventilation provision that met the current building regulations and regularly opened the windows in their bathroom, we might expect AER to be above the 0.5^{-1} threshold and also not see any damp or mould issues, but even in these situations, AER were below the health threshold (discussed more in Section 5.2.6) and mould persisted. It must be noted that the performance of the ventilation systems was not measured and the presence of mould might be partly or wholly attributable this and other factors, including sources of moisture/humidity in other parts of their home, temperature, quantity of showers/baths, type of sealant, etc. This highlights the challenge of identifying the cause of mould, but this was not the focus of this research.

Next, discussing the lower background AER: P1, P4, P5, and P6 are all relatively recently constructed dwellings, all with UPVC double glazing, integrated modern trickle vents and mechanical ventilation in wet rooms. As discussed in the literature review (2.2.1), these dwellings are expected to have been constructed to Building Regulations, which require a minimum standard of materials and workmanship to achieve a reasonable level of air tightness to conserve fuel and power (HM Government, 1985, 2021*b*). We would also expect that these dwellings were constructed in accordance with Part F of the Building Regulations and have been constructed with provision for background and purge ventilation (HM Government, 2021*a*). The more recently constructed dwellings have the lowest levels of background ventilation of the case studies, apart from P7, which is discussed below. The fact that the more recently constructed dwellings have the lowest background AER aligns with a growing body of evidence that modern homes have poor levels of ventilation - this was discussed in the literature review (Crump et al., 2005; Aizlewood and Dimitroulopoulou, 2006; Kukadia and White, 2006; MHCLG, 2019).

P5 was the most recently constructed dwelling and had a fully functioning, continuously operating decentralised mechanical extract ventilation (dMEV) system, which constantly extracted air from the kitchen and wet spaces, with make-up air via trickle vents installed above windows in the bedrooms and living rooms. Given this ventilation provision, we might expect to see higher levels of background ventilation than in the case studies without this level of background ventilation provision, but this is not always the case, and AER are low and below 0.5h^{-1} for this case study (0.29 h^{-1} n=11). One possible reason for low AER could be related to the fact that the participants reported to open/close trickle vents 'daily' - this behaviour could lead to trickle vents open for only short periods of time, severely limiting AER. This highlights a conflict, which was identified in the literature review (2.2.4) and is discussed in the final chapter, where closing trickle vents undermines this device as part of providing background ventilation and can have impacts for AER, IAQ, and occupant exposure to indoor pollutants. Another potential reason could be due to poor performance of the mechanical ventilation system, but this research did not measure the flow rates of the ventilation system in this case study due to the COVID pandemic. There is a need for ventilation systems to be cleaned and maintained to ensure they provide a safe, healthy indoor environment whilst consuming as little energy as possible

(Few, 2021). However, there is no mandatory requirement for maintenance of ventilation systems and a lack of clear advice for this (Few, 2021). P5 reported in the questionnaire to have not maintained any part of their ventilation system, but they rent their accommodation and might not necessarily be responsible for this.

P1 had a dMEV system, where the extract fan forms an integral part of the background ventilation; however, the fan was not operational and might explain the low background AER for that case study. The participants were owners of the home and aware that the ventilation system was not operational but had not had it repaired.

Finally, P7 is the oldest dwelling (<1919), which was constructed before Building Regulations were introduced. These regulations set minimum requirements for thermal performance and air tightness, and so considering the age of the dwelling alone, we might expect this case study to have higher levels of infiltration and background ventilation than the more recently constructed case studies. However, this dwelling has one of the lowest levels of background ventilation of all the case studies. The occupants had upgraded the original glazing to high performance acoustic triple glazing systems throughout most of the house to reduce noise from the nearby busy road. This high performance glazing has no trickle vents and as well as improving the acoustic insulation, has also likely improved the air tightness of the dwelling, which is the most likely reason for the low levels of background ventilation in this old dwelling. P7 reported the presence of mould and also that dampness or mould was one of the main sources of pollution in their home. In addition to this, mould was also observed in the bathroom and office space (near the bathroom) during the building survey. Although causality cannot be determined, there are a number of factors that are likely to contribute towards the presence of mould in P7. These are: (1) the lack of an operational mechanical ventilation system in the bathroom, (2) low background ventilation rates, (3) poor levels of thermal performance (constructed <1919), which can lead to condensation and moisture on internal walls, and (4) that the occupants opened the bathroom window for the least amount of occupied time of all case studies (Table 5.2), particularly during the winter (3%). This case study highlights a number of potential issues which policy could address. The first is that thermal upgrades to the fabric can vastly reduce infiltration and background ventilation rates, but policy does not require the installation of ventilation provision at the same time to ensure safe and healthy indoor conditions (previously discussed in Section 2.2.1). The second is that there is no mandatory checks of operation or performance of ventilation systems in the UK. The occupants were aware that mould was an important source of pollutants in their home, but might not be aware of the importance of ventilation for controlling moisture and potentially controlling the mould. All of these issues are discussed more in Section 5.6.

The results discussed in this section suggest that building characteristics and ventilation provision are not always accurate markers for ventilation rates, which agrees with the extensive review by Nazaroff (2021). The finding that individual room AER are significantly impacted by occupants' ventilation

practices (Section 5.2.1) and that building characteristics do not appear to be strongly associated with AER aligns with the findings of Bekö et al. (2011), who reported that occupants' behaviour was a stronger predictor of AER than building characteristics.

The results above highlight that in P1, P4, P5, and P6, despite the fact that these are modern dwellings constructed to recent standards and that there was provision for background ventilation from trickle vents and that the trickle vents were all open, background levels of ventilation were below $0.5h^{-1}$. The amount of occupied time that dwellings had AER below $0.5h^{-1}$ are explored in more detail in the next section.

Table 5.7: Table showing the estimated construction date (from questionnaires), whether there are trickle vents installed, any other notes on ventilation, and calculated AER when all windows and doors are closed for each case study.

	Dwelling built	Trickle vents	Other notes	AER (closed) [a]
P1	1991-2015	Yes all (open)	dMEV not operational	0.23
P2	1919-1944	No	Airbrick, cat flap	0.4
P3	Don't know - estimate 1965-1980	Yes permanently open routed	Leaky timber windows	0.39
P4	1991-2015	Yes all (open)	-	0.23
P5	1991-2015	Yes all (open)	dMEV	0.29
P6	Don't know - estimate 1981-1990	Bathroom	-	0.27
P7	<1919	Some (open)	New high performance acoustic windows	0.23

[a] All windows and doors closed

5.2.6 Poor levels of ventilation

Tables 5.7 and 5.4 illustrate that when all windows and doors are closed, the median AER of all case studies is below $0.5h^{-1}$, which agrees with the findings of other research (Crump et al., 2005; MHCLG, 2019; Few, 2021). This finding is particularly important when considered together with the results shown in the previous section (5.1), where the windows were closed for very large amounts of the occupied times - between 29% and 83%. Based off the experienced AER calculated in Section 5.2.2, Table 5.8 shows the amount of occupied time, split by season that the whole house AER was less than $0.5h^{-1}$. This table shows that apart from P2, AER were less than $0.5h^{-1}$ for most of the occupied time and almost all of the winter. This suggests that most of the case studies had poor levels of ventilation most of the time the homes were occupied, particularly during the winter. This supports a growing body of evidence that many homes in the UK are under-ventilated - see Section 2.2.4 (Crump et al., 2005; Dimitroulopoulou et al., 2005; Kukadia and White, 2006; Dimitroulopoulou, 2012; Fox, 2008; McKay and Ross, 2010; MHCLG, 2019; Few, 2021).

Table 5.8: Table showing percentage of occupied time that each case study has AER less than 0.5h^{-1} during the summer and winter and all data.

Participant	Percentage occupied time AER < 0.5 h^{-1}		
	All occupied time	Summer occupied	Winter occupied
P1	63%	42%	96%
P2	46%	23%	60%
P3	63%	52%	80%
P4	94%	91%	97%
P5 [a]	100%	100%	100%
P6 [b]	99%	100%	99%
P7 [b]	99%	97%	99%

[a] Limited AER results

[b] Very short amount of summer in monitoring campaign.

Across all case studies, when windows were open, only 17 of the 30 configurations in Table 5.4 have a median whole house AER greater than 0.5h^{-1}. This is important, as it means that even when windows were open, in just under half of all configurations, the AER was less than 0.5h^{-1}. There is a large variation of AER between case studies when windows were open and, in some cases this is statistically significantly higher than when windows were closed, and in others it is not. For example, when windows were open in P1, the median whole house and individual room AER was always significantly higher, but in P6 it was not (see Figure 5.1). Furthermore, opening of any windows in some case studies results in the whole house AER to increase above 0.5h^{-1} (e.g., P1), but for others, opening different windows has little effect and does not result in the whole house AER to rise above 0.5h^{-1} (e.g., P6). This illustrates the high variability in ventilation performance for different ventilation practices (how wide window is opened, cross-ventilation, stack ventilation, etc.) in different homes. This also highlights that when an occupant attempts to ventilate their home, this does not increase the whole house ventilation rate by much and in some cases not enough to exceed the health threshold. This finding shows that ventilation advice for one case study might not be appropriate for another.

However, when considering AER on a room-by-room basis (see Table 5.5), opening a window almost always results in the median AER for that room to increase significantly, and in most cases, above 0.5h^{-1}. The results show that opening windows had a large impact on individual room AER, but that this did not always have a large impact on the whole house AER. This makes sense, as we would not expect the same level of air exchange throughout a whole dwelling as that experienced in the room with the window open. These results highlight the importance of localised ventilation for 'purge' ventilation and controlling concentrations of pollutants, particularly when there has been an internal pollution event and the potential for occupants to be exposed to those pollutants.

It is worth restating that for all AER, it was not possible to establish how wide/far windows and doors were opened, which is a potential source of AER variation both within and across case studies. The previous chapter presented a novel method for inferring open, ajar and closed window and

door positions from sound measurements; however, this method was not implemented due to COVID restrictions.

The literature review highlighted the interdependencies of ventilation and IEQ, where AER alone does not describe the indoor environment or the health impacts of exposure to that IEQ. For example, it is conceivable that high levels of AER could correlate with high levels of pollutants and/or noise due to ingress from outdoors or an indoor source, and therefore, high levels of AER could also correlate with unhealthy IEQ conditions. It is therefore necessary to quantify IEQ in order to understand the potential health impacts of exposure and relate this to ventilation for a more nuanced understanding. The next Section 5.3 focuses on the relationship between ventilation practices and IEQ, quantifying the direction and magnitude of change for all IEQ components for different ventilation practices - this aims to identify how each aspect of IEQ changes with different ventilation practices. The final section of this chapter (5.4) focuses on peaks of pollutants, where these peaks are above the respective health thresholds and considers the amount of time for these peaks to decay to safe concentrations and the relationship between this decay time and different ventilation practices.

5.3 Ventilation practices and IEQ

The literature review highlighted that the various components of IEQ can all change in different ways with different ventilation practices. For example, indoor concentrations of CO_2 reduce, but noise increases. Lewis et al. (2023) described five factors influencing this change: first, the size of sources and sinks; second, outdoor conditions; third, air velocity and turbulence; fourth, air exchange rates between indoors and outdoors, and last are the dimensions of the space. Many of these factors are dynamic and context specific, and so variation is expected between different rooms and different homes.

Research into the relationship between ventilation and IEQ often examine IEQ components in isolation, and there is limited empirical research that describes the relationships between ventilation practices and all IEQ components together (Fox, 2008; Sundell et al., 2011; Mavrogianni et al., 2015). For example, Stamp et al. (2022) reported significant increases in indoor concentrations of particulate matter and nitrogen dioxide when a window was open relative to closed, but did not measure noise or carbon monoxide. Furthermore, much of the literature calculate the average conditions for a state of window as opposed to estimating the effect of the transition of state on IEQ (Fabi et al., 2012; Andersen et al., 2013). This analysis calculated the change in all IEQ components with the change in state of ventilation devices (windows and doors) during occupied times and used the high-resolution time series data to give a detailed set of results for each change in state.

The analysis method used in this section is described in detail in Section 3.2.4.4 on page 140. There are a large amount of detailed results associated with this analysis, and these results have been summarised in tables, which can be found in Appendix F.3 on page 401. In addition to the tables in the Appendix, the results have been further summarised in Table 5.9 and Figures 5.4 and 5.6 below.

The results presented in Appendix F.3 (page 401) show that generally after windows and doors to the outside were opened, the indoor temperature, absolute humidity, carbon dioxide, carbon monoxide, and volatile organic compounds decreased. This is expected, as the indoor-to-outdoor ratio (IOR) of these variables were typically greater than 1 (see Table 5.9 and Figure 5.4), and Section 5.2 showed an increase in the exchange of air between inside and outside when windows were opened. Many of the case studies are located near roads, which are sources of nitrogen dioxide and noise, and as expected, the concentrations of nitrogen dioxide and noise levels (apart from living in winter) increased after windows and doors were opened. This agrees with research by Aizlewood and Dimitroulopoulou (2006); Dimitroulopoulou et al. (2005); Dimitroulopoulou (2012), and Stamp et al. (2022), who reported higher indoor concentrations of NO_2 with higher ventilation rates and when windows were opened.

An unexpected finding is that on average, across the case studies, despite indoor concentrations of particulate matter being greater than outdoor concentrations before opening windows, the indoor concentration of all sizes of particulate matter increased after windows and doors were opened.

This finding suggests that for particulate matter, with an IOR>1, after windows are opened, their concentration does not simply reduce by direct removal, dispersion, and dilution as with gaseous pollutants. Two possible reasons are proposed; the first is that increased indoor air velocities after opening windows and doors caused suspension/resuspension of particulate matter indoors. Sun et al. (2022) reported that indoor PM was resuspended and remained suspended for longer when air velocities were higher (linear relationship $R^2 > 0.95$) - this was more prevalent for smaller PM (PM_1). The second possible reason is that occupants carried out certain activities which resulted in the release of PM after windows and doors were opened - such as opening windows before or during cooking, leading to an increase in indoor concentrations of particulate matter after the windows were opened. This research addresses a combination of physical and behavioural aspects of IEQ and ventilation; however, more research is required to measure the spatial and temporal variation of PM sources, occupants' activities and indoor air velocities to better understand possible causes for this unexpected relationship - this is discussed in Section 5.5.

The results show that the higher the indoor-to-outdoor ratio (IOR) was, the greater the reduction of each pollutant was after the windows were opened - the Spearman's rank coefficient shows that generally there is a statistically significant negative moderate (-0.40 to -0.59) to strong (-0.60 to -0.79) association between the change in IEQ and IOR. An example of this is shown in Figure 5.5, which shows a negative correlation between IOR before windows were opened and the change of CO_2 after windows opened for different rooms in all case studies.

A further analysis was conducted to determine the relationship between the change in AER and the change of IEQ variables after windows were opened. This analysis uses the dataset generated for calculating the experienced AER (Section 5.2.2) and calculates the change in AER for each event which is then related to the change of each IEQ component. The results show a negative association (Spearman's rank coefficient) between the change of AER and CO_2 (moderate), carbon monoxide (strong) and TVOC (weak). Around half of the associations for CO_2 and carbon monoxide are significant, but not significant for TVOC. On the other hand, the calculated Spearman's rank coefficient for all sizes of particulate matter (weak) and NO_2 (moderate) is positive, however, the associations are not significant. These results suggest that the higher the AER, the lower indoor concentrations of CO_2, carbon monoxide, and TVOC, but higher concentrations of particulate matter and NO_2.

After windows and doors were closed, across all case studies, temperature, absolute humidity, carbon dioxide, carbon monoxide, and volatile organic compounds generally increased. After windows and doors were closed, particulate matter increased in all rooms during the winter, but fine and ultra-fine particulate matter reduced in kitchens in summer. Noise levels were typically higher after closing windows and doors in living rooms and kitchens in the summer but lower in all rooms in the winter. The reasons for the seasonal variation in noise levels are not clear.

The change in IEQ components with changing ventilation conditions is not widely studied and the

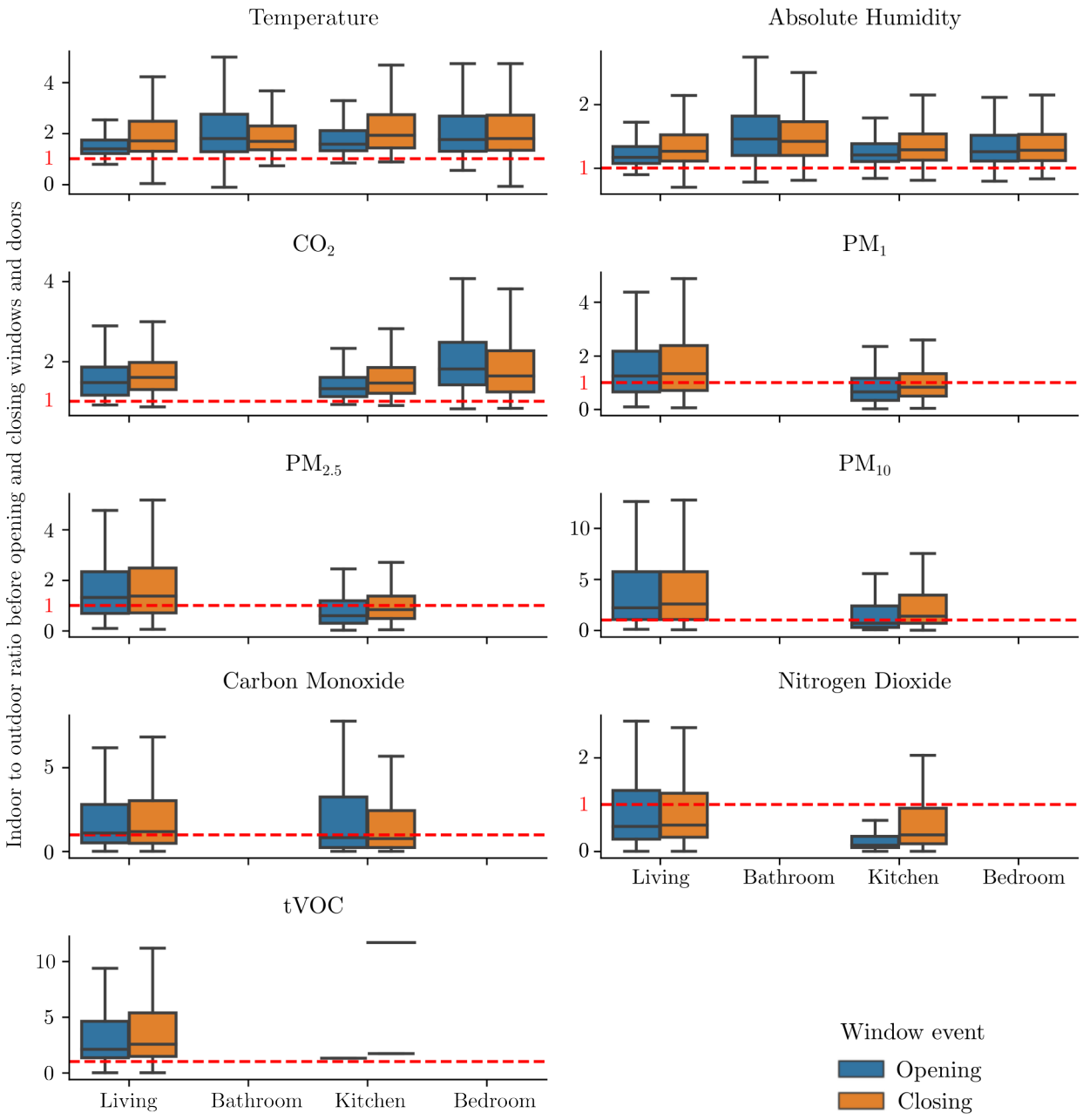


Figure 5.4: Box plots showing the distribution of indoor to outdoor ratios (IOR) for each variable and each room before windows and doors were opened (blue) and before they were closed (orange). Horizontal red dashed line showing IOR=1.

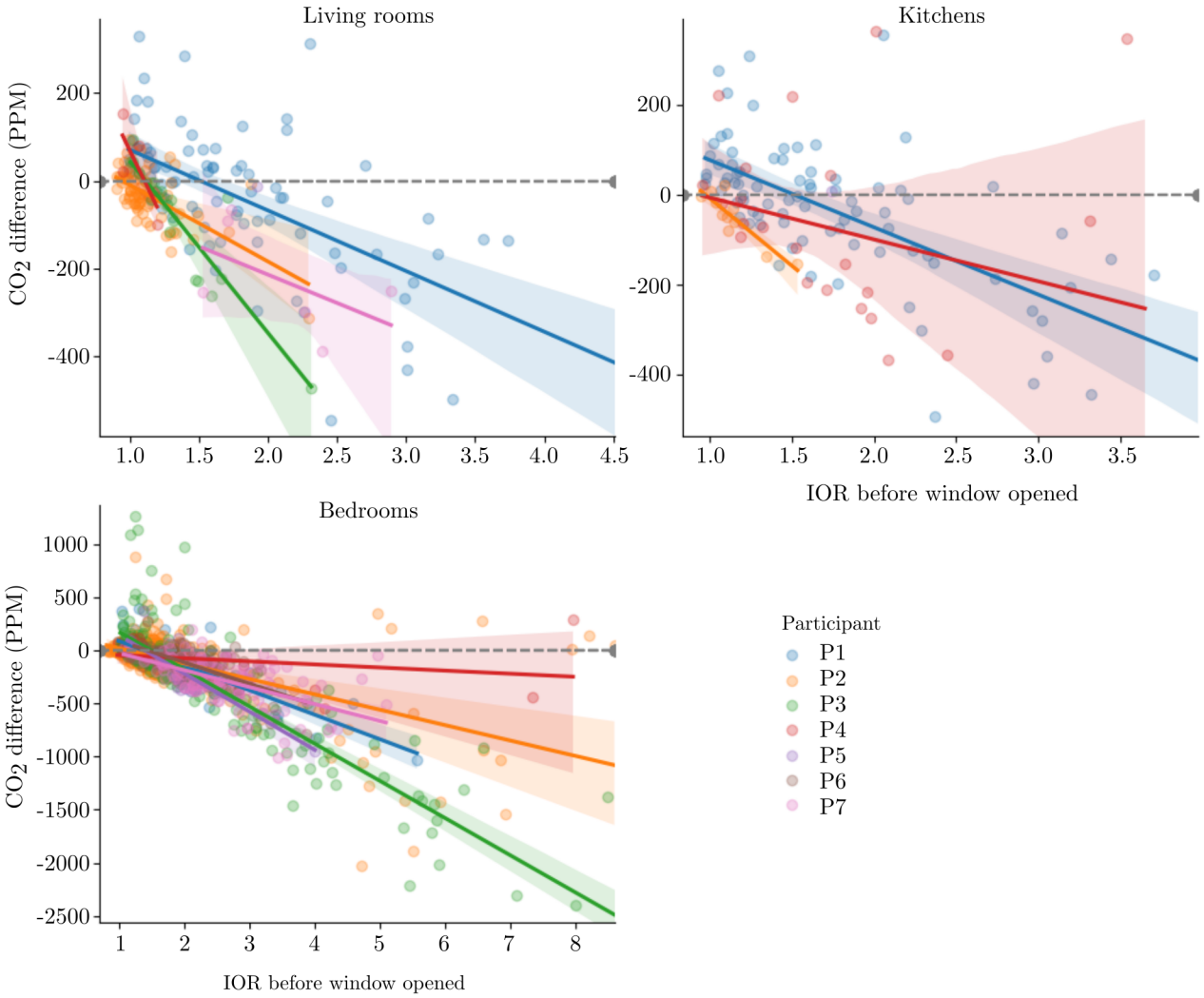


Figure 5.5: Scatter plots and linear regression lines showing the relationship between the IOR before a window opened and the change in CO_2 after opening.

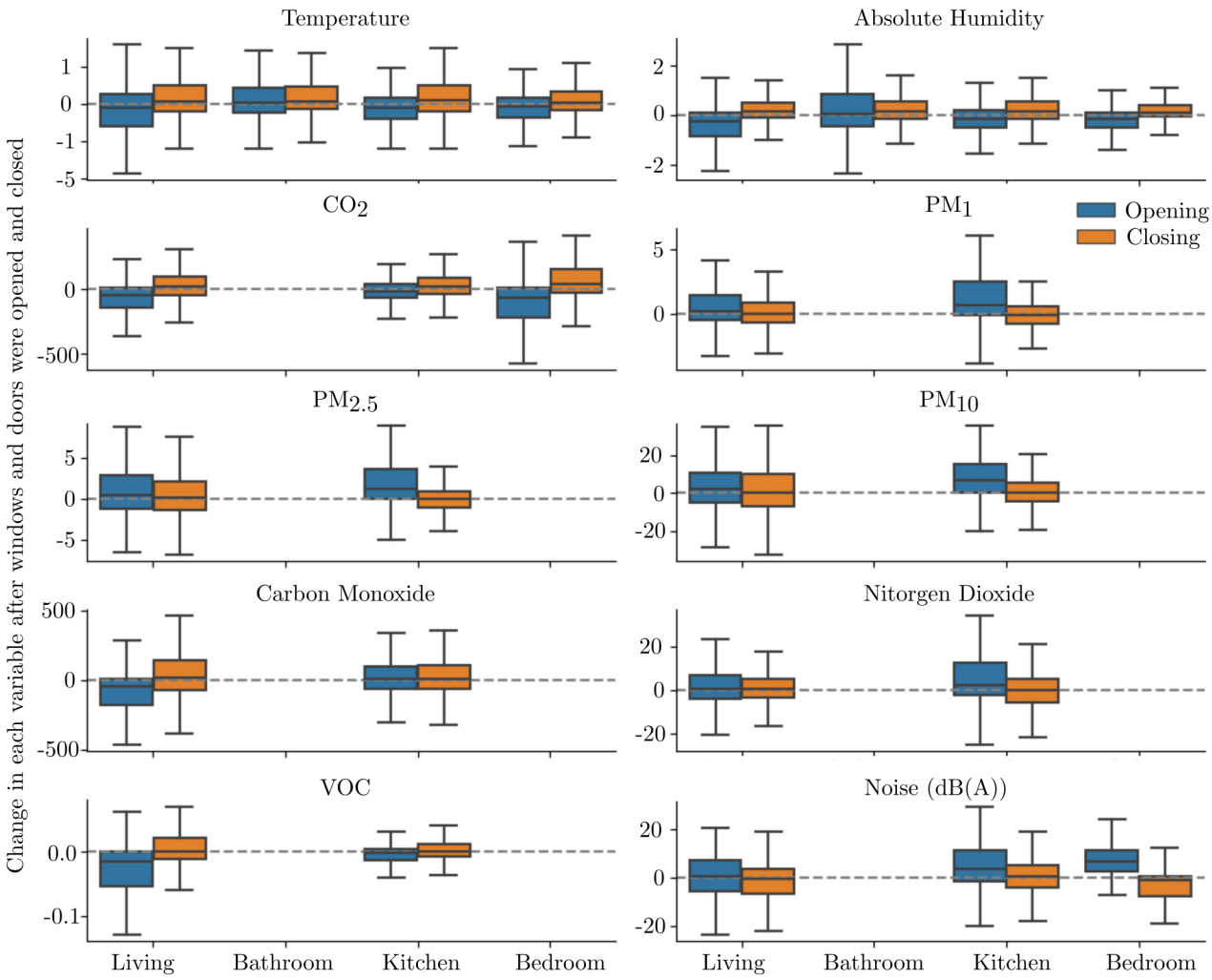


Figure 5.6: Box plots showing the distribution of the change of each variable after windows and doors in each room were opened (blue) and after they were closed (orange). Horizontal grey dashed line showing 0.

results from this research are compared with those reported by Zheng et al. (2021); Fan et al. (2022), and Stamp et al. (2022). The direction of change for temperature, relative humidity, carbon dioxide, nitrogen dioxide, and volatile organic compounds are the same as that reported by Zheng et al. (2021); Fan et al. (2022), and Stamp et al. (2022). However, the results for direction of change for particulate matter presented here are different to Fan et al. (2022), who found PM to reduce when windows were open. The measurements by Fan et al. (2022) were taken in bedrooms, which typically do not contain significant sources of particulate matter but will contain active sources of other variables such as carbon dioxide. Furthermore, the measurements were taken during sleeping periods, when there is much less likely to be active sources of particulate matter or resuspension from occupants' movement. Finally, Fan et al. (2022) reported the average of each variable during sleeping periods for each state of window as opposed to the change in IEQ after the change in state of window.

Table 5.9: Table showing the median IOR of each IEQ variable and each room type across all case studies before windows and doors were opened and closed. Table also shows the median change (magnitude) and direction of change (positive/negative) for each variable and each room type across all case studies after windows and doors were opened and closed.

	Opening								
	Indoor-outdoor ratio (IOR) before opening				Change in median after opening				
	Living	Bath	Kitch	Bed	Living	Bath	Kitch	Bed	Units
Temperature	1.39	1.80	1.59	1.76	-0.1	0.0	-0.1	-0.1	°C
Abs humidity	1.17	1.46	1.20	1.26	-0.24	0.04	-0.14	-0.14	g/m^3
CO_2	1.47	-	1.32	1.81	-42	-	-13	-66	ppm
PM_1	1.25	-	0.66	-	0.2	-	0.7	-	$\mu g.m^{-3}$
$PM_{2.5}$	1.32	-	0.60	-	0.5	-	0.6	-	$\mu g.m^{-3}$
PM_{10}	2.22	-	0.70	-	2.1	-	6.6	-	$\mu g.m^{-3}$
NO_2	0.54	-	0.14	-	0.9	-	2.5	-	$\mu g.m^{-3}$
CO	1.11	-	0.81	-	-49	-	5	-	$\mu g.m^{-3}$
TVOC	2.11	-	-	-	-0.01	-	-	-	ppm
Noise	-	-	-	-	0.7	-	3.6	6.6	dB(A)
	Closing								
	Indoor-outdoor ratio (IOR) before closing				Change in median after closing				
	Living	Bath	Kitch	Bed	Living	Bath	Kitch	Bed	Units
Temperature	1.71	1.69	1.92	1.80	0.1	0.1	0.1	0.0	°C
Abs humidity	1.26	1.42	1.28	1.28	0.13	0.14	0.14	0.1	g/m^3
CO_2	1.60	-	1.46	1.63	27	-	26	46	ppm
PM_1	1.33	-	0.83	-	0.0	-	-0.1	-	$\mu g.m^{-3}$
$PM_{2.5}$	1.38	-	0.82	-	0.1	-	-0.1	-	$\mu g.m^{-3}$
PM_{10}	2.56	-	1.39	-	0.5	-	0.2	-	$\mu g.m^{-3}$
NO_2	0.56	-	0.36	-	0.5	-	0.1	-	$\mu g.m^{-3}$
CO	1.19	-	0.77	-	16	-	10	-	$\mu g.m^{-3}$
TVOC	2.58	-	11.67	-	0	-	0	-	ppm
Noise	-	-	-	-	-0.6	-	0.3	-1.3	dB(A)

The results show that after windows and doors were opened, components of IEQ with indoor sources (temperature, absolute humidity, carbon dioxide, carbon monoxide, and volatile organic compounds) reduced, but IEQ components with outdoor sources (nitrogen dioxide and noise) increased and vice versa for after windows and doors were closed. Particulate matter also increased after windows were opened despite higher indoor concentrations. These results show that occupants' exposure to IEQ can be modified by ventilation practices, but this effect varies for the different components of IEQ, depending on the location and strength of sources, which also vary with time (Coward et al., 2001; Sundell et al., 2011). The complex and dynamic relationship between the different sources with ventilation and exposure, along with the variability in these relationships across different case studies, highlights the challenge of generalising these results. Due to limited evidence of the relationship between exposure to IEQ components at short timescales, it is not possible to evaluate if it is healthier to ventilate or not - this is discussed in greater detail in Section 5.6.1.

Section 2.2.2 found that the drivers and barriers for ventilation are vast and interact in complex ways with ventilation behaviour. In this research, the participants responded that the single main reason for opening the windows and doors was for cooling the house (P1), fresh air (P2, P5, P6, P7), connection/contact with outdoors (P3), and to remove moisture/damp (P4). Occupants located in areas with high environmental noise might be willing to accept higher noise levels when ventilating in order to achieve these goals. ANC (2020*a*); Humphreys (2005) describe that when occupants have this element of control, it moderates their response to exposure, and this is the same principle that underpins the adaptive thermal comfort model. An example of this was reported by Few (2021), who reported that participants reduced their opening of windows and tolerated stronger cooking smells in the winter to achieve better thermal comfort. There is however, a lack of understanding of what trade-offs occupants might be willing to accept to achieve their goals and how this might impact their health (Harvie-Clark et al., 2019).

5.3.1 Context specific insights and case studies

It is interesting to compare and contrast two different examples, where the both the technical and social data is used to explore the differences and provide contextual insights.

P2 is located near to a busy road, where the outdoor concentrations of NO_2 and $PM_{1,2.5\&10}$ are among the highest of all participants. After this participant opened the sliding door, on the opposite side of the dwelling to the busy road (typically for pets), there was a statistically significant increase in indoor concentrations of NO_2 during the summer and winter. This suggests that where a participant is located near an outdoor source of NO_2, opening and closing doors, even when they are not immediately adjacent to the sources of NO_2, can lead to a significant change in indoor concentrations of NO_2.

Contrastingly, P3 was located in a sheltered location, and outdoor concentrations of NO_2 and $PM_{1,2.5\&10}$ were among the lowest - two to three times lower than P2. The indoor concentrations of NO_2 and $PM_{1,2.5\&10}$ were higher than outdoors. From this information, we might expect that after the window or door to the living/kitchen was opened, that typically, indoor concentrations of these pollutants would reduce. However, after the living/kitchen door or windows were opened, indoor concentrations of NO_2 and $PM_{1,2.5\&10}$ all increased, and this was among the greatest increases of all participants. The social data collected in the questionnaires and also informally gathered information obtained during the uninstallation showed that P3 was occupied by two adults who smoked cigarettes outside their living room door. Environmental tobacco smoke (ETS) can be a major source of particulate matter, carbon monoxide, and nitrogen dioxide (Logue et al., 2012; Abdel-Salam, 2021). ETS could have entered the living space through the open door and might explain the high IOR, and the unexpected finding that NO_2 and $PM_{1,2.5\&10}$ all increased after the kitchen/living room door was opened. This example illustrates the benefit of mixed methods case study research, where collecting social data on the participants and their activities coupled with a detailed examination of this phenomena enabled

potential explanations for what would have otherwise been a confusing and counter-intuitive relationship. However, in this example cigarette smoke is only a possible cause and more information is required to confirm this - collecting data on occupants' activities and pollutant sources is discussed more in Section 5.5.

The following paragraph explains a common limitation associated with empirical IEQ research and further highlights the benefits associated with detailed case study research. P4 and P6 had an IOR of NO_2 in their kitchen of less than 1, where we might expect indoor concentrations to increase after a window is opened, but after windows open, there are substantial reductions in NO_2 (-3 to -3.8 $\mu g.m^{-3}$) during the winter and mixed results during the summer. This unexpected relationship between IOR and the direction of change of NO_2 might be explained by the placement of the outdoor NO_2 sensors relative to the kitchen space, particularly for P6 (n=50), where the outdoor sensor was placed on the front of the house, near the busy road, which is a source of NO_2, but the sliding door for the kitchen to P6 is on the opposite side of the house, where NO_2 concentrations could be significantly different. Importantly, the outdoor sensor was not measuring NO_2 concentrations that were representative of the rear of the house, and so the IOR was likely not accurate for the kitchen of P6. This explanation is only possible through a detailed study (including layout, sources, etc.), which would otherwise seem anomalous. This example also highlights an important limitation of this research and much other IEQ research, where typically only a single outdoor sensor is deployed for measuring outdoor environmental conditions, where that single location might not be representative of all locations of interest (Stamp et al., 2022; Wang, Cooper, Tahmasebi, Taylor, Stamp, Symonds, Burman and Mumovic, 2022). Deploying multiple outdoor sensors can substantially increase the time and cost associated with monitoring, but also, monitoring of multiple outdoor locations is not always physically possible. For example, it is not always possible to install sensors on all orientations of dwellings that are above ground level with suitable, accessible, safe, and secure locations with power. Often there is a need to compromise, and therefore it is important to recognise the associated limitations during analysis and not misinterpret the data.

5.3.2 VOCs - A detailed investigation

The indoor environment can potentially contain a combination of many different chemical compounds, some of which might be harmful to health and others which are not (Sharpe et al., 2014; Knight, 27/11/2019). However, chemical compounds are quantified in the Building Regulations and measured in a large body of research using a simplified measurement of the total concentration of VOCs (TVOC) in the air, which is indiscriminate of the compounds and their potential harmfulness (HM Government, 2021*b*). This can be problematic as the type of compounds and their concentrations are important for understanding their impact on health (Hollick and Sangiovanni, 2000; Shrubsole, Dimitroulopoulou, Foxall, Gadeberg and Doutsi, 2019). Much of the literature measure TVOC concentrations without any knowledge of the composition or relative concentrations of the chemicals in

the indoor air, which limits insights from a human health perspective (Dimitroulopoulou et al., 2005; Aizlewood and Dimitroulopoulou, 2006; McKay and Ross, 2010; Shrubsole, Hamilton, Zimmermann, Papachristos, Broyd, Burman, Mumovic, Zhu, Lin and Davies, 2019).

In order to identify the top 10 most abundant (highest concentration) VOCs in the case studies, Tenax sorbent tubes were exposed to the indoor air in the living rooms and bedrooms of P1-P5 (not P6 or P7) for approximately two weeks in April/May 2021 (July 2019 for P1) and subsequently analysed in a certified laboratory (see Section 3.2.2.3). The laboratory results of the top 10 VOCs for each case study are shown in Appendix F.4 (page 438). Stamp et al. (2021) highlight an important limitation when using sorbent tubes for analysing only the top 10 or top 5 VOCs - whereby certain compounds might be above guideline values but masked and not identified in the top compounds due to unharmful compounds at higher concentrations. In light of this, this analysis aims to identify the top 10 compounds with the highest concentrations and understand how these are related to health and not identify all compounds that might be harmful to health. The top 10 VOCs include 36 different chemical compounds across all case studies. Table 5.10 summarises the five most common chemicals across all case studies and the number of rooms where each compound was in the top 3 highest concentrations for that room. Nonanal ($C_9H_{18}O$); 1-Hexanol, 2-ethyl- ($C_8H_{18}O$); cyclopentasiloxane, decamethyl- ($C_{10}H_{30}O_5Si_5$); Hexanedioic acid, bis(2-ethylhexyl) ester ($C_{22}H_{42}O_4$), and limonene ($C_{10}H_{16}$) were identified in almost every room and also featured as chemicals with the highest (top 3) concentrations in those rooms.

Despite the literature describing a large number of observed and potential health impacts, there is a lack of clear health related guideline values for the aforementioned compounds, particularly for domestic indoor air exposure (Liddament, 1996). In addition to this, there is no literature describing the health impacts or guideline values for exposure to the combinations of chemicals identified. Of the 5 most common compounds, guideline values were found for all, apart from cyclopentasiloxane, decamethyl-, which is considered to have the lowest potential for human harm. The guideline values, however, were from disparate sources and did not all include averaging times, so it is not clear over what period these guidelines are applicable. Nonanal exceeded the ASHRAE (2020) guideline value (13 $\mu g.m^{-3}$) in 3 of 9 rooms, and hexanedioic acid, bis(2-ethylhexyl) ester exceeded the ASHRAE (2020) guideline value (25 $\mu g.m^{-3}$) in all of the (8 of 8) rooms it was identified. In most cases, the indoor concentrations of hexanedioic acid, bis(2-ethylhexyl) ester were substantially higher than the guideline value and up to 14 times higher in the living room and bedroom of P5. This is concerning, as the health impacts of this compound are not fully understood and it is described as possibly carcinogenic to humans (NCBI, 2023*a*). It is interesting to note that P5 reported that they felt avoiding exposure to chemicals (from personal care products, cooking, etc.) was 'very important' for health, but they had the highest concentrations of hexanedioic acid, bis(2-ethylhexyl) ester and also had concentrations of nonanal that exceeded the guideline values. They were also smokers.

The results show that there was a large amount of variation in the concentration and species of

compounds, but certain species were common and abundant across the case studies. The most common compounds are used in the manufacturing of many different popular household products. It is not the aim of this research to identify the sources of specific VOCs, but the pervasive use of certain compounds in manufacturing highlights the challenge of identifying exactly which products/items are responsible for emissions and how these might be controlled to reduce exposure.

The PID TVOC sensors used in this research measured VOCs with ionisation potentials < 10.6 eV (see Section 3.2.2.3), which includes most of the common compounds identified above. The use of sorbent tubes together with the measured temporal variation of TVOC enable a general indication of whether those compounds were likely to be high or low, which is useful for estimating poor IAQ and relating this to potential health impacts. However, a clear limitation is that these combined methods do not determine the exact variation of the different compounds over time.

In this research, TVOC measurements were in ppm; however, health-related thresholds and UK National standards/regulations are expressed as mass per unit volume (e.g., The Building Regulations Part F threshold is 300 μg.m^{-3}) (HM Government, 2021*a*). In order to enable comparisons, the Building Regulations (300 μg.m^{-3}) value was converted to ppm using the average molecular weight of all the 36 compounds identified above (168.3 g/mol), which equated to 0.043 ppm.

This threshold is used as a marker of magnitude on Figure 5.7 and to illustrate the finding that after windows and doors were opened, there is a substantial reduction in TVOC concentrations. As expected, this figure shows that indoor concentrations of TVOC reduced after windows and doors were opened to outside. In many cases TVOC concentrations reduced by as much as the absolute concentration of the threshold, indicating the substantial impact of ventilation on reducing TVOC concentrations and exposure. The results presented here reiterate a point made earlier in this section, which is that TVOC are unable to differentiate between compounds, and therefore, it is not possible to determine if concentrations of hexanedioic acid, bis (2-ethylhexyl) ester (identified as common, abundant, and potentially harmful) reduced to safe levels or not. In light of this limitation, TVOC can be used as an indicator of overall VOC levels, but cannot be directly related to human health or harm.

Table 5.10: Table showing the most common chemicals in the indoor air across the case studies. This table also shows the common uses, health impacts, number of rooms the chemicals were identified in, and whether this chemical had a concentration that was in the top 3 highest concentrations in that room.

Chemical	Rooms identified	Top 3 concentration	Common use	Health impacts
Nonanal [1]	9 of 9	4 of 9	Perfumes, essential oils, fragrances, and food flavouring (NCBI, 2023*a*).	Uremic toxin. Chronic exposure = renal damage, chronic kidney disease, and cardiovascular disease (NCBI, 2023*a*).
1-Hexanol, 2-ethyl-	9 of 9	0 of 9	Construction materials, solvents, dispersant, flavours, fragrances, and as a precursor for emollients and plasticizers (NCBI, 2023*c*).	Skin, eye, and mucous membrane irritant. Possibly toxic through ingestion, inhalation, and absorption (NCBI, 2023*c*).
Cyclopentasiloxane, decamethyl-	8 of 9	5 of 9	Cosmetics (deodorants, sunblocks, hair sprays, and skin care products), fragrance, hair conditioners, emollient, dry cleaning solvent, and more (NCBI, 2023*b*).	Low toxicity, not an irritant, and not genotoxic/mutagenic (PubMed, 2017).
Hexanedioic acid, bis (2-ethylhexyl) ester	8 of 9	7 of 9	Plasticiser for manufacturing polymers. PVC products such as food cling wrap packaging. Cosmetics, fragrances, personal care products, auto interior protectant, heavy-duty hand cleanser and lubricant (NCBI, 2023*b*).	Limited evidence of carcinogenicity in animals and no data for humans. Possible human carcinogen. Mildly toxic by ingestion and intravenous exposure (NCBI, 2023*b*).
Limonene	8 of 9	4 of 9	Household cleaning products. Flavourings, fragrances, cosmetics, personal hygiene products, solvent, and wetting agent. Component in manufacturing resins, insecticides, insect, and animal repellents. Floor waxes and furniture polishes. Also occurs naturally. (NCBI, 2023*b*)	Skin & eye irritant, ingestion causes irritation of GI tract. Kidney damage is possible if ingested in sufficient quantity. Associated with mouth and throat irritation, shortness of breath, and impaired lung function (NCBI, 2023*b*).

[1] Compounds may be an artefact due to reaction of ozone with the Tenax sorbent (Gradko, 2021)

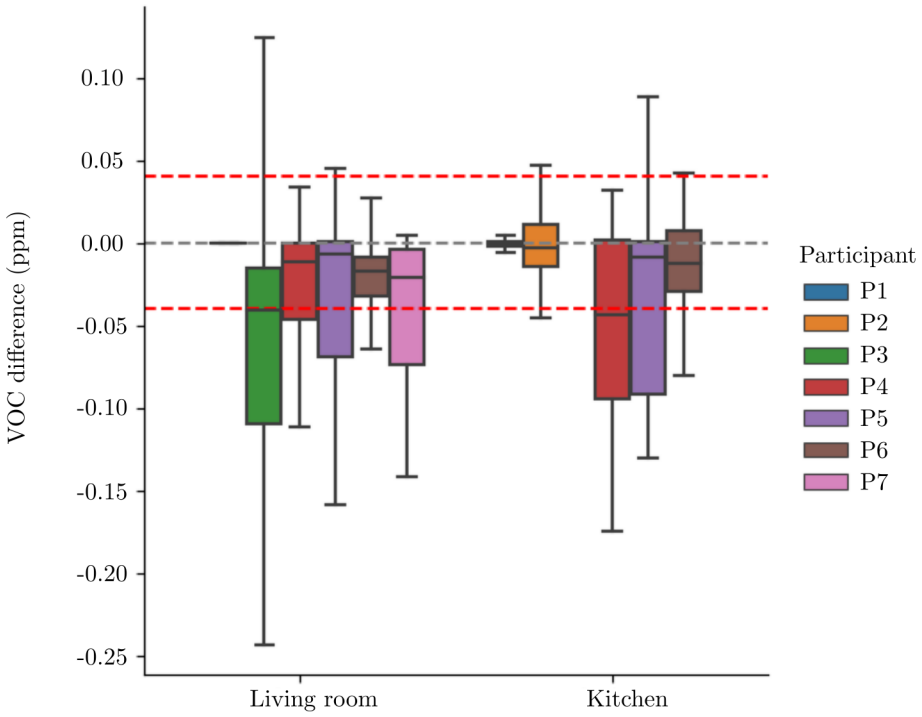


Figure 5.7: Box plots showing the distribution of the change of TVOCs after windows and doors were opened in each room type in each case study. Horizontal grey dashed line showing 0 and red line showing + and - 0.043 ppm.

5.4 Pollutant decays and health messaging

The concentration of a pollutant indoors is a balance between its sources and sinks, and so, during periods when there is an active source of a pollutant, it can form a peak in concentration, and after the source ceases to be active, this peak decays to the background concentration over time (Bekö et al., 2011). The rate of decay of pollutant peaks is dependant on five factors: (1) size of sources and sinks, (2) outdoor conditions, (3) air velocity and turbulence, (4) air exchange rates between indoors and outdoors, and (5) the dimensions of the space (Lewis et al., 2023). Many of these factors are dynamic and also highly variable within different rooms of each case study and also across the different case studies. The initial peak and its decay can lead to concentrations of the pollutant exceeding health guideline values for an extended period, potentially exposing the occupants to harmful conditions (WHO, 2021*b*). This section builds on the knowledge formed in the previous sections and aims to understand how different ventilation configurations and practices are related to the time it took for peaks of pollutants above their respective health threshold to decay back to the health threshold (see Section 3.2.4.5 for a detailed description of this analysis method). This section is focussed on how this data can be used to inform public health messaging on how long to ventilate to reduce exposure to peaks of indoor pollutants - the assumption is that the occupants will decide on when to open their windows, and the analysis here can

be used to inform a simple message around how long to keep them open. This is a direct response to the third theme that emerged from the literature review: the lack of knowledge of ventilation in the UK public. Section 5.6.2 presents a detailed discussion of the practicalities and challenges of providing public health messaging on ventilation, which is related to the analysis and results presented here. In addition to the published health thresholds, a further high/low threshold was empirically derived to classify each peak that exceeded the health threshold as a high or low peak - see Table 3.11.

Section 3.2.4.5 described that most of the published health thresholds used in this analysis (Table 3.11) are the 24-hour mean guideline values from the WHO (2021*b*) and an arbitrary threshold for PM_1 to enable insights into decay times. This 24-hour time period is much longer than the participants actually kept their windows open (see Section 5.1.2), but there was no internationally recognised short-term thresholds available for all pollutants from the WHO or similar reputable and authoritative source at the time of analysis. Therefore, the results presented here are illustrative, and this analysis can be updated when short-term guideline values are published and also when guideline values are published for PM_1. When short-term guideline values (e.g., 1 hour) are published in the future, they will likely have a higher threshold ($\mu g.m^{-3}$) than those for 24 hours. This means that the lower threshold values used here will bias the results to longer decay times.

The sample used in this research comprises seven case studies, which is not representative of the wider population. However, Section 5.4.2 explores how this method could be generalised in future research when using a representative sample and provides insights according to the sample of this research. In order to explore how this analysis method might be generalised, only the results for windows are presented and discussed. This exploratory analysis focusses on windows, as most of the existing stock (71% n=1,861) do not have trickle vents and purpose provided mechanical ventilation, and so, windows are likely to play an important role for controlling exposure to peaks of pollutants in many homes in Britain (Van Rooyen and Sharpe, 2024).

This section provides an overview of the key results. In Appendix F.5 (page 443), Figures F.1, F.2, F.3, F.4, F.5, and 5.9 provide a summary of the decay times for CO_2 , PM_1, $PM_{2.5}$, PM_{10}, carbon monoxide, and nitrogen dioxide. These figures show the decay times for each participant when windows were open and closed, grouped by high/low peaks and room type. This analysis method does not account for outdoor conditions or the use of mechanical ventilation.

Temperature, humidity, and TVOC do not form part of the results in this section. Temperature and humidity are highly variable and driven by a complex interaction of indoor and outdoor factors, which do not peak or decay in a way that can be meaningfully analysed using this method. Furthermore, temperature and humidity have many sources and these are buffered by the building fabric, where both cannot be accounted for using this analysis. TVOC sensors failed in four of the case studies, and it was not possible to baseline the TVOC sensors to use with the method applied in this section.

5.4.1 Pollutant peaks decayed faster when windows were open

Indoor peaks of pollutants which exceeded the health threshold also typically exceeded outdoor concentrations (IOR $>$ 1), and Section 5.2.1 found that the air exchange rate between indoors and outdoors was significantly higher when a window was open relative to closed. Therefore, as we would expect, the results in Table 5.11 show that for most case studies, the time for high peaks to decay to the health threshold, including when sources are still present, was lower when windows were open relative to closed, but with mixed results for low peaks. Similarly Hernandez et al. (2020); Sun and Wallace (2020), and Verniers et al. (2023) reported that the decay of pollutants was faster with higher ventilation rates and when windows were open. The finding that the decay times for high peaks were generally lower and, in some cases, significantly lower when windows were open relative to closed supports the expectation that ventilation may play a key role in reducing indoor concentrations and exposure to higher peaks.

P2 and P4 had the greatest number of high peaks of NO_2 in their homes, particularly in the kitchens. Both of these participants had natural gas open flame cookers, which have been shown to be key sources of NO_2 in kitchens (Raw et al., 2004; Crump et al., 2005; Dimitroulopoulou et al., 2005; Kornartit et al., 2010; Vardoulakis et al., 2015). Interestingly, in the kitchen of P2, for high peaks of carbon monoxide and NO_2, the median decay time was shorter when windows were closed than open. This counter-intuitive relationship might be due to the participant cooking with the window open and therefore a strong source being present when ventilation rates were higher. However, this cannot be confirmed as occupants' activities were not recorded.

Across all case studies, there were limited numbers of pollutant peaks that exceeded the relevant health threshold when windows were open, which aligns with Section 5.1.1, which reported that windows were closed most of the occupied times in the case studies. Verniers et al. (2023) reported that the use of ventilation reduced the concentrations of peaks of particulate matter and VOCs in controlled experiments using candles, cooking, and vacuuming, so it is possible that when windows were open, peaks were unable to form due to direct removal and dilution with outdoor air.

As expected, the results presented here suggest that opening a window can reduce overall exposure to indoor pollutant peaks and their decay over time. However, the dynamics of ventilation are complex, specifically when considering outdoor conditions and all aspects of IEQ - Section 5.3 reported that opening windows can also lead to the ingress of other pollutants and noise, which can have implications for health. Therefore, ventilation advice needs to be counterbalanced with these potentially deleterious effects on occupants' health. However, due to a lack of epidemiological evidence, it is not possible to evaluate the relative health impacts from individual or combinations of IEQ components at timescales relevant for ventilation, so it is not possible to determine whether opening a window is healthier or not for specific internal and external circumstances. Ventilation dynamics and the complexity around evaluating health impacts is discussed more in Sections 5.5 and 5.6.2.

Table 5.11: Table summarising the number of case studies which had a median decay time that was lower when windows were open relative to when they were closed. This table also shows the number of case studies where the difference between the decay times when windows were open and closed were statistically significantly different.

	Low peaks					
	Living		Kitchen		Bedroom	
	Lower open	Significant	Lower open	Significant	Lower open	Significant
CO_2	3 of 3	0 of 3	3 of 4	2 of 4	7 of 7	4 of 7
PM_1	3 of 5	1 of 5	1 of 3	1 of 3	-	-
$PM_{2.5}$	2 of 4	0 of 4	1 of 2	0 of 2	-	-
PM_{10}	Same	-	Same	-	-	-
CO	1 of 3	0 of 3	2 of 3	0 of 3	-	-
NO_2	2 of 3	0 of 3	1 of 2	1 of 2	-	-
	High peaks					
	Living		Kitchen		Bedroom	
	Lower open	Significant	Lower open	Significant	Lower open	Significant
CO_2	1 of 2	1 of 2	3 of 3	0 of 3	5 of 5	3 of 5
PM_1	5 of 5	2 of 5	3 of 3	1 of 3	-	-
$PM_{2.5}$	5 of 5	1 of 5	3 of 3	1 of 3	-	-
PM_{10}	3 of 4	1 of 4	1 of 3	0 of 3	-	-
CO	-	-	2 of 3	0 of 3	-	-
NO_2	2 of 2	1 of 2	1 of 2	0 of 2	-	-

This analysis uses decays captured from real homes, where sources were present and also might have been active during the decay. This research did not collect data on the temporal or spatial variation of mechanical ventilation, occupants' activities, or sources of pollutants, so it is unable to distinguish the context in which different decay times were measured. However, in real settings, sources may remain active during decays, so this is not a limitation, but a consideration of the method and the interpretation of the results. Furthermore, if the source was active and its emissions caused the simple moving average to increase, the algorithm would have determined the increase as the end of the decay, and if this was below the minimum duration, the algorithm would have ignored the decay (see Section 3.2.4.5). Alternatively, if the source was active during the decay, but did not cause the SMA to increase, this would effectively reduce the rate of decay and increase the decay duration.

5.4.2 Aggregated results for high peaks

Next, the decay times from all case studies and all pollutants are considered together to explore the generalisation of decay times for this sample of homes. This approach could be adopted with a larger representative sample to understand decay times, which can be used to inform public health messaging for ventilation. Section 5.6.2 discusses this approach in the context of providing public health messaging and explores the challenges associated with providing such advice.

Table 5.12 summarises the results of decay times across all case studies for each pollutant when only windows were open and the home was occupied. A key focus of this table is the median time ($\tilde{x}$) for high peaks of each pollutant to decay to the respective health threshold when windows were open - this column could be used to identify how long windows might need to remain open for the high peaks of all pollutants in all case studies to decay to safe concentrations. This table also shows the interquartile range of decay times for all pollutants, and the high IQR relative to the median illustrates that there is a large amount of variability in decay times across all case studies and the different pollutants - this is a similar finding to the previous sections in this chapter. The longest decay durations are for NO_2, CO_2 ,and PM_1, at 65, 60, and 55 minutes.

The most common source of CO_2 indoors is occupants' respiration and outdoor concentrations are typically lower than indoors (IOR $>$ 1), so opening a window and exchanging indoor air with outdoor air can reduce indoor concentrations (Zhang et al., 2017). On the other hand, NO_2 and PM_1 can have many sources indoors, such as gas fired cookers (P2 and P4) and also have sources outdoors from gas fired boilers (P2, P3, P4, P6, P7) and vehicles travelling on nearby roads (P2, P3, P4, P6, and P7) (Raw et al., 2004). The results suggest that even where there are outdoor sources, if the concentration of the peak indoors is higher than the outdoor concentration, opening a window could reduce indoor concentrations and exposure. However, as described in the previous section, opening windows can also lead to the ingress of other pollutants and noise, where the outdoor concentrations are higher than indoors (e.g., NO_2). Section 5.6.2 argues that health messaging needs to be simple and taking into account the three highest decay periods (65, 60, and 55 minutes), one hour is a round time period that is simple and easy to remember. However, without active monitoring in homes, this period might not be relevant for all homes and all pollutants. Section 5.6.2 discusses the complexity of providing advice to a diverse population and also the use of active monitoring technology for providing advice.

Table 5.12 and Figure 5.8 show the total number of high and low peaks and the number and percentage of these that took less than 60 minutes to decay to the health threshold when windows were open for all case studies. This table shows that when a high or low peak of any pollutant occurred, between 74% and 99% of those peaks decayed back to the health threshold when the window in that space was opened for up to 60 minutes. In total, 83% of all high and low peaks of all pollutants decayed to the health threshold when a window was opened for up to 60 minutes, this number reduces to 68% for 30 minutes. Figure 5.8 shows the distribution of decay times for low and high peaks of all pollutants and also shows vertical dashed lines for 60 minutes, indicating the amount of low and high decays that were less than 60 minutes.

The literature review (Section 2.1.2.1) highlighted that exposure to particulate matter is one of the leading risk factors for burden of disease in Europe (Hänninen et al., 2014) - because of this importance, the results for particulate matter are discussed here. The dynamics of particulate matter concentrations indoors are complex, and their concentration is dependent on: the size and nature of

Table 5.12: Table showing results of decay times across all case studies for only when windows were open and the case study was occupied. The table shows the number of high peaks, the median decay time ($\tilde{x}$) and interquartile range of decay times for high peaks for each pollutant across all case studies. This table also shows the number of high and low peaks when windows were open in all case studies and the number of these peaks where the decay time was less than 60 minutes along with the percentage of these peaks of the total.

	Decays when windows were open					
	High peaks			High and low peaks		
Variable	n	$\tilde{x}$ (mins)	IQR (mins)	n	n (<60mins)	Percent (<60mins)
CO_2	127	60	78	583	434	74
PM_1	48	55	76	190	144	76
$PM_{2.5}$	35	30	55	144	124	86
PM_{10}	55	10	25	334	331	99
CO	5	30	50	18	16	89
NO_2	56	**65**	65	127	92	72

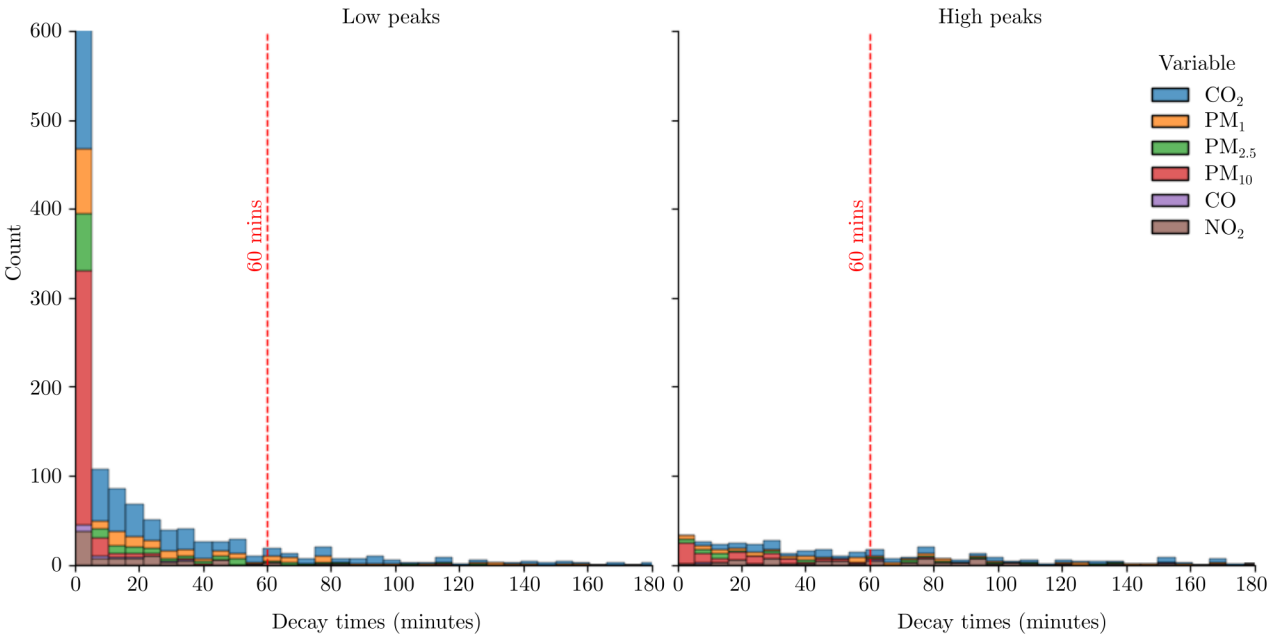


Figure 5.8: Figure showing the distribution of decay times for low and high peaks of all pollutants for all case studies, when windows were open and the case study was occupied. The vertical red dashed lines indicate 60 minutes.

the source, particle size (impacts suspension, resuspension, deposition), weight (impacts suspension, resuspension, deposition), chemical composition (impacts reactions, absorption and adsorption), air velocity (impacts turbulence, suspension, resuspension, deposition), air exchange rate (impacts removal and dilution), outdoor conditions, dimensions of the space, and composition of the indoor surfaces (impacts suspension, resuspension, deposition) (Hill et al., 2001; Lewis et al., 2023). The results reflect this and show that peaks of the different sizes of particulate matter decay in specific ways - peaks of PM_1 took longer to decay than $PM_{2.5}$, and peaks of $PM_{2.5}$ took longer to decay than PM_{10}. This aligns with Dimitroulopoulou et al. (2006); Abdel-Salam (2021); Lewis et al. (2023), and Westgate and Ng (2022), who reported longer decays of smaller particles, which had lower loss rates, and the decays were dominated by air exchange with outside. On the other hand, larger particles had shorter decays which were dominated by higher gravitational settling/deposition rates. The result of longer decays for smaller particulate matter is concerning, as smaller particulate matter is reported to be more harmful to humans (Schraufnagel, 2020). The paper by Hill et al. (2001) and the results presented here suggest that removal, dispersion, and dilution from air exchange with outdoors might be a more dominant process for smaller particulate matter. This highlights the importance of ventilation for reducing exposure to smaller particulate matter and reducing the risk of harm to occupants. On the other hand, Spilak et al. (2014) reported and the results from Section 5.3 suggest that during periods when there is no indoor source of fine particulate matter, ventilation can increase indoor concentrations and exposure, so the timing of ventilation is also likely to be important for exposure.

5.5 Limitations and future research

This section begins with discussing direct limitations from this research alongside opportunities for future research and then broadens into wider research opportunities and challenges.

Sample and COVID

This research has a limited sample of seven case studies, and the convenience purposive sample is not be representative of the wider population. The sample bias is discussed in detail in Section 3.2.6.1. The small sample size has limited the statistical significance of some results in this chapter. In addition to the sample, due to the COVID pandemic, the data collected may not be representative of occupancy, IEQ, or ventilation outside of the pandemic - this is discussed in Section 3.2.6.3.

Sources and activities

A key limitation described throughout this chapter is that it was not possible to establish causality for the observed relationships. It is likely to be very difficult to establish direct causality between

health and ventilation, but an improved understanding of the links between health, ventilation, and IEQ would bring a more nuanced understanding and enable policy and research to prioritise efforts to reduce exposure and protect health. To address this, future research could collect data on the temporal and spatial variation of occupants' movement, activities, sources, and emission characteristics of IEQ components. Although not generalisable, this data would enable the characterisation of emissions arising from different activities and, from this, the opportunity to understand how different activities impact IEQ and exposure for those occupants. Van Dongen (2007); Hauge (2013); Few (2021) describe occupants' ventilation behaviours as contextual and embedded into everyday domestic practices and activities - therefore, collecting temporal and spatial data on occupants' activities might bring insights into how ventilation behaviours are related to other practices and exposure. For example, are specific windows opened before/during/after cooking takes place, and what is the difference in IEQ and exposure when windows are closed vs open at different points during different activities? By measuring the movement of participants in a dwelling, exposure can be more accurately estimated, and the relationship between their activities, their movement in a dwelling, and ventilation can be better understood - for example, do participants remain in rooms where there is a peak of a pollutant, and also do they remain in rooms whilst ventilating? Furthermore, this data might be able to better inform public health information on ventilation, as this could be related to specific activities. Temporal and spatial data on occupancy, activities, and ventilation events can be collected by using cameras and training machine learning algorithms, similar to research by Zhao et al. (2019). Furthermore, window and door events, including the ajar position, can be collected by using the method described in Chapter 4. The ethical implications of collecting the data described in this paragraph would need to be carefully considered alongside the practical implications for large scale studies.

Ventilation configurations

A limitation of the method from Section 5.2 is that occupants did not leave their homes unoccupied with the windows and internal doors in configurations that were representative of when they were present in their homes. In some cases, there are no measurements of AER for certain configurations, for example, all case studies closed their living room balcony/garden doors when they left their homes. There are a number of possible reasons for participants closing all windows and doors when leaving their homes unoccupied, including habit, ingress of outdoor pollution (P2 & P7 - questionnaire responses), security (P2, P3 & P6 - questionnaire responses), thermal comfort, and cost of heating. Additionally, during the monitoring campaigns the UK Government imposed legal movement restrictions on the public which resulted in participants working from home, leaving home infrequently and for short amounts of time (Barber et al., 2022). Few (2021) also reported that participants did not leave homes in configurations representative of when they were occupied, which for both pieces of research resulted in a limited number of AER results for those configurations. Internal doors have been reported to play

an important role for occupants' exposure during certain activities, but there is a lack of evidence of the impact of internal doors on AER and IEQ in real occupied homes (Few et al., 2019; Qingyang et al., 2021; Few, 2021). Future research could explore the relationship between AER and IEQ with different ventilation configurations, including internal doors through an experimental empirical research design. This experimental empirical approach might bring additional insights to the relationship between different configurations and AER/IEQ.

A limitation throughout this chapter is that measurements of both the airflow and temporal operation of mechanical ventilation systems were not captured during the monitoring campaigns. These measurements were not possible due COVID restrictions and the participants installing monitoring equipment themselves. In this research mechanical ventilation systems comprised of single room mechanical extract ventilation fans in bathrooms (P3, P4, P6, P7), decentralised mechanical extract systems serving multiple rooms (P1, P5) and recirculating cooker hoods (all case studies). Despite these measurements not being conducted, there are a number of studies in the UK that have reported inadequate performance of installed ventilation systems when compared with current Building Regulations (McGill et al., 2015; MHCLG, 2019). Measurements of the airflow and temporal operation of mechanical ventilation systems could bring insights into the effectiveness of their operation for reducing exposure to peaks of pollutants.

Drivers of behaviour

This research used questionnaires alongside physical measurements to try and understand why the occupants ventilated the way they did (Dubrul, 1988), but Section 5.1.3 found that the participants questionnaire responses did not accurately match their measured ventilation practices. The questionnaires were issued once during the longitudinal campaigns and constrained in length to limit survey fatigue. However, the result is a temporal and spatial resolution mismatch between the technical and social measurements (Mavrogianni et al., 2016). Future research could collect social data on ventilation more frequently and with more questions on specific windows and practices. This social data could be better reconciled with the temporal and spatial resolutions of the technical data, which might bring deeper insights into the temporal and spatial variation of ventilation behaviours and the reasons for any variation (Love and Cooper, 2015). However, this additional burden on the participants could result in survey fatigue, which in turn could impact response accuracy (Heinzerling et al., 2013). New devices could be developed using existing technology to reduce this burden, for example, a battery-operated multiple choice keypad could be located adjacent to each window for the participant to record the reason for opening/closing each window. If event sensors are deployed that have the facility to connect to the internet, another possibility is to develop a mobile phone application that could request information from the participants following an event to ask them the reason for the event. Future research could investigate if issuing multiple questionnaires during longitudinal campaigns improves the accuracy of

responses and is acceptable to participants. Additionally, future research using a larger and more representative sample of participants could investigate if occupants are able to recall their ventilation practices accurately and, if not, the reasons for this.

Relationship between exposure and health

Due to the lack of evidence of the relationship between health outcomes and exposure to (individual and combinations of) environmental hazards at timescales that are relevant for ventilation, it was not possible to identify priority IEQ components or evaluate harm from simultaneous exposure to different components of IEQ for different ventilation scenarios - this is discussed more in Section 5.6.2. Furthermore, Section 5.3.2 highlighted a lack of published guidance on safe concentrations for abundant and pervasive chemical compounds identified in the case studies. More evidence on the relationship between short-term exposures and health would allow researchers to explore the impact of ventilation on health more thoroughly. In addition to a better understanding of the exposure-health relationship, research could determine effective methods for evaluating different IEQ components in a way that exposes the relative risks, benefits, and disbenefits. However, it is recognised that this research is a significant undertaking. Insights from the discussed future research would enable researchers and public health professionals to improve estimates of burden of disease and to evaluate strategies for reducing exposure to the many different IEQ components, including ventilation.

In addition to the above, there is the added complexity with noise and sound measurements, where noise is a psycho-social stressor and not a toxicant, and therefore, the source and nature of the sound and the attitudes of occupants towards it can act as a moderator and/or mediator of the exposure-health pathway (Fenech, 2022). Because occupants are often unable to control undesirable sources of sound from outdoor sources, their perception of this sound can modify their ventilation behaviours and might lead to occupants not opening windows or closing them due to outdoor noise (Andersen et al., 2009; Eze et al., 2017; Notley et al., 2014). Because of these factors, it is important with noise and sound measurements to distinguish between desirable and undesirable sounds, which is challenging when conducting long-term monitoring campaigns measuring sound. Future research could collect information from occupants on their attitudes towards sounds from indoor and outdoor sources and attempt to temporally and spatially resolve this to understand its relationship with ventilation behaviours. One example of this might be for occupants to record the time, location, source, and type of noise when noise was a barrier to opening a window or resulted in them closing a window. It is recognised, however, that these measurements would be time and labour intensive for participants. Similar to the idea above, new devices could be developed using current technology to capture this information from research participants.

Further large-scale research of IEQ

This chapter found poor standards of ventilation provision and ventilation rates in both old and recently constructed homes, which supports a growing body of evidence (Crump et al., 2005; MHCLG, 2019; Few, 2021). In addition to these two factors, there are other factors that could contribute towards continued poor levels of ventilation in homes and the potential for this to worsen in the future. These factors include continued national and international efforts to reduce carbon emissions from buildings (increasing air tightness standards), the recent cost of living crisis in the UK (potentially leading to reduced ventilation), lack of knowledge of the importance of ventilation or how to ventilate, and the construction of dwellings in more polluted and noisier environments (urban settings and close to transport infrastructure) (Dimitroulopoulou, 2012; McGill et al., 2015; Van Rooyen and Sharpe, 2024). This builds a strong case for further large-scale research in UK homes to understand the relationship between ventilation and IEQ and, more importantly, to determine if measured conditions in homes are safe. A deeper understanding of the relationship between ventilation and IEQ from a diverse representative sample can help identify potential opportunities for improving IEQ, which can be balanced against energy and carbon emissions. Future research could consider if buildings constructed to current standards meet minimum levels of ventilation and to specifically consider the appropriateness of current policies for protecting occupants' health (HM Government, 2021*a*). Additionally, given the importance of upgrading the old stock of buildings in the UK, future research could consider the suitability of guidance for ensuring appropriate levels of ventilation following significant retrofit work (BSI, 2019*b*). Finally, given the dynamic and variable nature of the internal and external factors influencing occupants' behaviour, it is important to understand the changing way that people use their homes to ensure that strategies and policies remain relevant and impactful.

5.6 Summary and discussion

5.6.1 Ventilation provision, its use, and how this impacts ventilation rates and IEQ

5.6.1.1 Ventilation provision, background ventilation, and future challenges for retrofit

The UK building stock is the oldest in Europe and possibly the world, with 75% of homes were constructed before 1980, which is before the 1985 Building Regulations introduced minimum requirements for thermal efficiency and ventilation provision (HM Government, 1985; Piddington et al., 2020). 75% of this existing stock is predicted to exist in 2050, and the need to upgrade the energy efficiency of these old homes to reduce carbon emissions and abate climate change is evident (Crump, 2011; CCC, 2019). Typically, homes built before the introduction of the Building Regulations experience higher levels of uncontrolled ventilation (infiltration and exfiltration) through leaky fabric, but as the Building Regulations introduced requirements for improved thermal efficiency and airtightness, homes have become more airtight and experience less uncontrolled ventilation (Crawley et al., 2019). The Building Regulations also introduced requirements for new homes to have purpose provided ventilation provisions (HM Government, 2021*a*). This is reflected in a recent study of 1,861 homes, which reported that only 22% of homes built before 1991 had mechanical extract ventilation and trickle vents, compared with 59% built after (Van Rooyen and Sharpe, 2024). Although the percentage is higher for homes constructed after 1991, this suggests that 41% of dwellings, to which the 1985 building regulations apply, did not have this provision (Van Rooyen and Sharpe, 2024). Research has highlighted shortcomings in both the provision and performance of ventilation systems, suggesting that ventilation is not fully enforced and non-compliant provision is not likely to be discovered or rectified, which could be addressed through a reform of the Building Control process in the UK (Zero Carbon Hub, 2016*b*; CCC, 2019). Even in dwellings with ventilation provision compliant with current standards, research often reports that the performance does not achieve minimum standards (McKay and Ross, 2010; Dimitroulopoulou, 2012; MHCLG, 2019). The reported poor levels of ventilation provision are important when considering the thermal efficiency upgrades to the older homes, which often have the direct aim or secondary benefit of reducing heat loss from uncontrolled infiltration and exfiltration (Hartless and Standen, 2013; BSI, 2019*b*). This reduction in infiltration and exfiltration can have the unintended consequence of reducing ventilation rates in these homes, which can increase occupants' exposure to high temperatures and pollutants from indoor sources which can impact occupants' health (Hamilton et al., 2015; RCPL, 2016; Symonds et al., 2019). Guidance exists for retrofitting homes, which include recommendations for ventilation provision to protect the health of occupants, but this remains as Guidance and is not legally required for all homes (BSI, 2019*b*). It is critical, that energy retrofit policies include the requirement

for providing appropriate ventilation to protect occupants' health - a concept commonly referred to as 'Build tight, ventilate right' (Knight, 2014; CCC, 2019; Few, 2021).

Although the sample used in this research is limited, the points from the previous paragraph are evident. P1, P4, P5, and P6 were the most recently constructed in the sample (between 1981 and 2015) and had the lowest background ventilation rates when unoccupied (0.23 to 0.29^{-1}), whereas P2 and P3 were older (between 1919 and 1980) and had higher background ventilation rates (0.39 - 0.40 $^{-1}$). This suggests that the more recently constructed dwellings were more airtight, and this might be due to the standards introduced by the Building Regulations. Of the four dwellings constructed after 1985, one case study (P6) did not have trickle vents and mechanical extract ventilation provision compliant with standards in force at the time of construction, and another case study (P1) had a dMEV system that was not operational. In the remaining two case studies, despite having operational ventilation provision compliant with standards, these two homes had the lowest background ventilation rates at 0.23 and 0.29^{-1}, which is below the suggested health threshold of 0.5^{-1}. This adds to growing evidence that ventilation rates in many homes constructed to current Building Regulations are below the health threshold (Aizlewood and Dimitroulopoulou, 2006; Crump et al., 2005; Kukadia and White, 2006; McKay and Ross, 2010; Dimitroulopoulou, 2012; MHCLG, 2019; Few, 2021). Jones et al. (2015) estimated that 79% of English homes have a median ventilation rate less than 0.5^{-1} and may require additional purpose provided ventilation to limit harm. To illustrate the final point of the previous paragraph, P7 was the oldest dwelling (pre-1919) in the sample, which we might expect to have the highest background ventilation rate, but it had the lowest background ventilation rate of 0.23^{-1}. This is potentially explained by the fact that this dwelling had very few trickle vents, a non operational MEV system, and the occupants had recently installed high performance acoustic triple glazed windows. The installation of new high-performance windows, the lack of background ventilation, and a non-operational ventilation system are likely to have resulted in low ventilation rates and contributed towards favourable conditions for mould that was identified in this home.

In light of the example of P7 above and the importance of upgrading the old stock of homes in the UK and that these upgrades often reduce ventilation rates, policy could mandate improvements to ventilation provision during retrofit. As mentioned above, this exists as Guidance and is also a requirement of many grant schemes, but is not a legal requirement for all homes when retrofitting dwellings for energy efficiency, particularly as upgrades might be carried out incrementally (BSI, 2019*b*). Furthermore, The Government could also stimulate upgrades to the existing stock by providing funding similar to the Boiler Upgrade Scheme but for energy-efficient mechanical ventilation systems (HM Government, 2024). MVHR is one example of an energy-efficient mechanical ventilation system which can be retrofitted into homes and has been shown to provide healthier and more energy-efficient homes than those that are naturally ventilated (Sharpe et al., 2014; Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou, 2015; McGill et al., 2017). However, these systems are complex

and research into MVHR systems often reports misuse and a widespread lack of knowledge of how to operate them, which would also need to be addressed (McGill et al., 2015; Gupta and Kapsali, 2016). Knowledge of the health impacts of ventilation and how to ventilate homes is discussed more below and in Section 5.6.2.

As mentioned above the building survey identified that in the six homes with mechanical ventilation, two had systems that were not operational. Furthermore, the questionnaire highlighted that of the four case studies with operational mechanical ventilation systems, all reported that they had never maintained or cleaned any part of those systems. This adds to the existing growing body of literature reporting ventilation systems in poor working condition, poorly maintained, and not operational (Gupta and Kapsali, 2016; MHCLG, 2019; Few, 2021). Proper maintenance of ventilation systems is required to ensure ventilation systems provide air exchange between indoors and outdoors, which in turn can reduce exposure to indoor pollutants and reduce the risk of microbiological growth indoors. Few (2021) found that cleaning of an extract terminal in a case study resulted in a doubling of the air flow rate for that terminal. However, there is limited evidence showing a link between maintenance of ventilation systems and health in homes (Wargocki, 2013). Given the importance of ventilation for protecting health and following the tragic case of Awaab Ishak, recent Government Guidance has been published recommending that social and private landlords ensure that ventilation systems are routinely checked, serviced, and are fully operational (DHSC et al., 2023). However, this guidance does not address owner-occupied homes in the UK, which make up most of the housing stock (63.1%) and are one of the groups with the lowest amount of ventilation provision compliant with current standards - only 25% of outright-owned homes have mechanical ventilation and trickle vents (Piddington et al., 2020; Van Rooyen and Sharpe, 2024). Frontczak and Wargocki (2011) found that there is a poor understanding of the importance of ventilation for health in the Danish public, and if this also applies in the UK, public health information on the importance of ventilation for health could promote owner occupiers to ensure their ventilation systems are serviced and operational. If the homeowners are presented with the potential health gains associated with investing in ventilation technologies, prospect theory states that they will be more likely to accept this than when presented with the losses (Kahneman and Tversky, 1979). One final issue affecting ventilation provision and maintenance in the UK is that there are no accredited training programs or dedicated trade bodies for the installation and servicing of ventilation systems in the UK, which could have an impact on the quality of associated work (Bone et al., 2010).

5.6.1.2 Ventilation practices and its impact on AER, IEQ, and health

The times that windows and doors were opened and closed (events) were recorded from all case studies. Additionally, times that each case study was occupied was inferred from these events and CO_2 data. The analysis in this thesis focuses on occupied periods, which is distinct from the literature and enables the results to be more closely related to the conditions the occupants experienced, which is most

relevant for exposure and health (Nazaroff, 2021; Stamp et al., 2022). Analysis of this data showed that windows and doors were closed for most of the occupied times, and this was greatest during the winter, with some case studies keeping all windows and doors closed for up to 90% of the winter whilst occupied (Section 5.1.1). Wang et al. (2022) measured window opening in 17 apartments and also found windows closed most of the time during the winter and open more during the summer season. The finding of seasonally dependant ventilation practices aligns with research by Andersen et al. (2009); Roetzel et al. (2010); Fabi et al. (2012); Andersen et al. (2013); Jones et al. (2017); Sun and Wallace (2020); Liu et al. (2022). The combination of poor background ventilation provision in some case studies and the finding that windows remained closed most of the occupied time suggest that some case studies might experience poor ventilation rates, and this in turn might lead to an increased concentration of pollutants from indoor sources, increasing occupants' exposure and increasing the risk of harm to health (Dimitroulopoulou, 2012). In order to investigate this, air exchange rates (AER) were estimated using the CO_2 decay technique when each case study became unoccupied. As briefly mentioned in the previous section, these calculations showed that the median whole house AER were below the health threshold of 0.5^{-1} in all case studies when windows and doors were closed ('background ventilation rates').

As expected, the whole house and individual room AER were higher when windows were open relative to when they were all closed, and whole house AER increased with increasing numbers of open windows. This agrees with ventilation theory (Dick J.B and Thomas D.A, 1951) and empirical measurements of AER by Roulet and Scartezzini (1987) and Howard-Reed et al. (2002). However, this research found differences between the whole house and individual room AER, and in many case studies, opening windows did not result in the whole house AER to increase significantly and not above the health threshold. When considering individual rooms, opening windows typically doubled the AER in that room and almost always caused the AER in that room to exceed the health threshold. However, whole house and individual room AER were found to be highly variable both within and across different case studies. The results suggest that the occupants can experience very different ventilation rates depending on where they are in their home, and this is strongly related to their ventilation practices, which were highly variable (Few, 2021). This is contrasted by research which characterise ventilation as a single value, which does not reflect the variability (Sundell et al., 2011; Fisk, 2018). In some cases, windows were opened more frequently in the winter than in the summer, but for most cases, windows were opened for significantly longer during the summer than during the winter. The results show high variation of practices and AER over time within each room of each case study, across different rooms in the same case study and across the different case studies. This large variation in practices is reported throughout a wide body of literature, which highlight the challenge of generalising ventilation practices and AER (Van Dongen and Phaff, 1989; Kvisgaard B, 1990; Kukadia and White, 2006; Andersen et al., 2009, 2013). This variation also highlights the significant challenge associated with deriving guidance

and policy that is relevant for all groups of the population - this is discussed below (Section 5.6.2).

A new concept of 'experienced AER' was presented in Section 5.2.2, which estimated the average AER during the summer and winter when each case study was occupied. The results show that experienced AER was below the health threshold (0.5^{-1}) in most case studies during the summer and winter, but generally statistically significantly higher in summer relative to the winter. As expected, case studies with the highest experienced AER also had the highest background ventilation rates, opened windows more often and for longer. Further analysis of the results in Section 5.2.6 showed that six of the seven case studies had AER less than the health threshold for over 63% of all occupied periods. This was highest during the winter when five of the seven case studies had AER less than the health threshold for over 96% of the occupied time. The results presented in this research support a growing body of evidence that many homes in the UK are not adequately ventilated - Aizlewood and Dimitroulopoulou (2006) reported four of eight homes with AER less than the health threshold, Crump et al. (2005) reported 68% during the winter and 30% during the summer, Kukadia and White (2006) reported four of five homes with AER less than the health threshold.

The results from this research show that in many cases, when a window was open, the ventilation rates were higher, but many case studies were located near roads, where the open windows also caused pollutants (e.g., NO_2) from vehicles and noise to ingress indoors. This highlights the challenge of using simple metrics such as AER alone as a metric/proxy for evaluating 'healthy' IEQ. AER alone is not likely to be representative of a healthy indoor environment; therefore, it is important to directly measure the components of IEQ which impact health to fully evaluate all relevant components of the indoor environment and their relationship with ventilation. For example, it is possible that homes practice effective source control and carefully timed ventilation, which could result in low levels of indoor pollutants and a healthy indoor environment but with a low AER. On the other hand, it is also possible that homes with high AER can have poor IEQ. The differences in outdoor conditions also highlight that advice to occupants to open windows might not always be appropriate for all homes, as this might lead to unhealthier conditions indoors. Furthermore, this advice might not always be practical, possible, safe, affordable, or acceptable to occupants.

In order to investigate the relationship between IEQ and ventilation practices, Section 5.3 analysed the change in all IEQ components after windows and doors were opened and closed. After windows and doors to the outside were opened, indoor measurements of temperature, absolute humidity, carbon dioxide, carbon monoxide, and volatile organic compounds generally decreased, and the amount that these components decreased was typically higher for higher IOR. Typically, indoor concentrations of nitrogen dioxide and noise levels increased after windows and doors were opened. Unexpectedly, despite PM having an IOR greater than 1, indoor concentrations of PM increased after windows and doors were opened. After windows and doors were closed, across all case studies, temperature, absolute humidity, carbon dioxide, carbon monoxide, and volatile organic compounds increased in the summer

and winter. After windows and doors were closed, particulate matter increased in all rooms during the winter, but fine and ultra-fine particulate matter reduced in kitchens in the summer. Noise levels were typically higher after closing windows and doors in living rooms and kitchens in the summer but lower in all rooms in the winter. These results show that after a window or door is opened or closed, some aspects of IEQ improved, but others worsened. There is a lack of evidence of the relative and combined health impacts of IEQ exposure at timescales relevant for ventilation, which make it challenging to assess the improvement and worsening of these IEQ components together - this is discussed in more detail in Section 5.6.2. Modelling research often rely on assumptions around occupants' ventilation behaviour, ventilation rates, and the impact of these on IEQ - the results presented in this thesis have demonstrated the vast variability in these factors in real buildings and highlight the challenge associated with simplifying this behaviour for modelling (Nicol, 2001; Andersen et al., 2009; Mylona and Davies, 2015). Furthermore, the variability highlights limitations associated with models that do not account for this variability. The methods and analysis techniques presented in this thesis can be used to inform future research on how to undertake studies to provide empirically derived insights for such modelling.

The ventilation strategy described in Approved Document Part F1 for new homes comprises of three parts, the first is the provision of background ventilation to provide constant low ventilation rates to control air quality, the second is provision of mechanical extract ventilation in bathrooms and kitchens to control pollutants and moisture from cooking and bathing, and the third is provision of purge ventilation by windows for occasional ventilation during periods of high pollutant release (e.g., painting) (HM Government, 2021*a*). Given the finding that all case studies experienced poor levels of background ventilation, only one case study had extract ventilation in their kitchen (only recirculating hoods in others), and only four case studies had operational ventilation in the bathrooms, the occupants' use of windows can become more important for controlling indoor air quality, particularly during activities that emit harmful pollutants indoors. In order to investigate this, the analysis in Section 5.4 considered the time for peaks of pollutants to decay to their respective health thresholds when windows were open and closed. The section prior to this (5.2) found higher rates of ventilation when windows were open, and given that outdoor concentrations were lower than the indoor concentration of peaks, as expected, the results generally showed that high peaks decayed to the threshold quicker when windows were open relative to closed. The decay times, however, were highly variable within and across the case studies, which is expected given the wide range of factors influencing indoor concentrations of pollutants and ventilation (see Section 2.2.2). Opening windows, however, can lead to ingress of noise and other pollutants, which are challenging to evaluate at timescales relevant for ventilation - these challenges are discussed more below.

Section 5.1.3 found a poor level of agreement between questionnaire responses and actual measurements of ventilation practices. However, the survey was completed only once during the long campaigns, which suggests that a single survey might not be able to adequately capture the real variation of ventilation

behaviours in longitudinal monitoring campaigns. Furthermore, questionnaires were completed by a single occupant, where most case studies had multiple occupants. This finding is important given that much of the ventilation literature is based on questionnaire responses, and if respondents are unable to accurately report on their ventilation practices and behaviours, this could have consequences for longitudinal monitoring campaigns and also potentially for a large body of literature on ventilation.

5.6.2 Public health information on ventilation and IEQ

Providing advice to the public on IEQ and/or ventilation is particularly important, as humans do not possess the ability to detect the presence of or absolute concentrations of many components of the indoor environment that are harmful to health (Seppeanen and Fisk, 2004; Jones, 2017). On the other hand, humans can also be very sensitive to some components of IEQ, such as noise and temperature, however, sensitivity is highly variable (Defra, 2014; Lomas and Porritt, 2017; Fisk, 2018). Humans can also acclimatise and habituate to sensory stimuli and might not be able to effectively detect changes in IEQ components over time (Seppeanen and Fisk, 2004; Jones, 2017). Additionally, often substances that are harmful to health are masked by and associated with pleasant sensory stimuli, for example, cooking and scented candles/josticks, which can emit harmful chemicals and particulate matter but also associated with pleasant smells (Few, 2021). Because of these factors a respondent's perceived 'good' IAQ does not necessarily mean that it is healthy or safe, with other research reporting high levels of satisfaction levels but poor measured IAQ (Edwards, 2021). In this research there was a wide range of reported satisfaction with IAQ, from 'very dissatisfied' (P7), 'fairly dissatisfied' (P1 and P3), 'neither satisfied nor dissatisfied' (P4), 'fairly satisfied' (P2 and P5) to 'very satisfied' (P6).

In this research, four of seven participants reported that they felt ventilation was fairly important for their health, and the remaining three felt it was very important. But, despite this importance, only four of the seven participants had received information on how to use the ventilation provision in their homes. Participants reported that this information was obtained from their professional experience or the internet. This research has a small convenience sample where many participants are active researchers or professionals in public health and the built environment and are more likely to have seen/read/learned about ventilation. There is a growing body of evidence reporting widespread lack of knowledge of both the importance of ventilation for health and also how to ventilate their homes (Aizlewood and Dimitroulopoulou, 2006; Dimitroulopoulou, 2012; Frontczak et al., 2012; Baborska-Narożny et al., 2017; MHCLG, 2019; Van Rooyen and Sharpe, 2024). Guidance exists on when to ventilate, but there is limited advice/guidance on how long to ventilate (Few, 2021; Kumar et al., 2022; CLASP and EPHA, 2023). This lack of knowledge in the public could contribute to poor ventilation rates in homes, and it is possible that providing simple, empirically derived, and targeted advice on when and how long to open windows in their homes could reduce exposure to peak concentrations of pollutants from indoor sources in a way that is less expensive than installing new ventilation provision and can have an immediate

impact. Section 5.4 investigated the time for peaks of pollutants to decay to their respective health threshold and provides an illustrative example of how this type of analysis could be used to inform public health messaging on how long to keep windows open after an indoor peak of pollutants. However, there are a number of challenges associated with selecting appropriate advice given the conflicting results and demands - this is discussed below.

Firstly, Section 5.4 highlighted a large amount of variation of the decay times across the different pollutants both within and across the different case studies, which make aggregating the data and deriving suitable advice challenging. Within each case study sources of variability in decay times can arise from varying physical arrangements in the different spaces (room volume, window size and geometry, sinks for pollutants), differences in outdoor conditions for different spaces (outdoor pollutants, noise, wind, and solar exposure), and variation in ventilation behaviours in different spaces (duration, frequency, and width of opening windows). In addition to this in-home variation, there are also differences in decay times across the different case studies which can arise from differences in monitoring periods, outdoor conditions (including temperature, wind speed, and direction), occupants' ventilation behaviour, dwelling geometry, and other physical characteristics of the dwellings (including air permeability, infiltration, and potential for cross flow and buoyancy driven ventilation), the size of windows and how much they are opened, internal temperatures (driving indoor-outdoor pressure differences), and internal door configurations. This agrees with Fabi et al. (2012) who described ventilation behaviour as a complex process that is dependant on many different internal and external factors, and the result is that ventilation can have a wide ranging impact on IEQ.

The second challenge is that there is likely to be a large amount of variation in the wider population, which then highlight the difficulties of disseminating advice - advice that is appropriate for one part of the population might be inappropriate for another - some might over ventilate and others might under ventilate. This is partly illustrated through the results in Figure 5.9, which show a series of bar graphs for the decay times of high and low peaks of NO_2 for different rooms in each case study. This figure highlights that if this sample were advised to ventilate for 60 minutes following a peak, this might be long enough for all participants apart from P2. P2 had decays of high peaks of NO_2 in their kitchen which exceeded 60 minutes (median 85 minutes), and so, 60 minutes might not be long enough to keep windows open for peaks of NO_2 to reduce to safe concentrations.

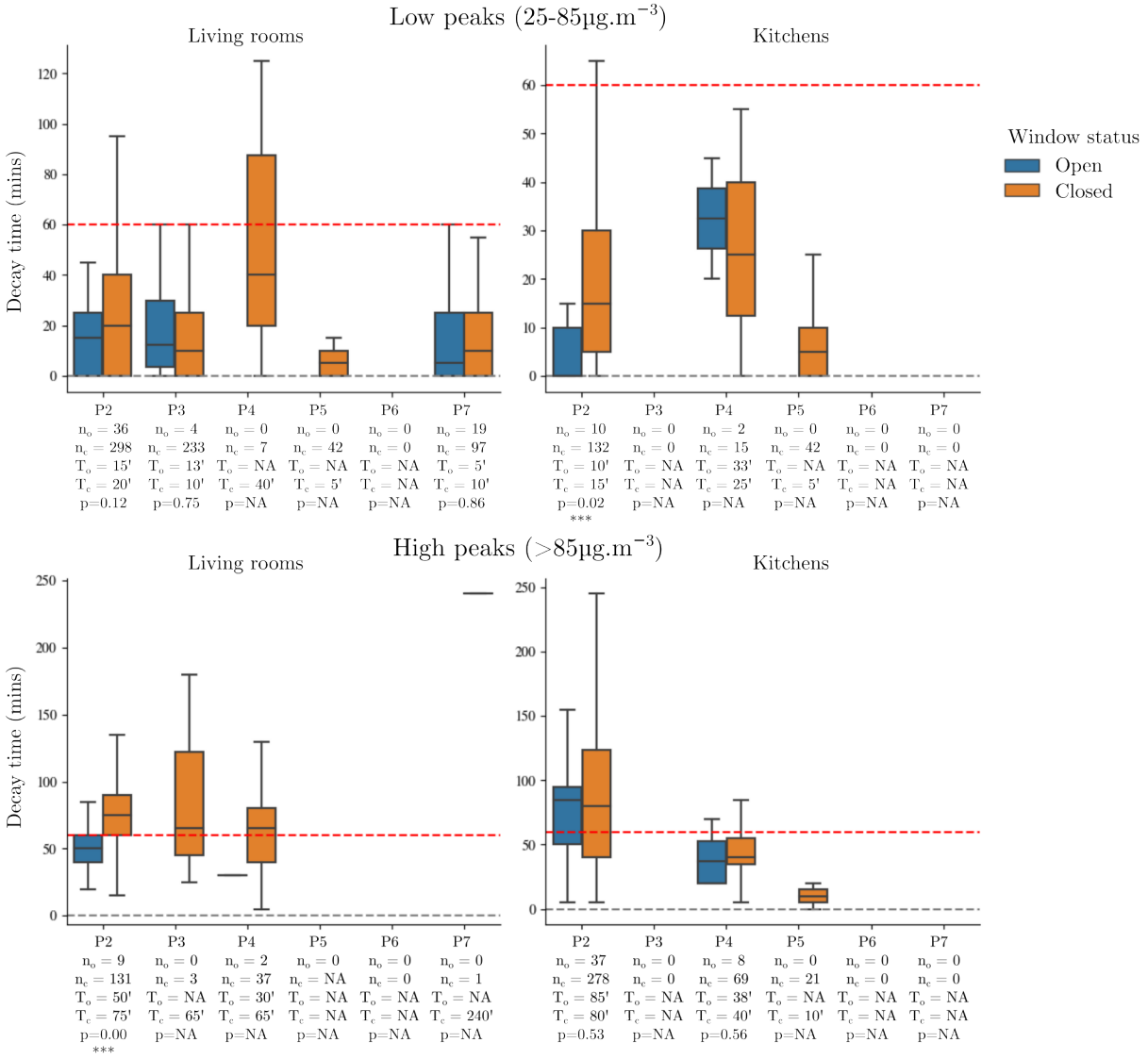


Figure 5.9: Series of bar graphs showing the time for low (25-85μg.m^{-3}) and high (>85μg.m^{-3}) peaks of nitrogen dioxide to decay to the health threshold (25μg.m^{-3}) for each room in each participant, when windows were open (blue) and closed (orange).n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.

The next major challenge is accounting for other factors associated with ventilation and the implications of providing ventilation advice. For example, the cost of heating and the impact of ventilation on thermal comfort were common barriers to ventilation reported by the participants - these barriers present a conflict between cost, energy, carbon emissions, comfort, and health (Bone et al., 2010; CMO, 2022). The choice of ventilation duration could be evaluated more widely to include the combined effects of energy (and carbon dioxide emissions), climate change, comfort, health, and well-being, whilst considering common drivers, barriers, and potential unintended consequences. One fundamental challenge with this evaluation is that it is not possible to directly compare health impacts with financial (cost of ventilation provision and use), energy, and climate change. These are all very

important to consider, but are disparate concepts/constructs with no common metric for evaluation. Which is more important and which should be prioritised? One possible option would be to develop guidelines for specific sources, scenarios or activities. Using the example in the previous paragraph, P2 had a gas cooker, where the higher peaks of NO_2 might be a result of using this appliance, and so specific guidance could be disseminated for homes with gas cookers before/during/after cooking. However that advice might be longer and more complex, which could be dismissed, forgotten, or misinterpreted, where a single simple message for the whole population might be more effective and impactful. This discussion does not go into the detail of public health communication, which is a specialist field of its own (CDC, no date).

In the combined living/kitchen spaces of P1 and P2, the median decay time for low peaks of CO_2 and high peaks of PM_1 to decay to their respective health thresholds were substantially lower when the balcony/sliding doors were open relative to the only the window in the same space - P1 CO_2 sliding door = 3 minutes, window = 15 minutes, P1 PM_1 sliding door = 25 minutes, window = 73 minutes, P2 CO_2 sliding door = 5 minutes, window = 20 minutes, P2 PM_1 sliding door = 35 minutes, window = 55 minutes. The amount that windows and doors open and the resulting aperture have a direct impact on AER, and therefore, when a larger window or door is open, AER are likely to be higher and the decay times of pollutant peaks shorter (Roetzel et al., 2010; Liu et al., 2022). The amount that windows and doors are opened can be measured during campaigns (see Chapter 4), and future research might consider investigating the relationship between how far windows open with both exposure and energy use - it might be possible to open windows wider but for shorter durations, which might reduce exposure to indoor pollutants whilst also reducing heat loss. The results in this paragraph highlight the challenge that the same advice for different households could lead to potential issues - some homes may over ventilate, leading to excessive heat loss, ingress of noise and, outdoor pollutants, and on the other hand, some homes might not receive sufficient ventilation leading to increased exposure to indoor pollutants.

Occupants' activities indoors can lead to the release of pollutants (e.g., cooking) which can result in a peak of indoor pollutants that are harmful. Occupants have the opportunity to respond to the known or expected release of pollutants by ventilating the space before/during/after this activity in order to reduce exposure. Therefore, the time for the peak to reduce to safe concentrations is important for exposure - Section 5.4 found this was around one hour when windows were open. The final challenge highlighted here is related to the lack of evidence on the relationship between exposure and harm to both individual components of IEQ and combinations of components at short-term timescales that are relevant for ventilation. This is exacerbated by the fact that the indoor environment can contain many different pollutants at varying concentrations and in an enormous possible number of combinations - IEA (2017) reported that the indoor air can contain over 300 different pollutants. The lack of evidence of the relationship between exposure to individual and combinations of IEQ components at short timescales

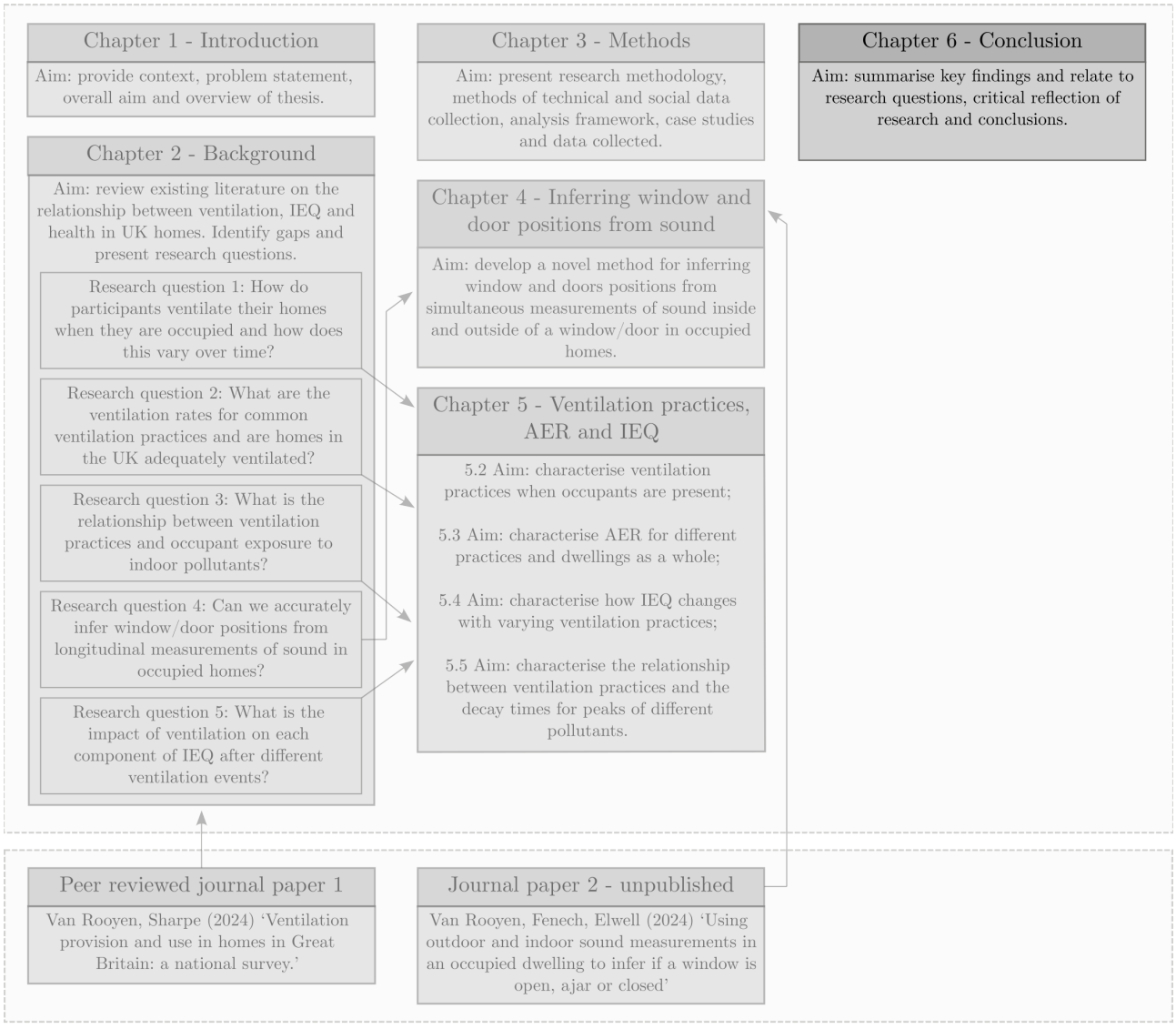
makes it difficult to fully evaluate the health impacts of different ventilation practices (Seppanen, 1987; Carrer et al., 2015; WHO, 2021*b*). This point is illustrated for P2. This home is located on a busy road, and the results showed that after a window or door was opened, noise and air pollutants (particulate matter and nitrogen dioxide) increased. Indoor pollutants were also generated through the use of a natural gas cooker. A logical and important question for this scenario is: 'is it better for the occupants' health (exposure) to open windows or not?'. To answer this question for specific homes, it is possible to quantitatively measure exposure to all IEQ components for two scenarios: opening the window and not. However, there is insufficient epidemiological and toxicological information for short-term exposures to all IEQ components to fully evaluate harm for both scenarios and confidently answer this question (Carrer et al., 2015). Furthermore, linking to the first issue above, the change of IEQ components was found to be highly variable (e.g., time of day, activities, etc.), which further complicates this analysis. There are a number of studies that have attempted to resolve this issue by using DALY to estimate the harm from exposures to indoor air pollutants (Logue et al., 2012; de Jonge and Laverge, 2022; Morantes et al., 2023). However, there are potential issues with the methodological approach used by de Jonge and Laverge (2022), which uses toxicological and epidemiological relationships from long-term exposures and chronic health outcomes and applies these same relationships to short-term exposure data. The method used by Morantes et al. (2023) is similar to that of Logue et al. (2012); however, in the absence of epidemiological evidence, Morantes et al. (2023) used relationships from animal-based toxicological studies. This approach can introduce uncertainties, where there might be differences between the relationship derived from animal-based toxicological studies and human health.

One possible solution to the above issue is to use IEQ sensors, which provide objective information on IEQ to occupants. None of the participants in this research had IEQ sensors in their homes or used them for assessing IEQ, but these sensors are becoming cheaper and more pervasive in homes in the UK (Van Rooyen and Sharpe, 2024). There are a number of major household brands who have developed consumer grade products specifically to measure and inform building occupants of IAQ, and recent regulations in Scotland require new airtight homes to have CO_2 sensors installed as a means of providing ventilation awareness to occupants (The Scottish Government, 2022; Amazon, 2023). One clear advantage of this technology is that it can provide specific and objective measurements of IEQ to occupants, which has the potential to mitigate issues around under or over ventilating, as the occupants can adjust their ventilation practices to align with real time feedback. However, this technology also comes with many potential issues, including cost, accessibility, intelligibility, trust, whether or not it includes all relevant components of IEQ for health, accuracy, life of sensors, and calibration requirements for sensors. Many consumer grade devices do not include the full spectrum of IEQ components that are relevant for health, so even when using sensors, occupants may only be partially informed and there might be cases where this can result in unintended consequences. For example, CO_2 sensors are common in IAQ sensors, but if an occupant was located in a home with harmful outdoor pollutants and

opened windows based on indoor CO_2 concentrations alone, this might lead to an ingress of harmful pollutants and an increased exposures to these harmful pollutants from outdoors. Even if there was a sensor that could measure all IEQ components that are relevant for health, given the discussion above, the issue around whether or not it is healthier to ventilate or not remains - how do users of this technology prioritise different components of IEQ if one aspect improves and others worsen with ventilation practices?

Given the context of occupants lacking knowledge of the importance of ventilation for health and how to ventilate homes, poor ventilation provision, poor ventilation rates, and the need to improve the energy efficiency of existing homes into the future, source control is one option for policy to protect the health of the public from exposure to harmful environmental hazards outdoors and indoors (Seppanen, 1987; Hänninen, 2013; Royal College of Paediatrics and Child Health, 2020; Dimitroulopoulou et al., 2023). By eliminating or reducing sources of harmful environmental hazards from entering homes, the need for information, ventilation provision, and AER are potentially reduced. Source control here refers to all sources of environmental hazards, including consumer goods, construction materials, outdoor air pollution, and environmental noise - all of which can be directly or indirectly influenced by policy. In London it was estimated that 45% of nitrogen oxide emissions in 2010 were from road transport, which is also a major source of noise in the city (Howard, 2010). The Ultra Low Emission Zone (ULEZ) has reduced nitrogen oxide emissions from road transport by 50%, and the Mayor's commitment to introducing Zero Emission Zones (ZEZ) would reduce these emissions further and also reduce noise from road transport (Mayor of London, 2023). In addition to road transport, 13% of nitrogen oxide emissions are from domestic gas and 8% from non-domestic gas (Howard, 2010). The UK Governments' Heat and Buildings Strategy, which outlines the electrification of buildings, is likely to lead to a reduction in both indoor (natural gas cooking) and outdoor concentrations of nitrogen oxide emissions; however, the use of air source heat pumps as part of this strategy can also produce noise, so although there are benefits in some areas, there are disbenefits in others (Torjussen, 2019; HM Government, 2021*d*; Department for Energy Security and Net Zero, 2023). These are examples of policies that can control multiple sources of environmental hazards and have been shown to reduce exposure and improve quality of life, health, and well-being of those living in the areas affected by these policies (Chamberlain et al., 2023). These examples also highlight the need to consider multiple domains in order to balance benefits and disbenefits.

6 | Conclusion



People in Europe spend most of their time indoors and most of that time within their own homes (Schweizer et al., 2007). Whilst indoors, occupants are exposed to the indoor environment, and this exposure can impact comfort, well-being, and physical health (WHO, 2018*b*). Ventilation is the movement of air between indoors and outdoors, and this can alter the indoor environment and modify occupants' exposures (Wargocki, 2013; HM Government, 2021*a*). However, ventilation can also lead to heat loss, energy consumption, and increased carbon emissions from homes (CIBSE, 2015; Jones et al., 2015; Day et al., 2020). Despite the importance of ventilation, there is a lack of empirical evidence of the relationship between ventilation and indoor environmental quality in occupied homes in the UK. The first aim of this research was to investigate the relationship between ventilation (practices and AER) and IEQ in occupied homes in the UK, with a focus on exposure to components of the indoor environment that impact health: specifically overheating, indoor air quality, and noise. The second aim of this research was to develop a framework for informing ventilation advice for reducing exposure to (health relevant) peaks of indoor air pollutants.

Chapter 1 introduced ventilation, the key components of IEQ, and outlined the limited understanding of the relationship between IEQ and ventilation. This chapter provided an overview of the history and context for this research. Chapter 2 reviewed the current state of research and knowledge, along with identifying gaps in the literature. Three themes emerged from the literature: (1) many homes in Britain have a lack of ventilation provision compliant with long established minimum standards, (2) there is a widespread lack of knowledge of ventilation (impact of ventilation on health and also how to ventilate), and (3) many homes in the UK have poor ventilation rates. All three themes are interlinked, where lacking provision and/or lacking knowledge could lead to lower ventilation rates. The review concluded by summarising five key research gaps and presented five research questions to address them, the contribution of this thesis to answering them is summarised in Section 6.1. Chapter 3 then presented the research methodology and research design to collect data in order to answer the research questions. Section 3.2 described the mixed methods empirical research design. Technical methods included building surveys, measurements of indoor and outdoor air quality and noise, measurement of VOCs using sorbent tubes, and the measurement of window and door opening and closing events. Social methods involved a detailed questionnaire on ventilation practices and behaviours. The final sections of Chapter 3 discussed the data analysis framework, ethics, and introduced the seven case studies.

Chapter 4 presented a novel method for inferring window and door positions from simultaneous measurements of sound inside and outside a door or window. The method was developed to predict window and door positions, including the ajar position. The method was tested and validated in two different test cases; one in a noisy urban setting and the other in a quieter semi-rural setting.

Chapter 5 comprises four sections considering ventilation practices, air exchange rates (AER), IEQ, and the decay of pollutant peaks. The first section (5.1) analysed the ventilation practices of the seven

case studies while occupied. The second section (5.2) presented the results of whole house and individual room AER calculations and their relationship with ventilation practices from the previous section. These calculations used the CO_2 decay method to calculate AER when each case study became unoccupied. The third section (5.3) presented the results of a study into the change of each IEQ component after windows and doors were opened and closed. The fourth and final section (5.4) presented the results of an analysis which identified the peaks of IEQ components and the time for those peaks to decay to their respective health threshold. These decay times were related to ventilation configuration during the decays.

In this final chapter, the first section (6.1) restates each of the research questions and relates the key findings from the results chapters (4 and 5) to each of them. Section 6.2 provides a critical reflection of the research with a discussion of the impact and opportunities presented by the COVID-19 pandemic on this project. The final section of this chapter (6.3) summarises the main conclusions of this research.

6.1 Key findings

6.1.1 Research question 1: How do participants ventilate their homes when they are occupied, and how does this vary over time?

Opening windows and doors enables air movement between indoors and outdoors, which impacts indoor temperatures, IAQ, and noise, which in turn impacts energy use, occupants' comfort, exposure, and health (Wargocki, 2013; CIBSE, 2015; WHO, 2018*b*). Therefore measurements of when windows and doors open and close can bring important insights when researching the relationship between ventilation and IEQ, energy and health. Despite the importance of ventilation for health and energy, the literature review (2.2.2) highlighted that there is limited empirical evidence on how building occupants ventilate their homes, particularly from longitudinal measurements in occupied homes under real-life conditions (AECOM, 2012*b*; Andersen et al., 2013; Nazaroff, 2021). This research used electronic event sensors to record the time that each window and door opened and closed in seven different case studies from longitudinal monitoring campaigns of durations between 86 and 444 days.

This research adapted the occupancy status algorithm developed by Few and Elwell (2019) and Few (2021) to determine periods when each case study was occupied. From this information, it was possible to distinguish ventilation practices and ventilation configurations which occurred when each case study was occupied. This approach of focusing on occupied periods is distinct from other research and enables investigations into the conditions the occupants are exposed to, which can be linked to health. Section 5.1 in Chapter 5 presented the results for occupants' ventilation practices when each case study was occupied; below is a summary of the key findings.

The different case studies have different forms and different layouts and therefore have unique

ventilation configurations (combinations of open windows). The results show a large amount of variation in the frequency of opening, duration of opening, and amount of occupied time that windows were opened (1) within the same room of each case study, (2) across different rooms in each case study, and (3) across the different case studies. This large amount of variability is expected given the large amount of internal and external factors influencing ventilation behaviour identified in the literature review (2.2.2). This is also reflected in the questionnaire responses, where the participants reported a wide range of drivers and barriers associated with their use of windows.

Most of the participants felt that ventilation was important for health (three reported 'fairly important' and four reported 'very important'), but despite this all case studies (apart from P2) had their windows and doors closed for most of the time that they were occupied. Apart from P2, in all case studies, the windows and doors were closed for between 57% and 83% of all occupied times. There were clear seasonal differences with windows and doors closed for more of the occupied time during winter than summer - apart from P2 all windows and doors were closed for between 69% and 90% of the occupied time during the winter. Furthermore the results show that windows and doors were typically opened for short periods of time and closed more frequently during the winter than the summer. Across all case studies, 13 out of 25 windows and doors were open for statistically significantly longer during the summer than winter.

On average, windows and doors were open for the greatest cumulative amount of occupied time in bathrooms (32%), followed by kitchens (16%), bedrooms (15%), and least in living rooms (9%). Each time a window or door was opened, it was opened for the longest in bedrooms, closely followed by bathrooms, and the least in kitchens and living rooms. In three of seven case studies, bedroom windows were open for a statistically significantly shorter amount of time in the winter than the summer, suggesting that in around half of the case studies, bedroom ventilation practices are dependent on the season.

There was a poor level of agreement between participant's questionnaire responses and measurements of ventilation practices captured by event sensors. In bedrooms, only 29% of questionnaire responses agree with measurements, 46% in living rooms, and 42% in kitchens. This suggests that the survey might not be able to adequately capture the real variation of ventilation behaviours in longitudinal monitoring campaigns. Furthermore, many case studies had multiple occupants, but the questionnaire was completed by only one occupant.

6.1.2 Research question 2: What are the ventilation rates for common ventilation configurations/practices, and are homes adequately ventilated?

As outlined in the introduction to the previous section, ventilation is the exchange of air between indoors and outdoors, which can alter IEQ, modify occupants' exposures, and impact occupants' health (Wargocki, 2013; Hernandez et al., 2020; Royal College of Paediatrics and Child Health, 2020). This

association between ventilation and health underpins standards for ventilation in homes, which are reflected in guidance and regulations in the UK (CIBSE, 2015; ASHRAE, 2017; HM Government, 2021*a*). Therefore, when researching the relationship between ventilation and health, empirically estimating air exchange rates (AER) can bring important insights. Despite the importance of ventilation, the literature review highlighted a lack of empirical evidence of air exchange rates in occupied homes in the UK and how this varies with ventilation configuration and season (Few and Elwell, 2019; Royal College of Paediatrics and Child Health, 2020; Nazaroff, 2021).

Ventilation rates are often quantified in terms of air exchange rates (AER); however, there are limited appropriate methods for quantifying the variation of ventilation rates in occupied homes over extended monitoring campaigns (Few, 2021). This research collected data on the spatial and temporal variation of CO_2 inside and outside of seven case studies and used the occupancy status algorithm in conjunction with an adapted version of the metabolic CO_2 decay method developed by Few and Elwell (2019); Few (2021) to calculate the individual room and the whole house AER for each case study at the point in time when each case study became unoccupied. Section 3.2.4.3 provides a detailed description of the method and its development. Section 5.2 in Chapter 5 explored the results of AER and their relationship with ventilation practices for each case study, and below are the key findings.

The results show that opening windows and doors to the outside can have a significant impact on increasing AER, but there is substantial variation of AER both within and across the different case studies and also between whole house and individual room AER. Median whole dwelling and individual room AER were lowest when windows and doors were closed, and higher AER were experienced when windows and doors to the outside were open. However across all case studies, surprisingly the median whole dwelling AER was statistically significantly higher for only half of all ventilation configurations when one or more window or door was open relative to when all were closed. This is reflected in the median whole house AER, which was 0.25 h^{-1} (IQR = 0.19 h^{-1}) when windows and doors were closed, and with one window, this rose to 0.35h^{-1} (IQR = 0.34 h^{-1}), two windows 0.41h^{-1} (IQR = 0.46 h^{-1}), three windows 0.60h^{-1} (IQR = 0.25 h^{-1}), and with four windows open 0.84h^{-1} (IQR = 0.46 h^{-1}). This agrees with other empirical research, which found increasing AER with increasing numbers of open windows (Roulet and Scartezzini, 1987).

On the other hand, individual room AER were statistically significantly higher in 6 of 9 rooms when a window or door was open relative to when closed. For bedrooms, living rooms, and kitchens, the median individual room AER were 0.36, 0.30 and 0.26h^{-1} with windows and doors closed, rising to 0.65, 0.42 and 0.60h^{-1} when windows were open in each room. These results indicate that individual room AER were approximately double when a window was open than when closed. The results show large differences between individual room and whole house AER. These differences are smaller for case studies with lower volumes and simple geometries, and larger differences were found for case studies with multiple floors and higher volumes.

Background ventilation (infiltration rates) AER were all below the health threshold of $0.5h^{-1}$ and highly variable across the case studies. Two case studies, one that is an old and leaky dwelling and another with old timber windows and permanently open trickle vents, had the highest background ventilation rates, which were 0.39 and $0.40h^{-1}$. The most recently constructed case studies (4 of 7) were constructed after the introduction of the 1985 Building Regulations in the UK, and all of these case studies have the lowest levels of background ventilation, between 0.23 and $0.29h^{-1}$, which is less than the $0.5h^{-1}$ health threshold. Due to outdoor noise, the oldest case study (<1919) had retrofitted high performance glazing systems and also had the lowest background ventilation rate of all the case studies at $0.23h^{-1}$. Together the finding that all case studies had AER below the health threshold when windows and doors were closed, and the finding that windows and doors remained closed most of the occupied time (Section 6.1.1) suggest that the case studies might be poorly ventilated during occupied times.

In order to investigate this, a novel construct 'experienced AER' was developed, estimating the whole house AER when each case study was occupied during the summer and winter. The results of this analysis confirm that the case studies experienced AER below $0.5h^{-1}$ for large amounts of the time they were occupied. Apart from one case study (P2, 46% occupied time $< 0.5h^{-1}$), AER were less than $0.5h^{-1}$ for between 63 and 100% of the occupied periods, and this was highest during the winter (80% - 100% occupied time $< 0.5h^{-1}$). These results add to a growing body of evidence of homes in the UK with AER below $0.5h^{-1}$, and these low AER could result in an increased exposure to pollutants from indoor sources, which could impact occupants' health (Crump et al., 2005; Dimitroulopoulou et al., 2005; Fox, 2008; McKay and Ross, 2010; MHCLG, 2019).

Experienced AER was typically significantly higher in the summer than during the winter, which is likely to be due to windows and doors being opened for more of the occupied period in the summer than winter (see previous Section 6.1.2). The two case studies that opened windows and doors most of the occupied time also had higher background ventilation rates (P2 & P3). These two case studies had the highest experienced AER, which was near the health threshold of $0.5h^{-1}$ in winter (0.46 & $0.39h^{-1}$) and exceeded this in summer in one of the two cases (0.61 & $0.39h^{-1}$). On the other hand, the remaining five case studies did not open their windows for as much of the occupied time, had lower background ventilation rates, and experienced AER was below the health threshold in the winter (0.23, 0.23, 0.23, 0.27, $0.29h^{-1}$) and in most cases during the summer (0.23, 0.23, 0.28, 0.29, $0.75h^{-1}$).

6.1.3 Research question 3: What is the relationship between ventilation practices and occupants' exposure to indoor pollutants?

The response to this research question aims to present a method for understanding the relationship between the time it takes for peaks of pollutants to decay to the respective health threshold and different ventilation practices.

Most homes in the UK which were built after the introduction of the Building Regulations in 1985 have been constructed with a ventilation strategy using background ventilators and intermittent extract fans, previously referred to as System 1 in Approved Document Part F1 of the Building Regulations (HM Government, 1992, 2013; MHCLG, 2019; HM Government, 2021*a*). However, 75% of homes in Britain were constructed before these regulations were introduced, and a recent study found that 71% of homes in Britain do not have mechanical extract ventilation (bathrooms and kitchens) and trickle vents (Piddington et al., 2020; Van Rooyen and Sharpe, 2024). Similarly, in this research, four of the seven case studies did not have operational ventilation provision that met these standards. In addition to poor ventilation provision, there is a growing body of evidence of a lack of knowledge of how to ventilate homes, and the previous section (6.1.2) has also highlighted a growing body of evidence of poor ventilation rates in UK homes (Dimitroulopoulou, 2012; MHCLG, 2019; Van Rooyen and Sharpe, 2024). This combination of factors could lead to occupants being exposed to harmful indoor conditions, particularly during and after activities that release harmful pollutants indoors. Cooking is one example of a daily activity that can give rise to gaseous and particulate pollutants indoors, which can impact health, but this exposure can also be modified by ventilation (Sun and Wallace, 2021; CLASP and EPHA, 2023; Pan et al., 2024).

Section 3.2.4.5 describes the development of a method for identifying peaks in pollutant concentrations and calculating the time for these peaks to decay to their respective health thresholds. In addition to the published health threshold, a further high/low threshold was empirically derived, which classified each peak that exceeded the health threshold as a high peak or a low peak. The decay times were related to the ventilation configuration during the decay and provide a possible means of empirically deriving evidence for informing public health messaging on how long occupants should ventilate to reduce exposure to pollutant peaks. Section 5.4 in Chapter 5 explored the results of the relationship between ventilation practices and the time for peaks of pollutants to decay back to the relevant health thresholds, and below are the key findings, which together answer research question 3.

The results for decays in each case study show that, as expected, the time for high peaks of most pollutants to decay to the threshold was lower when a window was open relative to when windows were closed, including when the sources were present. These results show high variation in the decay times both within individual case studies and across different case studies, and also across the different pollutants. Two participants with open flame gas fired cookers had the greatest number of high peaks of NO_2 in their homes, particularly in the kitchens. The results also show that peaks of PM_1 took longer to decay to the health threshold than $PM_{2.5}$, and $PM_{2.5}$ took longer than PM_{10}. This is notable, as the smaller particulate matter is generally considered more harmful (WHO, 2021*b*).

When aggregating the decays from all case studies, this analysis attempts to illustrate how this method might be applied to a larger more representative sample for deriving evidence to support public health messaging - the results for this sample are therefore illustrative. When considering the high

peaks of all pollutants, the longest median decay times were for NO_2, CO_2, and PM_1, at 65, 60, and 55 minutes. A simple health message based on these results could therefore be for occupants to keep windows open for 60 minutes after carrying out activities that result in a peak of pollutants indoors. For this research, when a high or low peak of any pollutant occurred, 83% of those peaks decayed to the health threshold when a window was opened for up to 60 minutes, this reduced to 68% for 30 minutes.

6.1.4 Research question 4: Can we accurately infer window and door positions from longitudinal measurements of sound in occupied homes?

AER are dependant on the effective ventilation area, which for windows and doors is directly proportional to the amount that windows and doors are open (Dick J.B and Thomas D.A, 1951; Howard-Reed et al., 2002; Roetzel et al., 2010). Therefore, when researching the relationship between ventilation and IEQ, energy and health, measurements of how far windows and doors are open could bring additional insights.

Data on window and door positions can be collected using people (participants or researchers) or equipment / technology; however, both are subject to limitations. Using people can be labour and cost intensive, have a limited temporal resolution, and suffer from a lack of completeness and accuracy (Kukadia and White, 2006; Fox, 2008; Love and Cooper, 2015). Most technological solutions are not designed to measure intermediate/ajar positions (Dubrul, 1988; Wright et al., 2018; Few and Elwell, 2021).

Chapter 4 presents a novel method for inferring window and door positions (including ajar) from simultaneous measurements of sound inside and outside of a window and door. This method initially trains a statistical model using different frequency bins, statistical percentiles and window positions known a priori. This training phase is required to be carried out for every home in which this method is applied. Following the training, this model is then used to predict window and door positions according to the open, ajar, and closed positions. This method was tested and validated in two different occupied case study dwellings over a longitudinal campaign - an urban dwelling subject to high levels of noise and a dwelling in a quieter semi-rural setting.

A novel low cost noise measurement platform was developed specifically for this research to simultaneously measure sound inside and outside of a window or door. This device was tested against a professional grade instrument and shown to be accurate and effective for relative measurements of sound. Between 90-95% of the measurements from these devices were within ±3dB(A) of a Class 1 sound meter.

Initially, LA_{eq} was used to train linear and logistic models, which were used to predict window and door positions for each test case. These models yielded accuracies of up to 95% (logistic) in the urban test case but only 79% (logistic) in the semi-rural test case. Visual and statistical analysis of the data highlighted greater separation between the distributions (means between groups and variation

within each group) for each position when considering one-third octave bands and statistical percentiles. Following this, linear and logistic regression models were trained using five datasets, with: (1) all one third octave bands, (2) only data where LA_{eq} outdoors was greater than indoors, (3) excluding one third octave bands less than 1kHz, (4) excluding one-third octave bands below 20Hz in the semi-rural test case, and (5) using one-third octave bands selected by sequential forward feature selection (SFS).

The different model types and datasets resulted in varying levels of prediction accuracy and the highest accuracy models are reported and discussed here. For the urban case study, an overall prediction accuracy of 96% was achieved using a logistic multivariate regression model trained using all one-third octave bands from the L_5 percentile. However, 98% of ajar predictions were incorrect, where this misclassification is attributed to the lack of ajar positions in the training data (<1%) and suboptimal microphone positioning due to participant placement. For the semi rural case study, an overall prediction accuracy of 88% was achieved using a linear multivariate regression model trained using all one-third octave bands from the L_{90} and L_{95} percentiles. 75% of ajar window positions were correct. Conditional filtering as well as using sequential forward feature selection had marginal improvements to overall model performance; however, these came at the cost of reducing the number of observations, computational costs, and additional time to process the data into subsets. Given the modest increase in accuracy relative to the cost, use of all data is more appropriate for this method.

The results show that there was no single noise metric or model type that resulted in the highest prediction accuracy for both case studies. Lower percentiles resulted in the highest accuracies for the urban case study, and higher percentiles achieved the highest accuracies for the semi-rural case study. These results suggest that outdoor sound environments characterised by regular, short duration, loud noise events would work best with lower percentiles, and quieter environments without distinctive, dominant regular sounds would work best with higher percentiles. The results suggest that where there are few ajar positions in the data, the dichotomous nature of logistic models will be most appropriate, and where there are more ajar positions, linear models are more appropriate. An alternative hypothesis is that logistic models are more effective for loud, distinct sources of sound. However, when applying this method in practice, the researcher could determine the best performing combination of metric and model type during the training phase and use that for predictions.

Although the highest performing models are not 100% accurate, the method described in Chapter 5 has potential to provide insights for research where there is a need to generally understand the variation of window positions over long-term monitoring campaigns. However, given the reduced accuracy for the ajar position, this method might not be appropriate for research where a high accuracy is required for this position. Additionally, this method requires careful consideration of privacy, which was highlighted by participants in this research. Unfortunately, due to the ongoing COVID pandemic, this method was not deployed in the main monitoring campaign.

6.1.5 Research question 5: What is the magnitude and direction of change of each component of IEQ after different ventilation events?

The summaries in the previous four sections outlined that ventilation can alter IEQ and modify occupants' exposures occurring indoors, which in turn can impact occupants' health (Wargocki, 2013; Hernandez et al., 2020; Royal College of Paediatrics and Child Health, 2020). The indoor environment comprises of a number of different components, such as noise, IAQ, and temperature, and the literature review (Section 2.2.5) highlighted that these different components can change in different ways with varying ventilation practices. For example, Fan et al. (2022) reported lower CO_2, TVOC, particulate matter, temperature, and humidity after windows were opened, but Locher et al. (2018) reported higher indoor noise levels after windows were opened. Section 2.2.5.5 of the literature review highlighted that there is very limited research which consider all components of IEQ simultaneously and how the different components change together with varying ventilation practices in occupied homes in the UK.

This research collected longitudinal measurements of IEQ components identified as important for health, along with times when external windows and doors were opened and closed (events). This data was analysed to calculate the magnitude and direction of change of each IEQ variable after external windows and doors in all case studies were opened and closed. Section 5.3 in Chapter 5 explored the results of the relationship between ventilation practices and the change in each IEQ component, and below are the key findings.

The results show that the magnitude of change of all IEQ variables after external windows and doors opened and closed were highly variable both within individual case studies and across different case studies. This is expected given the wide range of internal and external factors that influence IEQ and ventilation identified in the literature review (2.2.5).

Apart from NO_2 and noise in most rooms, the indoor concentrations of most variables were higher than outdoors before windows and doors were opened. Following on from this, after occupants opened windows and doors, indoor temperature, absolute humidity, CO_2, CO, and tVOC typically reduced, and after windows and doors were closed these variables typically increased. An unexpected finding is that despite higher indoor concentrations of particulate matter before windows were opened, after occupants opened windows and doors, indoor concentrations of particulate matter increased. Additionally, after occupants closed windows and doors, particulate matter generally increased apart from $PM_{1\&2.5}$ in kitchens during the summer.

There is a negative moderate to strong association between the change in IEQ and the indoor to outdoor ratio (IOR) after windows and doors opened. This association is significant in most cases, showing that the higher the IOR before windows opened, the greater the reduction of each variable after the window was opened.

Case studies located in close proximity to roads, which is a source of both NO_2 and noise, had

higher outdoor concentrations of NO_2 and noise than indoors when windows and doors were closed. After occupants opened windows and doors, typically indoor concentrations of NO_2 and noise increased. Noise levels were generally higher after closing living room windows and doors in the summer, but lower in all rooms during the winter.

After windows were opened, indoor concentrations of tVOC reduced significantly when compared with the Building Regulations guideline. Sorbent tubes were used to collect samples of volatile organic compounds during a 2 week period in the bedroom and living room of five case studies (P1-P5). The analysis of the top 10 VOCs identified a total of 36 different chemical compounds across these five case studies. The laboratory results showed that nonanal ($C_9H_{18}O$); 1-Hexanol, 2-ethyl- ($C_8H_{18}O$); cyclopentasiloxane, decamethyl- ($C_{10}H_{30}O_5Si_5$); Hexanedioic acid, bis(2-ethylhexyl) ester ($C_{22}H_{42}O_4$), and limonene ($C_{10}H_{16}$) were identified in almost every room and also featured as chemicals with the highest (top 3) concentrations in those rooms. Concentrations of nonanal exceeded guideline values in 3 of 9 rooms, and hexanedioic acid, bis(2-ethylhexyl) ester exceeded guideline values in all 8 rooms they were identified in. The most common compounds identified are widely used in the manufacturing of many different popular household products, which presents a challenge of identifying specific sources of these compounds in homes. Despite the widespread use of these compounds, there is limited evidence of their impact on health and a lack of recognised guideline values.

6.2 Critical reflection of this research

In this research, the use of mixed methods (socio-technical) has brought about a nuanced and deeper understanding of the relationship between ventilation and IEQ. The social data has provided possible explanations for physical phenomena which would have been difficult to interpret without the social data. The value of multidisciplinary socio-technical research is widely described in the literature, but typically there are significant differences in the spatial and temporal specificity of these datasets which remain to be resolved (Love and Cooper, 2015; Behar, 2016; Lowe et al., 2018). During the early phases of this project, walk-throughs and semi-structured interviews were planned; however, the COVID pandemic prevented this from taking place. At the end of all monitoring campaigns, national COVID restrictions were eased, and the author was able to attend each case study to carry out the building surveys and to uninstall equipment. During these visits the author engaged in informal discussions with participants around (1) sources of pollutants and noise, (2) how they ventilated their homes, and (3) drivers and barriers to ventilating their homes. In a number of situations throughout this thesis, this informally obtained anecdotal information was beneficial for understanding certain phenomena, and this has highlighted the value and additional insights that walk-throughs and semi-structured interviews can bring to this type of research. However, conducting walk-throughs and interviews to a

high standard alongside the physical monitoring campaign would be very challenging within the time and budget constraints of a PhD.

The relationship between ventilation and IEQ involves many complex interactions, and the adopted case study approach enabled the careful consideration of different factors for each of these interactions (Yin, 2009). This level of detail enabled a nuanced understanding of the relationships in their real world context which would not have been possible with a larger sample within the time constraints (Flyvbjerg, 2006). The limited purposive sample in this research means that the results are not representative of the wider population, but the methods and results can be used to inform research for a larger sample, and this thesis highlights issues of concern.

The COVID pandemic introduced a number of significant challenges described earlier in this thesis, but also brought about opportunities. One notable contribution, which was an unexpected outcome of the pandemic, is that this project has demonstrated that it is possible to conduct detailed ventilation and IEQ monitoring projects using complex equipment entirely remotely using the postal service. Due to the substantial participant burden associated with the detailed monitoring campaign, different technical solutions may be necessary when deploying a detailed campaign in a sample involving the general public. The pandemic prevented this research from implementing the method developed for inferring window and door positions from sound measurements, described in Chapter 4. Additionally, due to the pandemic, this research used a convenience sample of people from the built environment and public health sectors, which could bias behaviours and questionnaire responses. Due to national lockdowns, participants remained in their homes for extended periods, only left their homes infrequently and for short periods of time. Tahmasebi et al. (2022) reported that participants (n=8) opened windows for much shorter periods of time during the lockdown and so, although there might have been changes to duration of occupancy, window opening, and activities, there are other factors which would have likely remained unchanged (e.g., physical provision, performance of ventilation, behavioural factors, and AER) and it was necessary to interpret the data in this context.

There were a number of challenges working with the various types of equipment. Suitably precise and accurate IEQ monitoring equipment is costly, which limited the sample size and extent of the monitoring campaigns in this research - for example, there was only a single outdoor monitor for IAQ and noise (apart from noise at P2) at each property, where ideally there would have been multiple. Additionally, there were a limited number of event sensors, which resulted in a limited number of measurements for internal doors. Reflecting critically on the monitoring campaign, it might have been possible to reduce the number of case studies and instead monitor more window and door events and more indoor and outdoor locations. However, this would have increased the intrusiveness of the campaign, and reducing the number of case studies would have led to a reduced opportunity to understand different homes, occupants, and locations.

Section 5.5 highlighted that even with detailed monitoring, it was not possible to capture data for

certain behaviours in real occupied homes - for example, most participants did not leave windows open when not in their home and did not change internal door positions frequently. Researchers can request that participants carry out specific practices, which might be acceptable to the participants, and in this case, the opportunity to provide further insights.

IEQ monitoring equipment is challenging to setup and operate in a way that produces reliable measurements - this required careful preparation and familiarity with all equipment, particularly for the remote campaigns. In addition to this, the equipment has many different sensors, which can be costly and time consuming to calibrate - calibration of all sensors was not possible in this research, and carefully considered cross-referencing was used instead. Cross-checking field equipment with reference equipment is also time consuming and challenging, most specifically obtaining suitable, calibrated, reference grade equipment for all variables. During the campaigns, a number of sensors failed, lost their calibration, or drifted significantly, and there are specific idiosyncratic challenges when working with different sensors, identifying these problems, and resolving them. Despite these challenges, this research collected a large quality dataset, which will be publicly shared for other researchers to use, and further analysis is planned for this dataset in the future.

6.3 Conclusion

Buildings and their occupants combine to form complex socio-technical systems, where ventilation arises from the interaction of human actors with the building infrastructure (Fabi et al., 2012; Lowe et al., 2018). This interaction can be motivated and influenced by a vast number of different internal and external factors which interact in complex ways, examples of these factors include: cultural, socioeconomic, physiological, and environmental factors (Fabi et al., 2012; Day et al., 2020). Ventilation behaviour has the potential to influence occupants' comfort and health, but also building energy consumption, carbon emissions, and its associated impact on climate change - this places ventilation at the nexus of energy, health and the climate (Wargocki, 2013; CIBSE, 2015; WHO, 2018*b*; CMO, 2022; Zhang, 2023). Because of this socio-technical system and the expansive impacts, ventilation intersects a wide range of fields, including public health, physics, architecture, chemistry, urban planning, climate research, and environmental design (Sundell, 2017). This research used an empirical, mixed methods, multi-case study research design, with the aim of developing a detailed understanding of how occupants ventilated their homes, how those practices were related to AER and IEQ, understanding how ventilation is related to exposure of peaks of harmful components of IEQ, and to develop a framework for informing ventilation advice with the overall aim of reducing harm associated with exposure to harmful peaks of pollutants.

Air exchange rates and indoor noise levels are directly influenced by the amount that a window or

door is open, and therefore the amount that a window or door is open modifies occupants' exposure to IEQ (Dick J.B and Thomas D.A, 1951; Howard-Reed et al., 2002; Locher et al., 2018). An understanding of the temporal variation of window and door positions brings potential insights to research that is concerned with the relationship between ventilation and health (Few, 2021). However, there are very limited methods available to researchers for measuring the intermediate position of windows and doors during long-term monitoring campaigns in occupied homes (Few and Elwell, 2019; Andersen et al., 2013). The first part of this thesis presents a novel method of determining if a window is open, ajar, or closed from simultaneous measurements of sound inside and outside a dwelling. The method is designed for long-term monitoring campaigns in occupied dwellings. Additionally, this method provides a detailed time history of sound measurements, where sound is a key element of IEQ due to its direct impact on health (CMO, 2017; WHO, 2018*a*; Gong et al., 2022; Jephcote et al., 2023), associations with the wider determinants of health (Peris, 2020), and the modifying effect on occupants' ventilation behaviours (Andersen et al., 2009; Eze et al., 2017; Notley et al., 2014). A bespoke sound measurement platform was designed and constructed specifically for this task, which has two microphones that continuously measure sound data inside and outside of a window or door and process this data into standard statistical and frequency metrics. A trained machine learning algorithm classifies each 5-minute interval as open, ajar, or closed. This method was tested in two different case studies - one in a 'noisy' urban location and another in a 'quieter' semi-rural location. The method predicted window and door positions with accuracies between 88% (quieter location) and 96% (noisier location). This method can be used to generally understand the variation of window positions in long-term monitoring campaigns, but might not be suitable for research which requires high accuracy.

Ventilation is the movement of air between indoors and outdoors (HM Government, 2021*a*). As mentioned in the introduction, this air movement can alter indoor temperatures, IAQ, and noise, which can in turn impact energy use, occupants' comfort, exposure, and health (Wargocki, 2013; CIBSE, 2015; WHO, 2018*b*). When researching the relationship between ventilation and health, an understanding of actual ventilation practices and their relationship with experienced indoor conditions can bring important insights. However, there is limited evidence of ventilation practices and AER in occupied homes and its relationship with the various component parts of IEQ that impact health. The second part of this research explored ventilation practices, air exchange rates, and the change in concentration of IEQ components and pollutant peaks with different ventilation practices.

The results showed that each case study had unique ventilation configurations, and there was high variability in the frequency, duration, and amount of occupied time that different windows and doors were open across the case studies. This large variability could be due to differences in the many internal and external factors influencing ventilation behaviour (Fabi et al., 2012). Empirical research by Dubrul (1988); Van Dongen and Phaff (1989); Iwashita and Akasaka (1997); Kukadia and White (2006); Andersen et al. (2013); Taylor, Mavrogianni, Davies, Das, Shrubsole, Biddulph and Oikonomou

(2015); and the literature review by Roetzel et al. (2010) have all reported wide variation in ventilation behaviours. For most case studies, all windows and doors were found to be closed for most of the occupied time, and this was highest during the winter. Windows and doors were typically opened for longer in the summer than in the winter, but not necessarily more frequently. Morgan et al. (2017) and Wang et al. (2022) also reported windows were closed most of the time, and the seasonal variation of ventilation behaviour agrees with a large body of literature (See Section 2.2.2.3). There was poor agreement between participants' reported ventilation practices and measured practices. This suggests that a single survey might not be able to adequately capture the real variation of ventilation behaviours in homes with multiple occupants for longitudinal monitoring campaigns.

The calculated AER for the case studies were highly variable, both within individual case studies and across different case studies. As expected, whole dwelling AER were lowest when windows and doors were closed (median $0.25h^{-1}$) and increased with the number of windows and doors that were opened. Apart from one case study, background ventilation rates were highest in homes built before the introduction of the Building regulations (0.39 - 0.40 $^{-1}$) and lower in homes constructed after this (0.23 to 0.29^{-1}). There were large differences between the calculated individual room and whole dwelling AER, particularly for dwellings with a larger internal volume and complex geometry. Individual room AER were found to be approximately twice as high as when the window in that room was closed. However, analysis of the average AER included unoccupied periods does not accurately reflect conditions experienced by the occupants, and so a construct 'experienced AER' was introduced, which estimated the average whole house AER during occupied times only. This showed that six of the seven case studies had AER below the commonly cited health threshold of $0.5h^{-1}$ (Wargocki et al., 2002; Sundell et al., 2011; Dimitroulopoulou, 2012) for between 63 and 100% of all occupied periods and between 80 and 100% of occupied periods during the winter. This shows that most of the homes had AER below commonly accepted healthy levels for most of the time they were occupied, which adds to a growing body of evidence of homes in the UK that have AER below $0.5h^{-1}$ (Crump et al., 2005; Aizlewood and Dimitroulopoulou, 2006). The growing evidence of poor ventilation rates highlights the need for further empirical research into ventilation and IEQ in UK homes at scale to better understand the indoor conditions that occupants are exposed to. The experienced AER also showed statistically significantly higher AER during the summer relative to the winter, which aligns with other research reporting higher AER during the summer (Crump et al., 2005; Fabi et al., 2012).

This research calculated the magnitude and direction of change of the individual components of IEQ after windows and doors were opened and closed. This analysis found the indoor concentrations of most variables were higher than outdoors before windows and doors were opened, apart from NO_2 and noise. After occupants opened windows and doors, indoor temperature, absolute humidity, CO_2, CO, and tVOC typically reduced, and after windows and doors were closed these variables typically increased. Unexpectedly, despite higher indoor concentrations of particulate matter, after occupants

opened windows and doors, indoor concentrations of particulate matter increased. Typically, the higher the indoor to outdoor ratio before windows opened, the greater the reduction of each variable after the window was opened. Participants located near roads typically experienced an increase in indoor noise and NO_2 after windows were opened.

The final part of this research presented a method for informing ventilation advice, and the illustrative results provided complementary insights to the previous analyses. The final analysis considered the relationship between ventilation practices and the time for peaks of pollutants to decay back to their respective health thresholds. The results show that as expected, when a window was open, the time for high peaks to decay to the threshold was lower than when the windows were closed. However, no data was collected on the activities of the occupants or sources of pollutants, so this analysis was unable to determine the temporal variation of pollutants and their impact on the decay times. As such, the analysis includes times when sources might still be active, and this presents these decay times in the context of a real occupied home. This analysis suggests that occupants can substantially reduce their exposure during peaks by opening windows. When aggregating the decays of high peaks, the longest median decay times were for NO_2, CO_2, and PM_1, at 65, 60, and 55 minutes. Therefore, for this sample, occupants could be advised to open windows for 60 minutes when undertaking activities that may release pollutants indoors. When a high or low peak of any pollutant occurred, 83% of those peaks decayed to the health threshold when a window was opened for up to 60 minutes.

This thesis provides detailed empirically derived insights on actual ventilation practices and their relationship with conditions in occupied homes. The analysis identifies real conditions and contrasts this across homes, highlighting a large amount of variation in occupants' ventilation practices, air exchange rates, changes in IEQ with different practices, and decay times for peaks of different pollutants within each case study and also across the different case studies. This variation informs us of the challenge of generalisation of ventilation and its impact on IEQ, exposure, and health. Furthermore, the large variation in the way that buildings in the UK are built, occupied, used, and ventilated highlights the complex nature of research into ventilation, IEQ, energy, and health and underpins the challenge of deriving relevant policy to protect the health of the population whilst also conserving energy and protecting the environment (Lewis et al., 2023). Results of this research highlight the importance of occupants' ventilation practices on ventilation rates in homes. The results also highlight the importance of occupants' ventilation practices on indoor pollutants and its potential impact on exposure and health. The methods and results presented in this thesis can contribute towards informing public health messaging on ventilation and the wider research field of ventilation and IEQ. The dataset and results provide evidence to support changes to policy and practice, with the ultimate aim of protecting the health of occupants and reducing harm in the population now and into the future.

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A | Information sheet

Participant Information Sheet For Adults

Title of Study:
The relationship between ventilation practices and air quality, overheating and noise.
Department:
BSEER Energy Institute.
Name and Contact Details of the Researcher(s):
Cairan Alexander Van Rooyen 07887330540 cairan.rooyen.18@ucl.ac.uk
Name and Contact Details of the Principal Researcher:
Dr Cliff Elwell clifford.elwell@ucl.ac.uk

1. Invitation Paragraph

You are being invited to take part in a PhD research project. Before you decide it is important for you to understand why the research is being done and what your participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

Thank you for reading this.

2. What is the project's purpose?

Ventilation is an important determinant of the quality of the indoor environment and has an important role in determining your health and well-being. Ventilation practices directly impact your exposure to overheating, indoor and outdoor air pollutants and noise from outside your home.

This study aims to understand occupants' ventilation behaviour and how this impacts the quality of the internal environment.

This PhD project is being completed over 3 years.

3. Why have I been chosen?

I am seeking up to 4 occupied domestic buildings to monitor for this project. It is important for this research that your home is in a location with a noisy external environment and has possible sources of air pollution outdoors, such as a busy road.

4. Do I have to take part?

It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep (and be asked to sign a consent form). You can withdraw at any time without giving a reason and without it affecting any benefits that you are entitled to. If you decide to withdraw you will be asked what you wish to happen to the data you have provided up that point.

5. What will happen to me if I take part?

It would involve having a device measuring the indoor environment, including the following: temperature, humidity, carbon dioxide, carbon monoxide, volatile organic compounds, fine particulate matter and nitrogen dioxide in the kitchen, living room and one outside your house.

In the bedroom(s) of your house an instrument will measure, temperature, humidity and carbon dioxide. In the bathroom(s) of your house an instrument will measure temperature and humidity.

On all of your internal and external doors, windows and mechanical ventilation systems: small instruments will monitor when a door/window/ventilation system is opened or operated.

In order to understand noise indoors and outdoors, a further instrument will be installed that will measure noise externally and internally in your living room. This device measures sound pressure levels and only the difference between inside and outside, it does not record sound or audio and there is no way to make the sound pressure levels intelligible!

To mitigate any potential risk of spreading COVID, all devices will be couriered to your home, for you to install yourself. Purpose made Youtube videos will be provided to run through the complete installation of each item of equipment. In addition, the researchers will be available by mobile phone or online video conference platform (Zoom or Teams) to run through the installation of the equipment and work through any issues you might have.

All sensors should be placed on shelves or tables or attached to the wall using Command strips. It is very unlikely, but possible, that the Command strips could cause a small amount of damage to the wall when they are removed.

In all cases, there are several constraints on where the monitors can be placed, but you can refuse the suggested placement of any sensors. Once the sensors are in place they should not be moved for the duration of the study, however, please contact me if they are causing an inconvenience and we can discuss moving them or removing them from your property.

The equipment would take up to two hours to install and a further hour to remove at the end of the project. Following this, occasionally (every two months) we would ask for you to download the data from the monitors, this would take less than 30 minutes. The equipment would be in place for between 9 and 12 months.

We would ask that you share photographs of your home and the final installation of the sensors, but these would not include personal effects unless you agree that this is acceptable (curtains, cushions, furniture etc.), and photographs from which your house could be identified will not be taken (street signs, door number etc.). You will share only photographs that you are comfortable sharing with us.

After the initial installation of the equipment, we will provide an online questionnaire for you to complete. This questionnaire will be to find out more about you, the household, opinions of your home and how you use it. There might be one or two short (up to an hour each) follow up interviews / virtual walkthroughs completed online or over the telephone, one during the summer and the final one during the winter – these follow up interviews will be to discuss how you are ventilating your home.

6. What are the possible disadvantages and risks of taking part?

The loggers will take up some space in your home. There will be one in the living room, bedroom(s), bathroom(s) and kitchen. The loggers in the living room, kitchen and outside need to be plugged in, so will take up some of your power sockets – we will provide power extension cables. The noise monitoring equipment takes up some space, this will need to be placed somewhere where it cannot be knocked or damaged. Similarly, externally, there will be a microphone installed (with a suction cup), which takes a small amount of space.

You will be reimbursed by gift voucher for the cost of the electricity that the equipment consumes. The equipment consumes only a very small amount, which will total approximately £20 over a full year.

7. What are the possible benefits of taking part?

At the end of the project I will provide you with a plain English summary of the findings, along with the final PhD dissertation if you would like to see it. I would also be available to discuss the findings with you in as much detail as you would like.

This research employs comprehensive, high quality scientific instruments, which will enable us to quantify (in great detail) the quality of the indoor environment of your home and from this we can understand any potential health related risks to you and any other occupants. This will allow us to identify possible ways to improve the indoor environment to better protect the health and wellbeing of you and any other occupants.

By participating, you will be contributing towards and shaping research in this very important field. Your participation will provide empirical data that can support change to national policy that can protect the health and wellbeing of other people.

8. What if something goes wrong?

If this study has harmed you in any way or if you wish to make a complaint about the conduct of the study you can contact UCL using the details below for further advice and information:

Dr. Cliff Elwell, Central House, 14 Upper Woburn Pl, Bloomsbury, London WC1H 0NN
Phone: +44 (0)20 3108 5975
Email: Clifford.elwell@ucl.ac.uk

If you feel that your complaint has not been handled satisfactorily by the above, you can contact the Chair of the UCL Research Ethics Committee – ethics@ucl.ac.uk

9. Will my taking part in this project be kept confidential?

All the information that we collect about you during the course of the research will be kept strictly confidential. You will not be able to be identified in any ensuing reports or publications.

10. What will happen to the results of the research project?

The results of the study will be published in an PhD thesis in 2022. The results will be further discussed in a PhD viva in 2022.

It is hoped that the results of the research will be disseminated in academic journal papers throughout the following 2 years. Furthermore, it is hoped that the results of the research will be discussed with other academics, professionals and policy advisors at conferences throughout the following 2 years.

The anonymised data collected during the course of the project might be used for additional or subsequent research. Personal data will be deleted after the 2 years.

Anonymised technical and social data will be retained on the secure UCL servers for other researchers to use after completion of this research project. None of the data will be shared or transferred outside of the EEA.

11. Local Data Protection Privacy Notice

Notice:
The controller for this project will be University College London (UCL). The UCL Data Protection Officer provides oversight of UCL activities involving the processing of personal data, and can be contacted at data-protection@ucl.ac.uk

This 'local' privacy notice sets out the information that applies to this particular study. Further information on how UCL uses participant information can be found in our 'general' privacy notice:

For participants in research studies, click here

The information that is required to be provided to participants under data protection legislation (GDPR and DPA 2018) is provided across both the 'local' and 'general' privacy notices.

The categories of personal data used will be as follows:

Name
Address
Telephone number

The lawful basis that will be used to process your *personal data* are: 'Public task' for personal data.

Your personal data will be processed so long as it is required for the research project. If we are able to anonymise or pseudonymise the personal data you provide we will undertake this, and will endeavour to minimise the processing of personal data wherever possible.

If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact UCL in the first instance at data-protection@ucl.ac.uk.

12. Who is organising and funding the research?

The research is funded by The Engineering and Physical Sciences Research Council (EPSRC) and Public Health England.

13. COVID-19 Information

Coronavirus disease (COVID-19) is an infectious disease caused by a newly discovered coronavirus, SARS-CoV-2. The virus spreads primarily through droplets of saliva or discharge from the nose

when an infected person coughs or sneezes. Droplets fall on people in the vicinity and can be directly inhaled or picked up on the hands and transferred when someone touches their face.

This short information sheet provides brief details of the extensive measures employed by the research team to prevent the transmission of COVID-19 and to protect the researchers, you and anyone else in your home. This research involves a researcher posting monitoring equipment to your home, for you to install yourself and to regularly provide data from the instruments to the researcher. On completion of the monitoring, you will uninstall the equipment and return by post/courier.

a. The research team will ensure that no individuals who would be defined by the NHS as high risk (clinically extremely vulnerable) are included in the research. We will ask you to carry out a self-assessment of your household.
b. All monitoring equipment will be thoroughly and carefully disinfected prior to posting to your home.
c. When the equipment is received, it will be quarantined by you, to reduce any risk of spreading the virus.
d. The research team will monitor the risk associated with monitoring every two weeks and make any changes that might be required and you will be informed of any changes. In addition, the research team will regularly monitor an internal UCL portal, providing up-to-date information on COVID and any impacts on this type of monitoring.

14. Contact for further information

Please contact me if you require any further information:

Cairan Van Rooyen
Cairan.rooyen.18@ucl.ac.uk

If you decide to participate, you will be given a copy of the information sheet and the signed consent form to keep.

Thank you for reading this information sheet and for considering to take part in this research study.

B | Installation instructions

Installation instructions for participants.

Research project title:

The relationship between ventilation practices, indoor air quality, noise and overheating, and their impact on health.

Authors:

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Revision history:

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Revision 2	04.05.2021	Sorbent tubes added

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Chapter 1

Introduction.

Thank you for agreeing to taking part in this research joint-funded by PHE and UCL.

This document provides background information on this research project and instructions for participants on installing equipment. Due to the current COVID-19 pandemic, the technical monitoring campaign is being conducted entirely remotely, with no site visits by researchers.

Before installing equipment, please read the risk assessment in appendix A on page 23.

Please ensure you safeguard your safety at all times when installing the equipment, particularly the outdoor equipment.

DO NOT lean out of windows.

DO make sure both your feet remain firmly on the ground at all times when securing equipment.

DO make sure that cables do not present a trip hazard. If necessary, secure with tape (supplied).

DO inform the UCL researcher if any equipment is damaged or stolen.

If you are unsure about anything, please contact the researcher using the supplied contact details.

1.1 Research aim.

The aim of this research is to investigate the relationship between occupant ventilation practices and Indoor Environmental Quality (IEQ) factors, including: overheating, indoor air quality and noise and relate this to health thresholds and guidance.

Chapter 2

Receiving and quarantining equipment.

Prior to packaging and posting the equipment, all equipment was thoroughly and carefully cleaned and disinfected.

When the box containing the equipment arrives at your home, please handle using appropriate personal protective equipment (gloves and mask) to protect yourself from any potential viral particles that might be present on the outer surfaces of the box from its transport by courier.

Please quarantine the box in your home for a period of 7 days before opening the box. Following the 7 day quarantine of the equipment, it is not necessary to use any personal protective equipment when handling and installing the equipment.



(a) Disinfection prior to packaging and boxing.



(b) Wipes used for viral disinfection of equipment.

Figure 2.1: Disinfection prior to sending equipment.

Chapter 3

Unboxing and identification.

After the quarantine period, please open the box and unpack all the equipment from the bubble wrapping. Please take care, some equipment have fragile antennae. Figures 3.1, 3.2, 3.3 and 3.4 below provides names for each of the items of equipment for identification purposes.



(a) Eltek AQ110A transmitter.



(b) Eltek GD47AC transmitter.



(c) Eltek AQ outdoor enclosure (with AQ110A inside) and ribbon power cable coiled below.

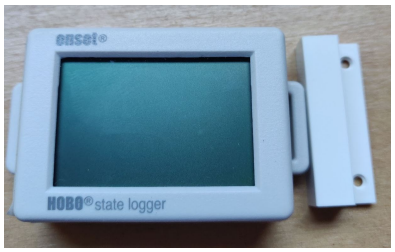


(d) Eltek MP12U 12V power supply.



(e) Eltek Squirrel SRV250 logger - TX aerial (left), GPRS aerial (right) and M2M SIM card.

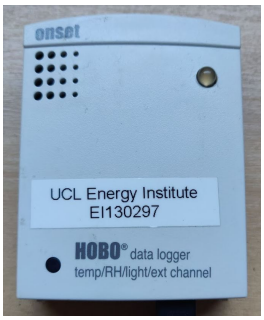
Figure 3.1: Photographs of Eltek equipment.



(a) Onset UX90-001M event sensor/logger and magnet (right hand side).



(b) Onset MX1102 sensor/logger.



(c) Onset U12-012 sensor/logger.

Figure 3.2: Photographs of Onset equipment



(a) Indoor microphone.



(b) Noise equipment power supply unit.



(c) Noise measurement 'main unit'.



(d) Outdoor microphone.

Figure 3.3: Photographs of noise equipment



Figure 3.4: Screwdriver, tape measure, USB cable, ‘duct tape’, cable ties and Command Strips

When all the equipment has been unboxed, please follow the installation instructions in chapters 4, 5 and 6.

Chapter 4

Installing the Eltek equipment.

The instructions below pertain to the Eltek equipment shown in figure 3.1. If you want more information on what these instruments are measuring and technical information on the instruments, please refer to the reference information document, which was issued separately to you - you dont need to read this if you aren't interested.

1. Gently screw (finger tight) the TX aerial (long unlabelled) into the TX adapter (left adapter) on the SRV250 (figure 3.1e) and the GPRS aerial (short and labelled as GPRS) into the GPRS adapter (right adapter).
2. Locate the SRV250 (figure 3.1e) near an outside wall of your home, ideally near a window, to obtain a good GPRS (phone) signal.
3. Plug in the SRV250 with one of the MP12U power supply plugs (figure 3.1d) and turn the power on.
4. Locate the outdoor AQ110A enclosure (figure 3.1c) outside your home - ideally on the side of your home that is exposed to noise/pollution - please discuss and agree the location with the UCL researcher prior to installation. This enclosure must be supported in the vertical plane and should be securely affixed to something suitable (balcony balustrading for example) - it should not 'lie down' flat, as water can ingress the casing and damage the equipment - see figure 4.1b. The enclosure can be fixed in place with the supplied cable ties. The outdoor transmitter is supplied with a flat ribbon cable, to enable you to pass this cable through doors/windows. This cable can be bent into shape to fit through high performance glazing systems - see figure 4.1a. Please use the duct tape to secure any cables in place.
5. Plug in the outdoor transmitter inside your home (female end of the ribbon cable) with one of the MP12U power supply plugs (figure 3.1d) and turn the power on.
6. The two remaining AQ110A transmitters will need to be installed in your living room and kitchen (labelled with sticky/Post it labels accordingly). Please follow the guidance below (4.1) regarding locating these devices.
7. Plug in the AQ110A transmitters with the MP12U power supply plugs (figure 3.1d) and turn the power on.
8. The remaining GD47AC transmitters (3.1b) are to be installed in your bedrooms. Please follow the guidance given below regarding locating these devices.
9. Plug in the GD47AC transmitters with the MP12U power supply plugs (figure 3.1d) and turn the power on.



(a) Ribbon cable installed through a modern high performance window, providing power to the outdoor AQ110A transmitter - this cable can be taped both inside and outside the window.



(b) AQ110A outdoor enclosure fixed to a post using the supplied cable ties.



(c) Right hand side of AQ110A transmitter showing the inlets top and bottom - do not cover these.



(d) Left hand side of AQ110A transmitter showing the air outlet at the top - do not cover this.

Figure 4.1: Installation figures for Eltek equipment

4.1 Guidance for locating air quality sensors/transmitters:

DO:

1. place the sensors on internal walls or on furniture at a height of between 0.8m and 1.8m (if possible) (Andersen et al. 2013, Baborska-Narożny et al. 2017);
2. lay the AQ110A (figure 3.1a) transmitters flat if necessary;
3. use the supplied duct tape to secure cables to the floor/walls/windows to ensure that cables are not a trip hazard;

DO NOT:

1. place the sensors in direct sunlight (Andersen et al. 2013, Baborska-Narożny et al. 2017);
2. place the sensors near sources of heat (radiators, cookers, TV or other large electronic appliaces) or cooling (air conditioning or fans) - locate more than 1m from heat/cool sources (Andersen et al. 2013, Baborska-Narożny et al. 2017);
3. place the sensors immediately adjacent to where occupants are located most of the time in each room - locate sensors at least 2m from beds, seating, sofas etc (Persily 1997);
4. place the sensors immediately adjacent to openable windows/doors to the outside - locate sensors deeper into the room;
5. place the sensors immediately adjacent to cookers or sources of air contaminants;
6. place the AQ110A transmitters (figure 3.1a) on their side or in a way that blocks the mesh inlets/outlets on the sides - see figures 4.1c and 4.1d;

If you have any questions/concerns - please ask!

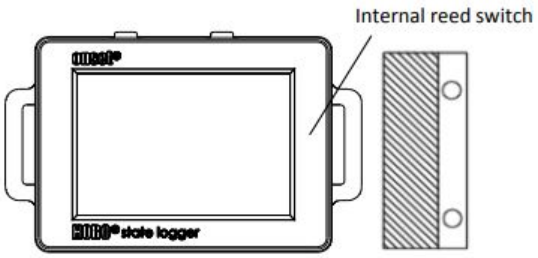
Chapter 5

Installing the ONSET equipment.

The instructions below pertain to the Onset equipment shown in figure 3.2. If you want more information on what these instruments are measuring and technical information on the instruments, please refer to the reference information document, which was issued separately to you - you dont need to read this if you aren't interested.

5.1 Installing the event sensors (UX90-001M) on windows and doors.

1. Attach Command strips to both the logger and the magnet (the logger is the device on the left with the LCD screen in figure 3.2a and the magnet is the smaller white plastic rectangular box on the right) and trim any excess from the Command strips - see figures 5.1c and 5.1d.
2. Attach a logger and magnet combination to the inside of each window and door in your home, following the procedure described below:
3. Attach the logger to the window or door frame and the magnet to the window or door itself. The magnet must be positioned as close as possible to the right hand side of the logger, as shown in figures 5.1a and 5.1f.
4. Confirm correct operation - When the window/door is closed, the LCD will display a closed indicator and when the window/door is open, the LCD will display an open indicator (see figure 5.1b showing the open indicator).



(a) State logger and magnet positioning (Onset Computer Corporation 2021).



(b) State logger LCD screen showing the open indicator (Onset Computer Corporation 2021).



(c) Attaching Command strips to the event sensors.



(d) Trim the Command strips on the event sensors.



(e) State logger installed on an open window.



(f) State logger installed on a closed window.

Figure 5.1: Installation figures for Onset UX90-001M state loggers

5.2 Installing the Onset battery powered sensors/loggers (MX1102 and U12-012).

1. Each logger has the room it is intended for marked on it with a sticky label/Post-it note.
2. Identify a suitable installation location in accordance with the guidance given in section 4.1 on page 9.
3. Attach Command strips to the rear of the loggers if necessary.
4. Position the loggers accordingly.

Chapter 6

Installing the noise equipment.

The purpose of this equipment is to measure simultaneous indoor and outdoor noise levels. Note: The equipment does not store audio recordings. It stores sets of numbers corresponding to noise levels at five-minute intervals. If you have any concerns, please speak to the research team - see contact details on the cover page.

The equipment consists of a main unit, an outdoor microphone with a large foam cover, an indoor microphone with a small foam cover, and a mains power supply (see figure 6.1). There are three inputs on one side of the main unit, which are clearly labelled (see figure 6.2). On the opposite side is a yellow button. The unit has an inbuilt 3G dongle to allow data to be sent to the research team automatically. No connection to your Wi-Fi is required.

1. Locate an appropriate window/door in your main living space, that is normally used for ventilation and/or cooling (e.g. opened on a sunny day) if necessary discuss the best choice with the research team.
2. The outdoor microphone (figure 3.3d) is designed to be attached to the outside of a window. It has a suction base with a simple twist lock mechanism. The large foam cover protects the microphone from the weather. Attach the outdoor microphone to the outside of the window - see figures 6.4 and 6.5 below. When attaching the suction base, both the base and the window must be clean and dry. This is important to ensure that the microphone will remain attached in all weather conditions incl. high wind, heavy rain and very hot temperatures. Carefully route the cable to the inside, use the provided silver tape to secure to window frame. This video shows how to use the twist lock mechanism: https://youtu.be/mh42PUH4ny0?t=96. **DO NOT lean out of windows. DO make sure both your feet remain firmly on the ground at all times when securing the outdoor microphone.** When positioning the outdoor microphone, please consider cable lengths for when the window opens and if there are any obstructions that the microphones might collide with when the window opens.
3. The indoor microphone (figure 3.3a) is designed to be attached either to the inside of the same window, or to the window reveal. Attach the indoor microphone to the window reveal using the supplied Command Strips, which can be removed without damaging surfaces. See figure 6.6 below for suggested mic positions. If the window opens inwards, please make sure that the indoor microphone does not interfere with the window movement. This video shows you how to use the 3M Command strips: https://youtu.be/HJ9RZt0_qMk?t=25
4. Place the main unit (figure 3.3c) on the window ledge (if sufficiently deep), or on the floor in a safe location. Please ensure the yellow button is not being pressed (for example if the unit is placed on its side).
5. Plug both microphone cables into the main unit, noting the labelling (in/out). Both microphones connect to the main unit via thin, flexible cable, terminated with locking 3-pin plugs. When

plugging in please make sure that the black pin on the plug is pointing upwards (see figure 6.3). To unplug: press the black pin in whilst gently pulling out.

6. Plug the power supply to the main unit and to mains. Switch on mains.
7. Press the yellow button firmly for 4 seconds and release.
8. To make the equipment as unobtrusive as possible there are no visible indicator lights or audible alerts when the system turns on. Once installed you can then let the research team know, so that they can remotely check and confirm that the system is operating properly.

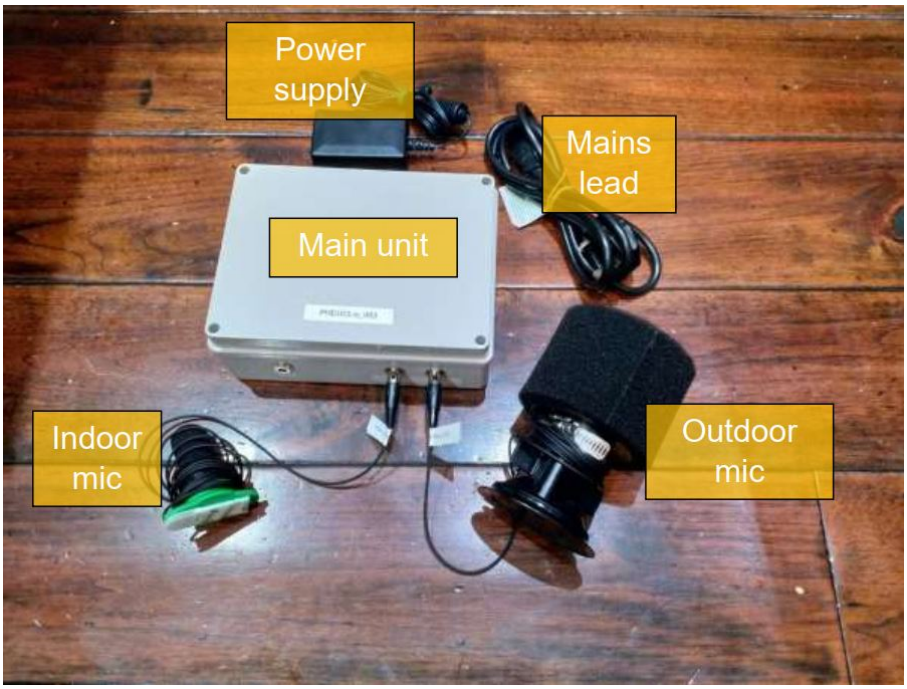


Figure 6.1: Overview of noise equipment (Fenech 2020).



Figure 6.2: Power input and microphone inputs on one side of the main unit and the yellow power button on the other side (Fenech 2020).



Figure 6.3: Black pin facing upwards on the microphone inputs (Fenech 2020).

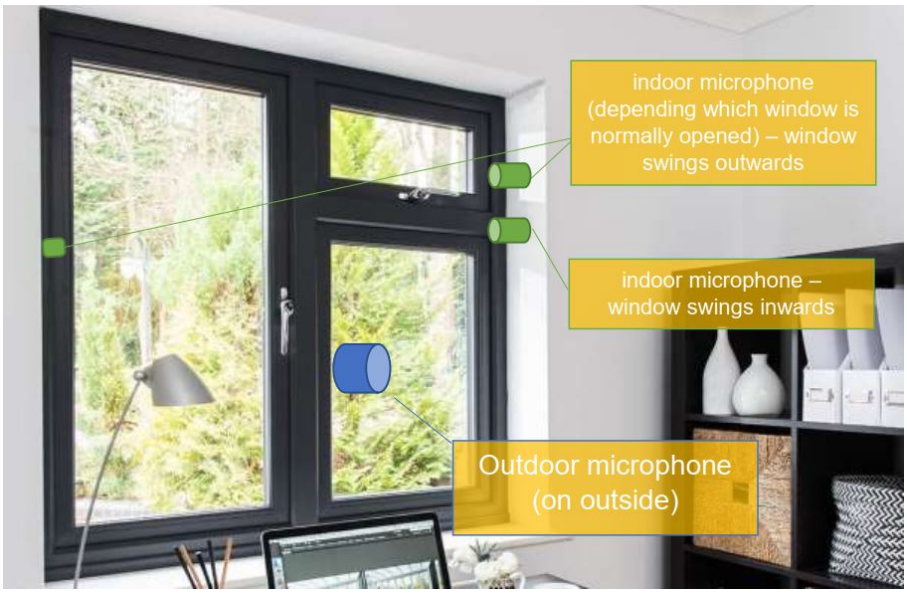


Figure 6.4: Suggested microphone locations (Fenech 2020).



Figure 6.5: Outdoor microphone location for sash window (Fenech 2020).



Figure 6.6: Suggested indoor microphone locations (Fenech 2020).

Chapter 7

Installing the sorbent tubes.

The purpose of this equipment is to passively collect samples of volatile organic compounds (VOCs) that are present in your home over a period of two weeks. Once the samples have been collected, they are sent to a laboratory to carry out specialised analysis to identify the top 10 VOCs that were collected over the sampling period. Further details of how the tubes and analysis work can be found in the supporting Reference Information document.

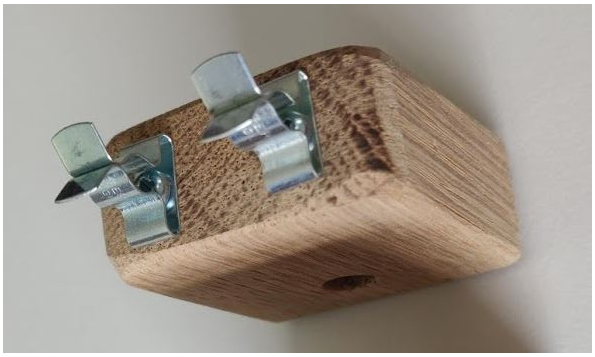
Photos are provided for identification of all of the equipment below in figure 7.1 and installation figures in figure 7.2.



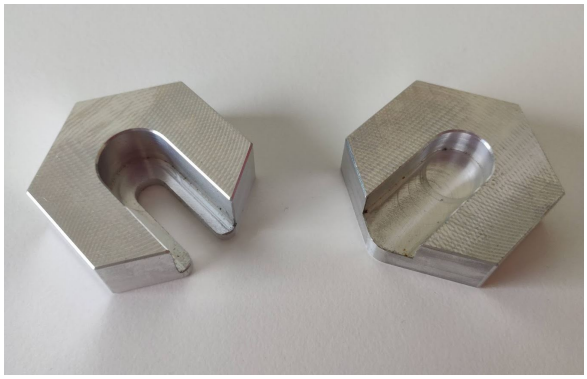
(a) Diffuser cap for sorbent tube.



(b) Sorbent tube.

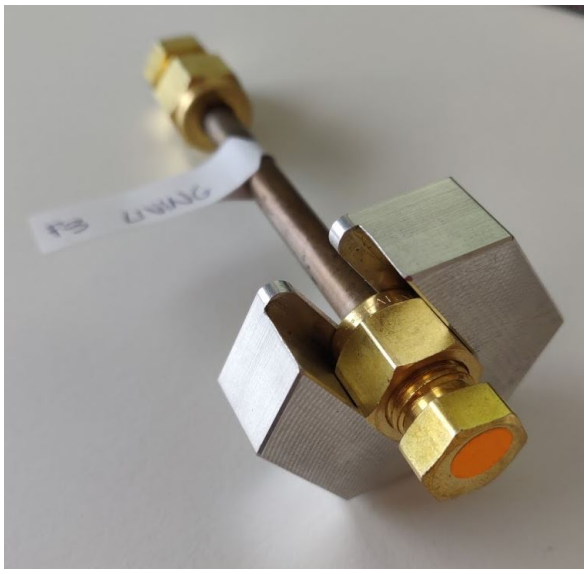


(c) Wooden spacer and clip for sorbent tube.

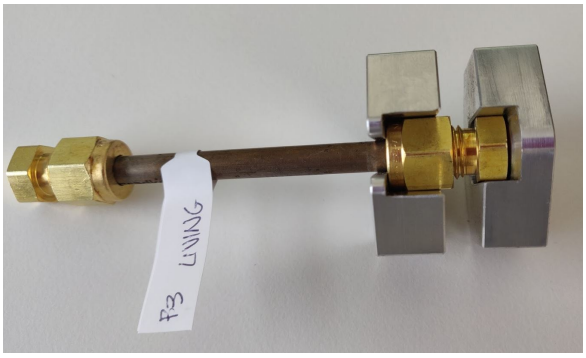


(d) Tubelock tool.

Figure 7.1: Identification figures for sorbent tubes



(a) Opening the sorbent tube with tubelock tool - part 1.



(b) Opening the sorbent tube with tubelock tool - part 2.



(c) Sorbent tube installed (Gradko ND).

Figure 7.2: Installation figures for sorbent tubes

1. Store in a dark place away from heat before exposure.
2. Identify the end of the tube with the coloured spot on the cap - see orange sticker in figure 7.1b and 7.2a.
3. Slot the end of the sorbent tube with the coloured spot into the tubelock spanner - figure 7.2a.
4. Place the second spanner over the sorbent tube cap - figure 7.2b.
5. Twist the spanners in opposite directions to loosen the cap from the sorbent tube and completely remove the collar and cap from the sorbent tube.
6. Push the diffuser cap (figure 7.1a) onto the end of the tube.
7. Position the tube vertically in the wooden spacer and clip (figure 7.1c) with the diffuser cap end (coloured spot) facing downwards during sampling - see figure 7.2c.
8. Fix the spacer to a wall or furniture with the command strip or cable ties provided. Please place in the relevant room, as the labels provided (living room or bedroom).
9. Please position the sorbent tubes as central in the room as possible and at a height of 1.5m, away from external windows/doors and away from sources of heat (radiators and direct sunlight) and moisture.

10. It is important that the end of the tube is in an area with free circulation of air. The tube should not be placed in any recess, to avoid sampling of stagnant air.
11. It is very important that moisure does not enter the tube - please install the tube away from direct sources of moisture - away from cookers, kettles, sinks etc.
12. Leave in place for 2 weeks.
13. After the two week period, please remove the diffuser cap and refit the collar and cap onto the sorbent tube - **finger tight - do not overtighten**. Please only turn the spanners for 1/4 turn to prevent damage to the tubes.
14. Gently pull the collar and cap to check that they are not loose.

Chapter 8

Measuring your home.

Information to follow.

Chapter 9

Downloading data.

9.1 Onset MX1102A

Information to follow.

9.2 Onset UX90-001M

Information to follow.

9.3 Onset U12-012

Information to follow.

Bibliography

Andersen, R., Fabi, V., Toftum, J., Corgnati, S. P. & Olesen, B. W. (2013), 'Window opening behaviour modelled from measurements in Danish dwellings', *Building and Environment* **69**, 101–113.

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Gradko (ND), 'VOC Instructions - Passive Sampling Only'.

Onset Computer Corporation (2021), 'HOBO MX1102A Data Logger datasheet: Carbon Dioxide - Temp - RH Data Logger'.

Persily, A. K. (1997), 'Evaluating Building IAQ and Ventilation with Indoor Carbon Dioxide', *ASHRAE Transactions* **103**.

Appendix A

Risk assessment.

Risk Assessment

Summary

Reference: **RA040695/1** **Sign-off Status:** **Authorised**

Date Created:	16/09/2020	**Confidential?**	No

Assessment Title:	The relationship between ventilation practices, indoor air quality, noise and overheating, and their impact on health - PhD monitoring campaign.
Assessment Outline:	This is the risk assessment for the monitoring campaign that forms part of Cairan Van Rooyen's PhD project - "The relationship between ventilation practices, indoor air quality, noise and overheating, and their impact on health". This project involves carrying out a remote monitoring campaign from December 2020 to September 2021, with no researcher-to-participant in-person contact. The risk assessment covers: 1. recruitment of participants; 2. remote installation (by participants) and uninstallation of numerous air quality and sound measuring instruments in up to 4 private dwellings; 3. working with research participants;

Area Responsible (for management of risks)		**Location of Risks**	Off-Site
Division, School, Faculty, Institute:	Faculty of the Built Environment	**Building:**	
Department:	Bartlett School Env, Energy & Resources	**Area:**	
Group/Unit:	All Groups/Units	**Sub Area:**	

Further Location Information:	Participants will be from within UCL and possibly Public Health England - students and staff. Most likely location of participants will be in central London or Oxford.
Is this a GMM Class 1 Risk Assessment?:	UNITED KINGDOM

Assessment Start Date:	25/11/2020	**Review or End Date:**	25/11/2021

Relevant Attachments:

Description of attachments:

Location of non-electronic documents:

Assessor(s):	Van Rooyen, Cairan
Approver(s):	CLIFFORD ELWELL
Signed Off:	CLIFFORD ELWELL (25/11/2020 15:04)
Distribution List:	

PEOPLE AT RISK (from the Activities covered by this Risk Assessment)

CATEGORY
Employees
Post-Graduates
Undergraduates

Risk Assessment

Reference: **RA040695/1** **Sign-off Status:** **Authorised**

1. Recruitment

Description of Activity:	This activity involves the recruitment of potential participants.

Hazard 1. Protecting high risk individuals

- Potential to transmit the virus and pose a hazard to susceptible individuals during monitoring.

- Black, Asian and minority ethnic (BAME) communities are disproportionately affected by COVID-19 and may be clinically vulnerable. Concerning evidence suggests that the impact may also be higher among men and those in the higher age brackets.

- There is evidence that COVID-19 has a greater impact in older age groups, particularly those over 50. Therefore, older people may be more at risk and they are also more likely to have long-term health conditions.

- Pregnant individuals, at whatever stage of pregnancy, are classed as at higher risk from COVID-19.

Existing Control Measures

- Potential participants will be asked to carry out a self assessment of their household and identify if any individuals are defined by the NHS as high risk (clinically extremely vulnerable). If the household has any occupants that are classified as high risk, the dwelling will be excluded from participating in this research.

Risk Level

With Existing Controls:

Risk Level **C - Medium / Moderate**

2. Installation and removal of monitoring equipment

Description of Activity:	Installation of various technical monitoring equipment that will remain in place in the occupied dwelling for the time agreed with the participants. The equipment will be: Eltek AQ110 air quality instruments, sorbent tube VOC monitoring, Onset Hobo MX1102, Onset U12-012, Onset HOBO UX90-001M (event sensors), sound pressure level loggers.

Hazard 1. Manual Handling

All equipment will be posted to participants for them to install - moving all the equipment into the participant's dwellings and installing the equipment requires manual lifting, handling and carrying the equipment. Most of the equipment is small and does not weigh much individually. However, when combined, the equipment is bulky. There is therefore a risk of musculoskeletal injury or other minor injuries (e.g., strains, cuts, abrasions and bruises) which may occur from pushing/pulling/lifting equipment or from tripping over equipment or cables.	**Existing Control Measures** - Participants will be informed to reduce packaging and equipment into individual components, to reduce into smaller manageable sizes; - Ensure access to first aid and to a system for calling emergency services if anyone is taken ill or injured; - Ensure that there are no trip hazards when manoeuvring equipment; - When posting equipment, weight will be maintained below 5kg if possible;

Hazard 2. Electricity

Electric shock / burn	**Existing Control Measures** - All electric equipment will be PAT tested; - All electric equipment should be inspected before use to check that cables are in good order and that there are no signs of damage such as cable fraying or scorching of components. Plug sockets should not be overloaded; - If an extension lead is required it should be fully extended and located so as to minimise trip hazard and have the correct cable and fuse rating for the equipment.

Hazard 3. Trip hazard	
Trailing cables, low steps, etc	**Existing Control Measures** - Participants are instructed to install cables in a safe and tidy manner. The participants are instructed to locate equipment and cables in such a way to minimise any trip hazard (for example by running them at the edges of the room/corridor). If laid across an accessible walking area, the cables should either be covered with a suitable cable protector or taped down with marked safety tape. - The participant installing the equipment should ensure that all occupants are made aware of any trip hazard. - The participant will be asked to provide photos and confirmation that equipment has been installed such that all trip hazards have been minimised.
Hazard 4. Damage to walls following use of command strips	
It may be necessary to fix a sensor to a wall or window frame, in order that it is conveniently located for participants and the purpose of the experiment. There is a remote risk that damage to paintwork could occur when the command strip is removed.	**Existing Control Measures** In the case that paintwork is damaged, a UCL contractor will repair the damage.
Hazard 5. Loss, damage, or theft of equipment	
Leaving equipment in place for extended periods could result in the accidental damage, loss, or theft of equipment.	**Existing Control Measures** The research will be covered by UCL and PHE Insurance for loss, theft, and damage to equipment.
Hazard 6. Infection transmission	
Members of the UCL community may contract or spread COVID-19.	**Existing Control Measures** CLEANING AND POSTAGE OF EQUIPMENT - All research equipment will be thoroughly disinfected 14 days prior to posting to site, using the procedures below: - If any member of the senders household has any symptoms that could be COVID-19, the sender will not prepare or post the equipment for the entire isolation period suggested by the government. - Wash hands thoroughly prior to handling any equipment. Hand washing to follow NHS guidelines for controlling the spread of COVID-19 https://www.nhs.uk/live-well/healthy-body/best-way-to-wash-your-hands/ - Wear a suitable face mask whilst handling equipment. Follow the guidance on the WHO website for mask use.

	https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/when-and-howto-use-masks - While wearing gloves, disinfect all equipment using: either a combined detergent disinfectant solution at a dilution of 1,000 parts per million available chlorine or a household detergent followed by disinfection (1000 ppm av.cl.). Follow manufacturer's instructions for dilution, application and contact times for all detergents and disinfectants. - Thoroughly disinfect all surfaces of equipment prior to packaging. https://www.gov.uk/government/publications/covid-19-decontamination-in-non-healthcaresettings/covid-19-decontamination-in-non-healthcare-settings - After the recipient has received the package, the recipient shall wash hands thoroughly as detailed above and disinfect the packaging as detailed above. - Leave packaged equipment in packaging for 7 days before opening. WebMD report that COVID-19 can survive on hard surfaces for up to 5 days. Once the package has been received, the participant should not open the package for 7 days. https://www.webmd.com/lung/how-long-covid-19-lives-on-surfaces INFORMATION - A COVID-19 information leaflet will be developed for participants taking part in this research, this will provide them with specific information on the measures that the researcher will take to ensure that the risks around the transmission of the virus are minimised as far as possible. This information leaflet will aim to make the participants feel safe and reassured about the monitoring and their safety. MONITORING - Every two weeks an agenda item will be included in formal supervisions with my primary supervisor to monitor the risk associated with monitoring and to revise the monitoring and associated risk assessment. - Every week the researcher will review the UCL framework for any updates. - The researcher will also keep abreast of any local restrictions or advice from Government that might impact the monitoring
Hazard 7. Ensuring participants read and adhere to risk assessment	
Participants could injure themselves if they do not familarise themselves with and follow the risk assessment.	**Existing Control Measures** - The researcher will require the participants to agree to follow this risk assessment and follow the specific guidance provided to them for installing the equipment. The participant will be provided with a copy of the risk assessment at the time of signing the consent form and asked specifically to sign that they have read, understood and will follow the risk assessment and other installation guidance provided to them by the researcher.

Risk Assessment

Risk Level
With Existing Controls:
Risk Level **C - Medium / Moderate**

3. Working with the research participants	
Description of Activity:	It will be necessary to interact with UCL staff and students and/or PHE staff in order to carry out this monitoring campaign. All participants will be fully informed of the risks, benefits, time, and procedures involved with the study prior to any work commencing, and full informed consent will be obtained prior to the start of the study. This will be done through the participant information sheet and consent form, as well as discussion offered (by phone, video call or email) to answer any queries prior to the commencement of the study.

Hazard 1. Antisocial behaviour	
There is a slim chance that participants may become frustrated or antisocial during the course of the research.	**Existing Control Measures** - It will be made clear to participants that they can withdraw consent at any time without prejudice. If a participant wishes to withdraw all testing will immediately cease and the testing equipment will be decommissioned.

Risk Level
With Existing Controls:
Risk Level **A - Very Low / Trivial**

C | Survey Checklist

Survey Checklist

By Cairan Van Rooyen

Survey date:

Insert date

Survey crew:

Cairan Van Rooyen

Address:

Dwelling type:

Insert dwelling type

Participant Number:

Insert participant number

Notes:

If sensitive details are recorded on this sheet, it will need be stored securely in accordance with GDPR.

Pre-Site Checklist

Pack the following:

- ☐ Student card as identification.
- ☐ Measuring tape.
- ☐ Laser measurer.
- ☐ Flat and philips screwdrivers.
- ☐ Torch.
- ☐ Large bags to carry equipment to vehicle.
- ☐ Hand sanitiser.
- ☐ FFP2 mask.
- ☐ Gloves.
- ☐ Water/food.

Notes:

Survey Checklist

- ☐ Measure and draw floor plan. Mark dimensions of room, windows and doors.
- ☐ Measure windows cill height and overall height.
- ☐ Floor / walls: carpet / vinyl floor / linoleum floor / plasterboard walls / chipboard walls / wall paper
- ☐ Measure how far windows open.
- ☐ Measure the proportion of the window which is opening.
- ☐ Record where any opening window is positioned - high level, low level etc.
- ☐ Note on drawing how windows open (top, side hung or tilt and turn).
- ☐ Can windows be left open securely?
- ☐ Record which windows have blinds / curtains?
- ☐ Measure trickle vent sizes.
- ☐ Note trickle vent details if present.
- ☐ Check if vents open or closed. Check the operation of vents and check that they have a hole through to the outside.
- ☐ Survey building fabric to estimate the constructions and build-ups.
- ☐ Mark up locations of mechanical ventilation equipment.
- ☐ Record details of mechanical ventilation equipment: manufacturer and model numbers.
- ☐ What type of grilles, size and how open are they (extract valves).
- ☐ Cooker hood - extract to outside or recirculating? Record locations of external grilles.
- ☐ Record mechanical ventilation controls; how are they operated? Is there a run on for fans?
- ☐ Measure door sizes and the amount that they are undercut from the floor finish.
- ☐ Record any doors that are self closing.
- ☐ Type of accommodation: bedsit, purpose built flat, conversion flat, centre-terrace house, end-terrace house, semi-detached house, detached house, bungalow, mobile home.
- ☐ Location of dwelling, rural, village in rural setting, suburban street large gardens, street in town with no or small gardens, city centre densely packed housing
- ☐ Attached Garage? Door to house? Do they keep the car in? If yes, what type of car (petrol/diesel?)
- ☐ Type of heating system.
- ☐ Fuel of heating system (gas / electric / oil / coal / open fire / wood burning)
- ☐ Secondary heating system(s) and secondary heating system fuel.
- ☐ Cooking fuel - hob, grill and oven.
- ☐ **Mark locations of all sensors with serial numbers on drawing.**
- ☐ Record locations and details of sources of indoor and outdoor:
    1. Air contaminants / pollution.
    2. Heat sources indoors.
    3. Noise / sound.

Notes:

Photograph Checklist

- ☐ Check with participants before and after taking any photos.
- ☐ Trickle vents.
- ☐ Mechanical ventilation systems, including cooker hood.
- ☐ General internal photos showing layout and furniture.
- ☐ Photos of all sensors in situ.
- ☐ All grilles indoors and outdoors.

Notes:

Equipment Record

Item	Location	Sensor Reference
Eltek AQ110	Outdoor	...
Eltek AQ110	Kitchen	...
Eltek AQ110	Living	...
Eltek SRV250	Living	...
Eltek GD47AC	Bedroom??	...
Eltek GD47AC	Bedroom??	...
Onset U12-012 (T/RH/Lt)		...
Onset U12-012 (T/RH/Lt)		...
HOBO UX90-001M (Event)		...
HOBO UX90-001M (Event)		...
HOBO UX90-001M (Event)		...
HOBO UX90-001M (Event)		...
HOBO UX90-001M (Event)		...

Item	Location	Sensor Reference
Noise RPi		...
HOBO UX90-006M (Occupancy)	Bedroom 1	...
HOBO UX90-006M (Occupancy)	Bedroom 2	...
HOBO UX90-006M (Occupancy)	Living	...
HOBO UX90-006M (Occupancy)	Kitchen	...
HOBO UX90-006M (Occupancy)	Hallway	...

Notes:

Drawing of dwelling

Spare

Spare

D | Questionnaire and justification

D.1 Questionnaire

This section contains a copy of the questionnaire that was issued to participants.

The relationship between ventilation practices, indoor air quality, noise and overheating, and their impact on health – participant questionnaire.

Question 1:

In what year was your house built?

Please select one.

	Before 1919
	1919 - 1944
	1945 - 1964
	1965 - 1980
	1981 - 1990
	1991 – 2015
	2016 - present
	Don't know

Question 2:

Do you own or rent the home in which you live?

Please select one.

	Own – outright
	Own – with a mortgage
	Own (part-own) – through shared ownership scheme (i.e. pay part mortgage, part rent)
	Rent – from a private landlord
	Rent – from my local authority
	Rent – from a housing association
	Neither – I live with my parents, family or friends but pay some rent to them
	Neither – I live rent-free with my parents, family or friends
	Other (please state) _____

Question 3:

Approximately, how long have you been living at this property?

Please select one.

	Less than 5 years
	5 to 10 years
	11 to 15 years
	More than 15 years
	Don't know

Question 4:

How important, if at all, do you feel the following factors are for your health?

Please select one option on each row

	Very important	Fairly important	Not very important	Not at all important	Don't know
Sleeping well at night					
Having a well ventilated home					
Following a healthy diet					
Regular exercise					
Having a clean home					
Spending time outdoors					
Avoiding exposure to chemicals (from personal care products, cooking etc) that might impact health in the home					
Air quality in your home					
Noise in your home					

Question 5:

Does anyone in your household have a health condition that affects the way you ventilate your home?

Please select one.

	Yes, there is – please state: _____
	No, there isn't
	Prefer not to say

Question 6:

Have you have received/ seen/ heard information or advice about how to use the ventilation provision in your house?

Please select all that apply.

	Advertisements (e.g posters, billboards)
	Through friends/ family
	From the builder/ seller who I purchased the property from
	From the housing association/ local authority/ landlord who I rent the property from
	Tradespeople (i.e. plumber, electrician etc)
	Online/ websites
	Other – please state: _____
	Don't know
	Not applicable - I don't recall seeing/ hearing information or advice about how to use the ventilation provision

Question 7:

What, if any, of the following do you think are the main sources of pollution in your house?

Please select all that apply

	Pollution from outside
	Furniture and carpets
	Building materials (e.g. asbestos)
	Fumes from cooking
	Cleaning materials (e.g. cleaning products like bleach etc)
	Pollution from neighbouring buildings
	Fumes from heating
	Personal care products (i.e. hairspray, deodorant etc.)
	Don’t know/ can't recall
	Pets
	Damp or mould
	Other – please state: _____
	Not applicable - there is no pollution in my home

Question 8:

Which ONE, if any, of the following do you think are the main sources of pollution in your house?

Please select one

	Pollution from outside
	Furniture and carpets
	Building materials (e.g. asbestos)
	Fumes from cooking
	Cleaning materials (e.g. cleaning products like bleach etc)
	Pollution from neighbouring buildings
	Fumes from heating
	Personal care products (i.e. hairspray, deodorant etc.)
	Don’t know/ can't recall
	Pets
	Damp or mould
	Other – please state: _____
	Not applicable - there is no pollution in my home

Question 9:

Have you made any changes to the way you ventilate your home as a result of the COVID-19 pandemic?

Please select one

	Yes – please state: _____
	No

Question 10:

Do you know what type of ventilation provision is installed in your home?

Please select one

	Yes – please state: _____
	No

Question 11:

Do you have mould, mildew or significant condensation on walls or surfaces in your home?

Please select one

	Yes – please state where you have noticed this: _____
	No

Question 12:

In which, if any, of the following areas of your home do you have an electrically powered extractor fan for ventilation?

Please select all that apply

	Bathroom/ ensuite (wall/ ceiling)
	Kitchen (wall/ ceiling)
	Kitchen (cooker hood)
	Other – please state: _____
	Don’t know/ can't recall
	Not applicable – there is no electrically powered extractor fan in my home

Question 13:

How often, if at all, does the extract fan run in your bathroom and/ or kitchen:

Please select one option for each column

Run continuously (all the time)	Kitchen	Bathroom
Run intermittently (you turn it on and off when required)		
Runs intermittently (it turns on and off automatically)		
Not functional (does not work)		
Don’t know/ can't recall		
Other: _____		

Question 14:

Which, if any, of the following ventilation systems are installed in your home?

Please select all that apply

	Mechanical ventilation with heat recovery (MVHR)
	Passive stack ventilation
	Positive input ventilation
	Don’t know/ can't recall
	Not applicable - I don't have any ventilation systems installed in my home

Question 15:

Which, if any, of the following factors ever stop you or members of your household using the mechanical ventilation system in your home?

Please select all that apply

	Cost of electricity for running the ventilation
	Lack of maintenance/ cleaning
	Noise from the mechanical ventilation system
	Don’t feel the need to use it
	Don’t know how to use it
	Can’t reach or operate it
	Outdoor air pollution (including outdoor odours/ smells)
	Pollen/ allergies
	Outdoor noise
	Insects/ pests
	Worried about heat loss/ cost of heating
	Causes draughts
	Cools the room too much
	Health issues
	Don’t know/ can't recall
	Other – please state: _____
	Not applicable - nothing stops me or members of my household using the mechanical ventilation system

Question 16:

Thinking about ventilation systen maintenance (including cleaning the inside of the unit)...

Which, if any, of the following components have you ever maintained in your home?

Please select all that apply

	Grille
	Fan
	Ducts
	Other – please state: _____
	Don’t know/ can't recall
	Not applicable - I have never maintained any component

Question 17:

For the following question by 'trickle vents' we mean small slot vents normally found at the top of windows.



Do you have trickle vents installed anywhere in your home?

Please select one

☐	Yes, on all windows
☐	Yes, but not on all windows
☐	No
☐	Don’t know/ can't recall

Question 18:

Without checking, do you know if the trickle vents in each of the following rooms are currently open or closed?

Please select one option on each row

	Open	Closed	Some are open and some are closed	Don’t know	Not applicable - I do not have trickle vents in this room
Kitchen	☐	☐	☐	☐	☐
Living room	☐	☐	☐	☐	☐
Main bedroom	☐	☐	☐	☐	☐
Other bedrooms	☐	☐	☐	☐	☐

Question 19:

How often do you or a member of your household open or close trickle vents in your home?

Please select one

☐	Daily
☐	Weekly
☐	Monthly
☐	Less often – please specify _____
☐	Never
☐	Don't know

Question 20:

Which, if any, of the following ever stop you from opening trickle vents in your home?

Please select all that apply

- [ ] Didn't know they were there
- [ ] Don't feel the need to use it
- [ ] Don't know how to use it
- [ ] Can't reach or operate it
- [ ] Outdoor air pollution (including outdoor odours/smells)
- [ ] Pollen / allergies
- [ ] Outdoor noise - To block noise from outside
- [ ] Insects / pests
- [ ] Worried about heat loss / cost of heating
- [ ] Causes draughts
- [ ] Cools the room too much
- [ ] Health issues
- [ ] Other (please specify)
- [ ] Don't know/ can't recall
- [ ] Not applicable – I do not have any problems or concerns.

Question 21:

Thinking specifically about the day time in the winter months (i.e. December to February)…

How often, if at all, are the windows open in the following rooms in your home **during the day?**

Please select one option on each row

	Never	Less often than once a month	Once a month	Once every couple of weeks	Once a week	A few times a week	Daily	All the time (i.e. all day every day)	Don't know/ can't recall	This room has no windows/ the windows don't open
Kitchen										
Living room										
Main bedroom										
Other bedrooms										

Question 22:

Thinking specifically about the night time in the winter months (i.e. December to February)…
How often, if at all, are the windows open in the following rooms in your home **during the night?**

Please select one option on each row

	Never	Less often than once a month	Once a month	Once every couple of weeks	Once a week	A few times a week	Daily	All the time (i.e. all day every day)	Don't know/ can't recall	This room has no windows/ the windows don't open
Kitchen										
Living room										
Main bedroom										
Other bedrooms										

Question 23:

Thinking specifically about the day time in the summer months (i.e. June to August)…
How often, if at all, are the windows open in the following rooms in your home **during the day?**

Please select one option on each row

	Never	Less often than once a month	Once a month	Once every couple of weeks	Once a week	A few times a week	Daily	All the time (i.e. all day every day)	Don't know/ can't recall	This room has no windows/ the windows don't open
Kitchen										
Living room										
Main bedroom										
Other bedrooms										

Question 24:

Thinking specifically about the night time in the summer months (i.e. June to August)…
How often, if at all, are the windows open in the following rooms in your home **during the night?**

Please select one option on each row

	Never	Less often than once a month	Once a month	Once every couple of weeks	Once a week	A few times a week	Daily	All the time (i.e. all day every day)	Don't know/ can't recall	This room has no windows/ the windows don't open
Kitchen										
Living room										
Main bedroom										
Other bedrooms										

Question 25:

Which, if any, are the main reasons why you/ household open windows and doors in your home?

Please select all that apply

- ☐ Too warm (to cool down the house)
- ☐ To get rid of moisture or damp
- ☐ To get rid of smells
- ☐ To dry clothes
- ☐ For fresh air/ to recirculate air in the room
- ☐ To remove smoke (i.e. from smoking, cooking, fires etc.)
- ☐ Connection/ contact with outdoors
- ☐ Other (please specify) _____
- ☐ Don't know

Question 26:

Which ONE, if any, of the following are the main reason why you/ household open windows and doors in your home?

Please select one

- ☐ Too warm (to cool down the house)
- ☐ To get rid of moisture or damp
- ☐ To get rid of smells
- ☐ To dry clothes
- ☐ For fresh air/ to recirculate air in the room
- ☐ To remove smoke (i.e. from smoking, cooking, fires etc.)
- ☐ Connection/ contact with outdoors
- ☐ Other (please specify) _____
- ☐ Don't know

Question 27:

Which, if any, of the following factors stop/ prevent you and/ or members of your household from opening windows or doors in your home?

Please select all that apply

- [ ] Don't feel the need to open them
- [ ] Don't know how to open them
- [ ] Can't reach or operate them
- [ ] Outdoor air pollution (including outdoor odour/ smells)
- [ ] Pollen/ allergies
- [ ] Outdoor noise
- [ ] Insects/ pests
- [ ] Security
- [ ] Worried about heat loss/ cost of heating
- [ ] Causes draughts
- [ ] Cools the room too much
- [ ] Health issues
- [ ] They do not open fully (due to window restrictors or similar)
- [ ] Other (please specify) _____
- [ ] Not applicable - nothing prevents me/ us from opening windows or doors in the home

Question 28:

Thinking about a typical night...

Do you normally keep your bedroom door open or closed?

Please select one

- [ ] Open
- [ ] Closed
- [ ] Not applicable (i.e. my room does not have a door/ is open-plan/ I don't have a bedroom etc.)

Question 29:

Overall, how satisfied or dissatisfied are you about the indoor air quality in your house?

Please select one

- [ ] Very satisfied
- [ ] Fairly satisfied
- [ ] Neither satisfied nor dissatisfied
- [ ] Fairly dissatisfied
- [ ] Very dissatisfied
- [ ] Don’t know

Question 30:

To what extent do you agree or disagree with the following statement?

"My house gets uncomfortably warm in the summer"

Please select one

- [ ] Strongly agree
- [ ] Tend to agree
- [ ] Neither agree nor disagree
- [ ] Tend to disagree
- [ ] Strongly disagree
- [ ] Don’t know

Question 31:

How many people, if any, smoke in your household?

Please select one

- [ ] None
- [ ] One
- [ ] Two
- [ ] Three
- [ ] Four
- [ ] More than 4
- [ ] Prefer not to say

Question 32:

How many people, including yourself, live in your household? Please include both adults and children.

Please select one

- [ ] 1
- [ ] 2
- [ ] 3
- [ ] 4
- [ ] 5
- [ ] 6
- [ ] 7
- [ ] 8
- [ ] 8 or more
- [ ] Don't know
- [ ] Prefer not to say

Question 33:

On a typical weekday, how many people are normally in your household?

Please type your answers as a whole number in each of the boxes below

During the day (9am - 4:59pm)	In the evening (5pm - 11:59pm)	At night (12am - 8:59am)

Question 34:

On a typical weekend, how many people are normally in your household?

Please type your answers as a whole number in each of the boxes below

During the day (9am - 4:59pm)	In the evening (5pm - 11:59pm)	At night (12am - 8:59am)

Question 35:

Are you the parent/ guardian of children of any of the following ages?

Please select all that apply. If you do not have any children, please select the "Not applicable" option

- [ ] Under 6 months old
- [ ] Between 6 and 12 months old
- [ ] 1 year old
- [ ] 2 years old
- [ ] 3 years old
- [ ] 4 years old
- [ ] 5 years old
- [ ] 6 years old
- [ ] 7 years old
- [ ] 8 years old
- [ ] 9 years old
- [ ] 10 years old
- [ ] 11 years old
- [ ] 12 years old
- [ ] 13 years old
- [ ] 14 years old
- [ ] 15 years old
- [ ] 16 years old
- [ ] 17 years old
- [ ] 18 years old
- [ ] Older than 18 years old
- [ ] Not applicable - I do not have any children

Question 36 to 39:

For the following questions, we'd like to get an understanding of who **usually** sleeps in each bedroom in the house (even if this is not their intended place to sleep e.g. with children etc.). Please think about each of your bedrooms in turn when asking the following questions, from largest to smallest…

Question 36:

Thinking about the main bedroom in your house (i.e. Bedroom 1) who usually sleeps here for the majority of the time?

Please use the grid below to indicate how many adults/ children usually sleep in this room

	Children (i.e. ages 0 to 12)	Teenagers (i.e. ages 13 to 17)	Adults(i.e. over 18 years old)
0			
1			
2			
More than 3			
Prefer not to say			

Question 37:

Thinking about the second bedroom in your house (i.e. Bedroom 2) who usually sleeps here for the majority of the time?

Please use the grid below to indicate how many adults/ children usually sleep in this room

	Children (i.e. ages 0 to 12)	Teenagers (i.e. ages 13 to 17)	Adults(i.e. over 18 years old)
0			
1			
2			
More than 3			
Prefer not to say			

Question 38:

Thinking about the third bedroom in your house (i.e. Bedroom 3) who usually sleeps here for the majority of the time?

Please use the grid below to indicate how many adults/ children usually sleep in this room

	Children (i.e. ages 0 to 12)	Teenagers (i.e. ages 13 to 17)	Adults(i.e. over 18 years old)
0			
1			
2			
More than 3			
Prefer not to say			

Question 39:

Thinking about the fourth bedroom in your house (i.e. Bedroom 4) who usually sleeps here for the majority of the time?

Please use the grid below to indicate how many adults/ children usually sleep in this room

	Children (i.e. ages 0 to 12)	Teenagers (i.e. ages 13 to 17)	Adults(i.e. over 18 years old)
0			
1			
2			
More than 3			
Prefer not to say			

Question 40:

What ethnic group best describes you?

Please select one option only. (We ask the question in this way so that it is consistent with Census definitions.)

- [ ] English / Welsh / Scottish / Northern Irish / British
- [ ] Irish
- [ ] Gypsy or Irish Traveller
- [ ] Any other White background
- [ ] White and Black Caribbean
- [ ] White and Black African
- [ ] White and Asian
- [ ] Any other Mixed / Multiple ethnic background
- [ ] Indian
- [ ] Pakistani
- [ ] Bangladeshi
- [ ] Chinese
- [ ] Any other Asian background
- [ ] African
- [ ] Caribbean
- [ ] Any other Black / African / Caribbean background
- [ ] Arab
- [ ] Any other ethnic group
- [ ] Prefer not to say

Question 41:

What gender do you identify as?

Please select one option only

- [ ] Male
- [ ] Female
- [ ] Other
- [ ] Prefer not to say

Question 42:

How old are you?

Please select one option only

- [ ] 18-24
- [ ] 25-34
- [ ] 35-44
- [ ] 45-54
- [ ] 55+
- [ ] Prefer not to say

Question 43:

Which statement best describes your employment status?

Please select one option only

- [ ] Working full time
- [ ] Working part time
- [ ] Full time student
- [ ] Retired
- [ ] Unemployed
- [ ] Not working/ Other
- [ ] Prefer not to say

Question 44:

Which statement best describes your marital status?

Please select one option only

- [ ] Married/ Civil Partnership
- [ ] Living as married
- [ ] Separated/ Divorced
- [ ] Widowed
- [ ] Never Married
- [ ] Prefer not to say

Question 45:

Which of the following social media/messaging services have you used in the last month?

Please select all that apply

- [ ] Facebook
- [ ] Twitter
- [ ] LinkedIn
- [ ] Pinterest
- [ ] Instagram
- [ ] Snapchat
- [ ] Facebook Messenger
- [ ] WhatsApp
- [ ] Skype
- [ ] Don’t know
- [ ] Prefer not to say

D.2 Questionnaire justification

Many of the questions in the questionnaire were exploratory, but many were also derived from a specific relationship identified in the literature or based off similar questionnaires in the literature. Below is a justification for a number of questions asked in the questionnaire.

Question 2 (tenure)

Andersen et al. (2009) found dwelling ownership influenced the proportion of dwellings that had open windows and occupants' heating behaviours.

Wording as Government Statistical Service (29/05/2020*b*).

Question 15 (mechanical ventilation barriers), 20 (trickle vent barriers), 27 (windows barriers)

The literature has identified many barriers to occupants' ventilation practices. The literature shows that occupants choose not to use ventilation systems due to noise (Van Dongen and Phaff, 1989; Zero Carbon Hub, 2016*a*; Gupta and Kapsali, 2016; Lomas and Porritt, 2017; ANC, 2020*a*), they do not know how to use the ventilation systems, or why ventilation is important (Dimitroulopoulou, 2012). This is an exploratory question for this research project.

Question 21, 22, 23 & 24 (window opening frequency)

There is a vast amount of literature that have identified links between season and ventilation behaviours (Fabi et al., 2012; Van Dongen and Phaff, 1989; Andersen et al., 2009; Roetzel et al., 2010). These series of questions aim to identify any links between season, frequency with which windows are open, and time of day.

Question 25 & 26 (window opening drivers)

The literature has identified many reasons/drivers for occupants' ventilation practices. This is an exploratory question for this research project.

Question 29 (IAQ satisfaction)

A very similar question was asked in questionnaire by Frontczak et al. (2012).

Question 31 (smokers in household)

Tobacco smoke is linked with higher indoor levels of particulate matter, CO, acetaldehyde, and BTEX (European Commission - Institute for Health & Consumer Protection, 1992; Brown et al., 2015; Coward et al., 2001)

Question 32 (household size)

Brundrett (1977) found that family size was an important factor influencing window opening behaviour of the household. Brown et al. (2015) found BTEX levels were associated with occupant density. Coward et al. (2001) found a statistically significant relationship between occupant density and aspects of IAQ. Vardoulakis et al. (2015) found people living in overcrowded accommodation were at high risk

of adverse health effects of IAQ.

This same question was asked in questionnaires by Coward et al. (2001); Brown et al. (2015)

Question 41 (gender)

Andersen et al. (2009) found females opened windows more often when they felt the environment was brighter. Sakellaris et al. (2016) found gender influenced the relationship between IEQ and comfort. Schweizer et al. (2007) found females spend more time at home than males, this is important for exposure to the indoor environment.

This same question was asked in questionnaires by Frontczak et al. (2012).

Question 42 (age)

Elderly occupants are cited as one of the most vulnerable groups in the population to adverse indoor air quality, noise, and overheating (Hajat et al., 2014; Vardoulakis et al., 2015; Dengel et al., 2016; Lomas and Porritt, 2017; CIBSE, 2020). Fabi et al. (2012) found different ventilation behaviour between old and young.

Wording as Government Statistical Service (29/05/2020*a*).

Question 43 (employment status)

Schweizer et al. (2007) found that employment status of the occupants had an influence on the amount of time they spent indoors, which in turn will affect their exposure to IEQ. Brown et al. (2015) found significantly higher formaldehyde concentrations in dwellings where the HoH was employed.

This same question was asked in questionnaires by Coward et al. (2001); Frontczak et al. (2012); Brown et al. (2015).

E | Measurement schematics for case studies

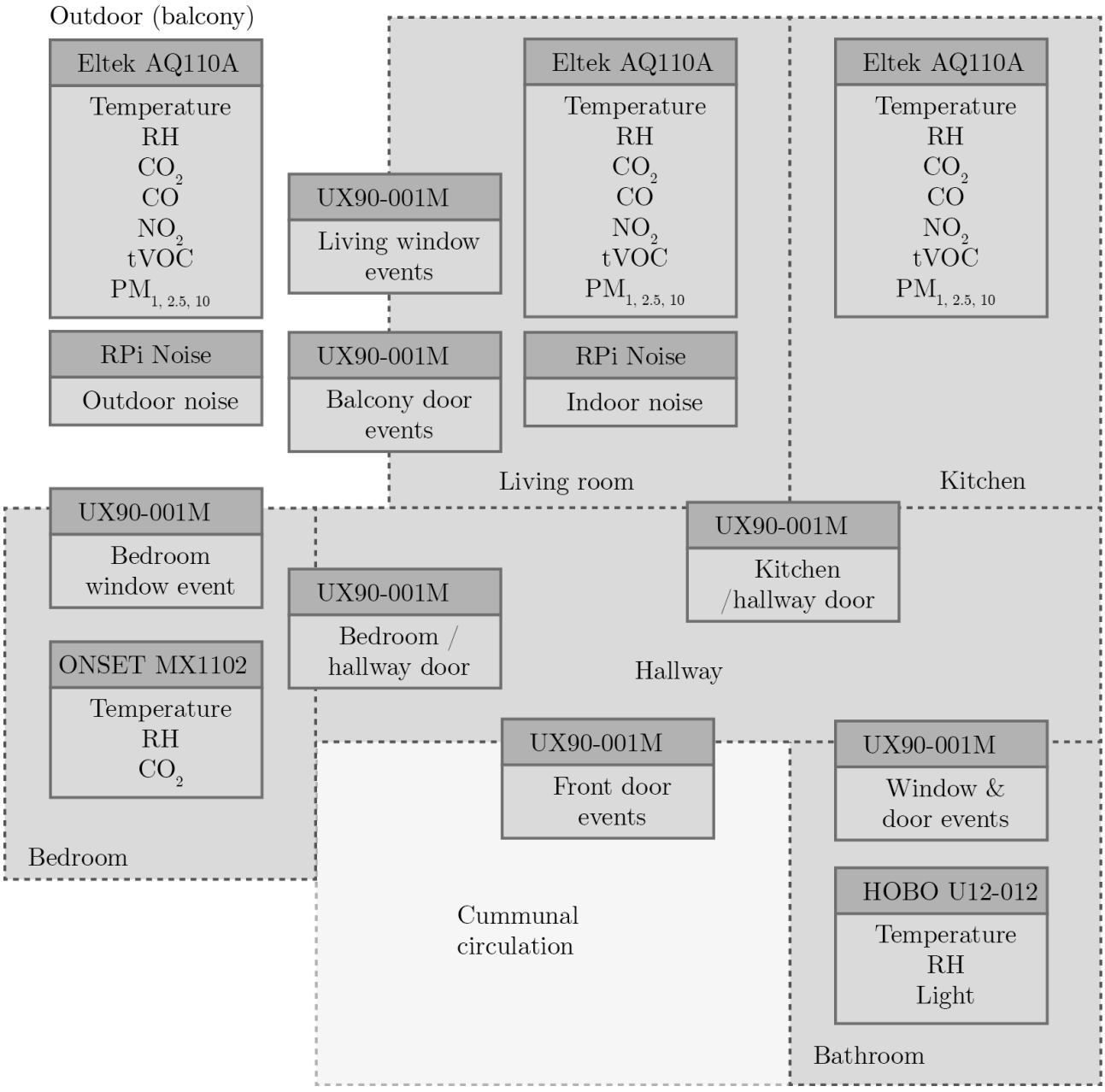


Figure E.1: Schematic diagram of case study P1, showing spaces inside and outside the dwelling, along with variables measured in each space.

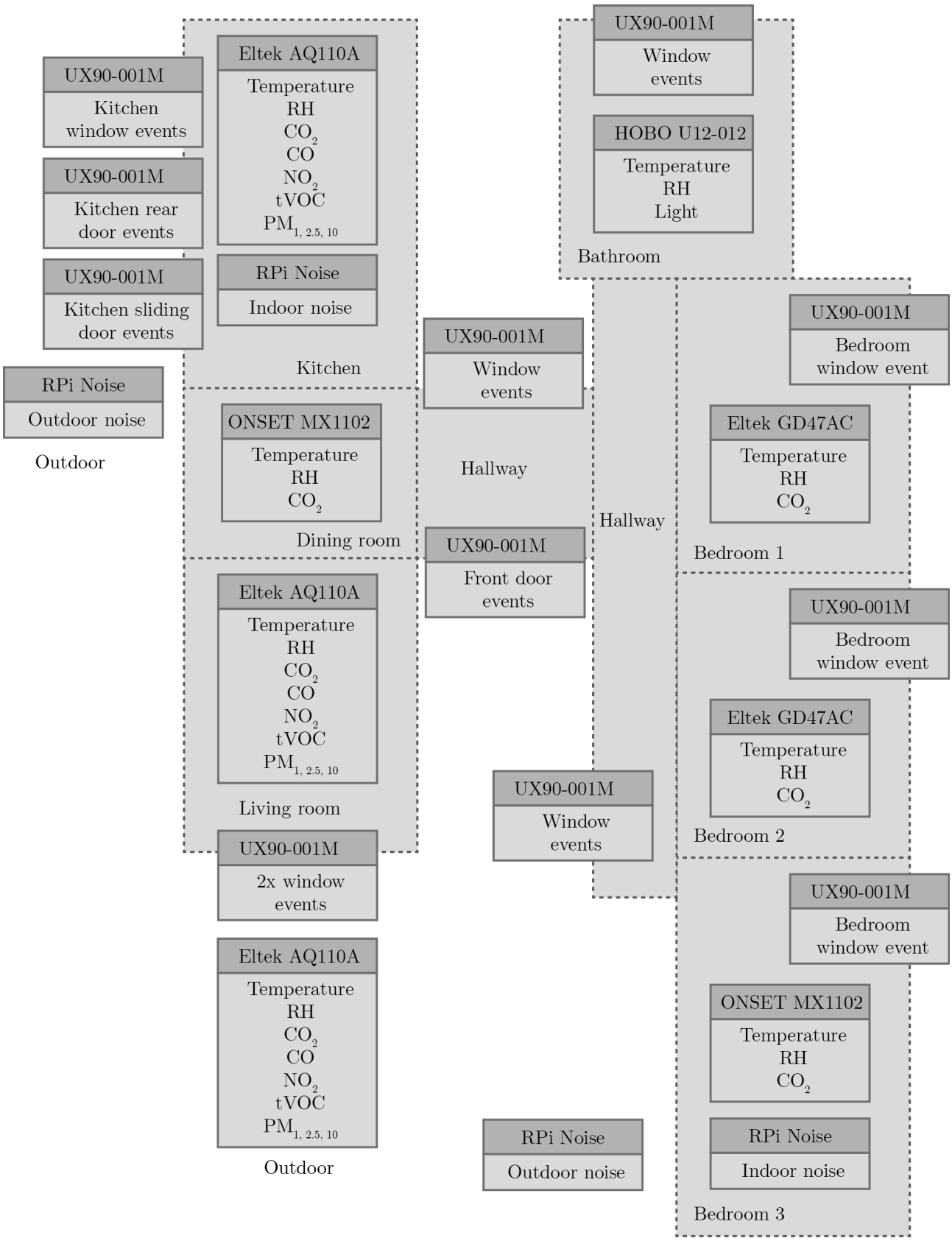


Figure E.2: Schematic diagram of case study P2, showing spaces inside and outside the dwelling, along with variables measured in each space.

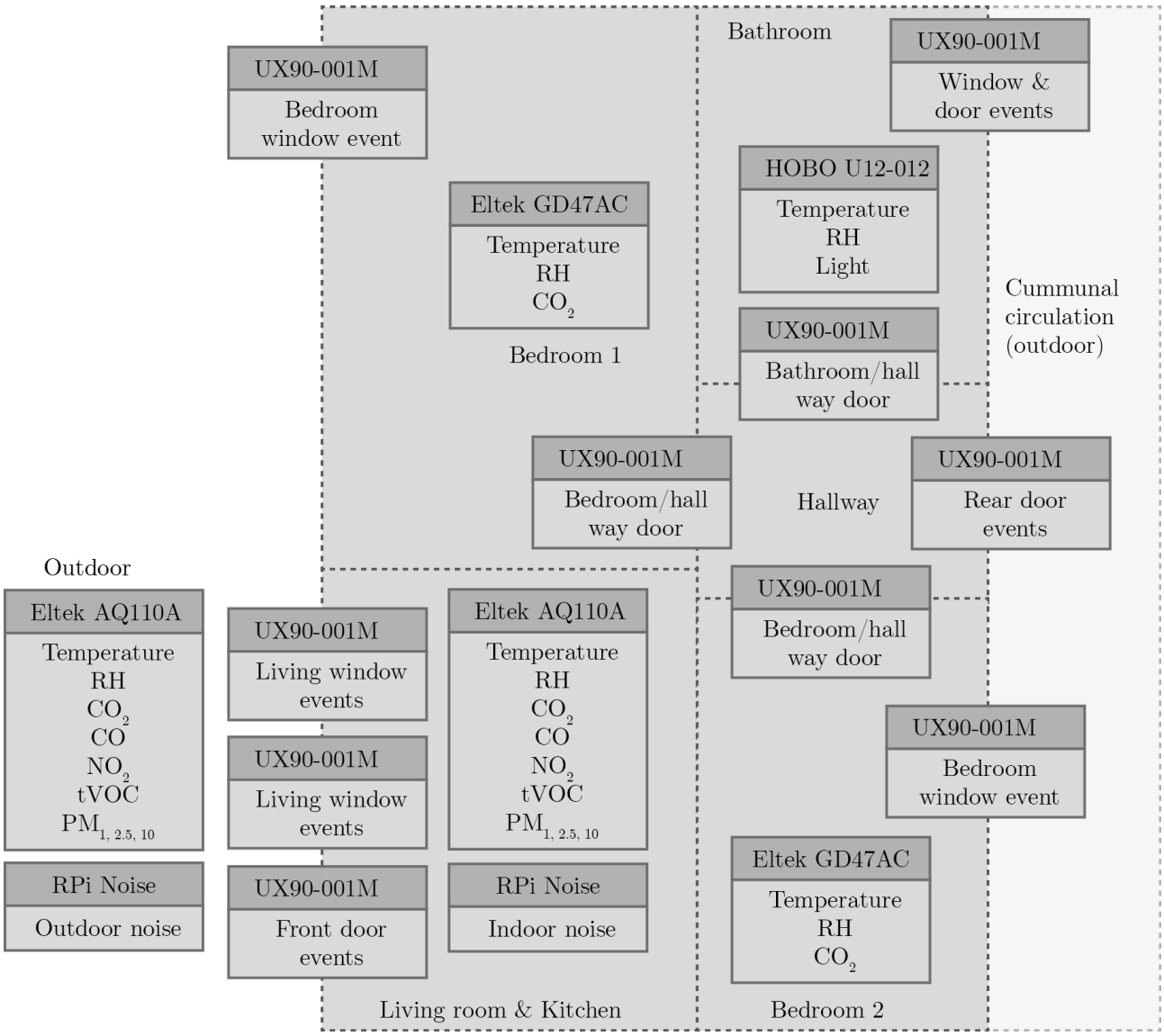


Figure E.3: Schematic diagram of case study P3, showing spaces inside and outside the dwelling, along with variables measured in each space.

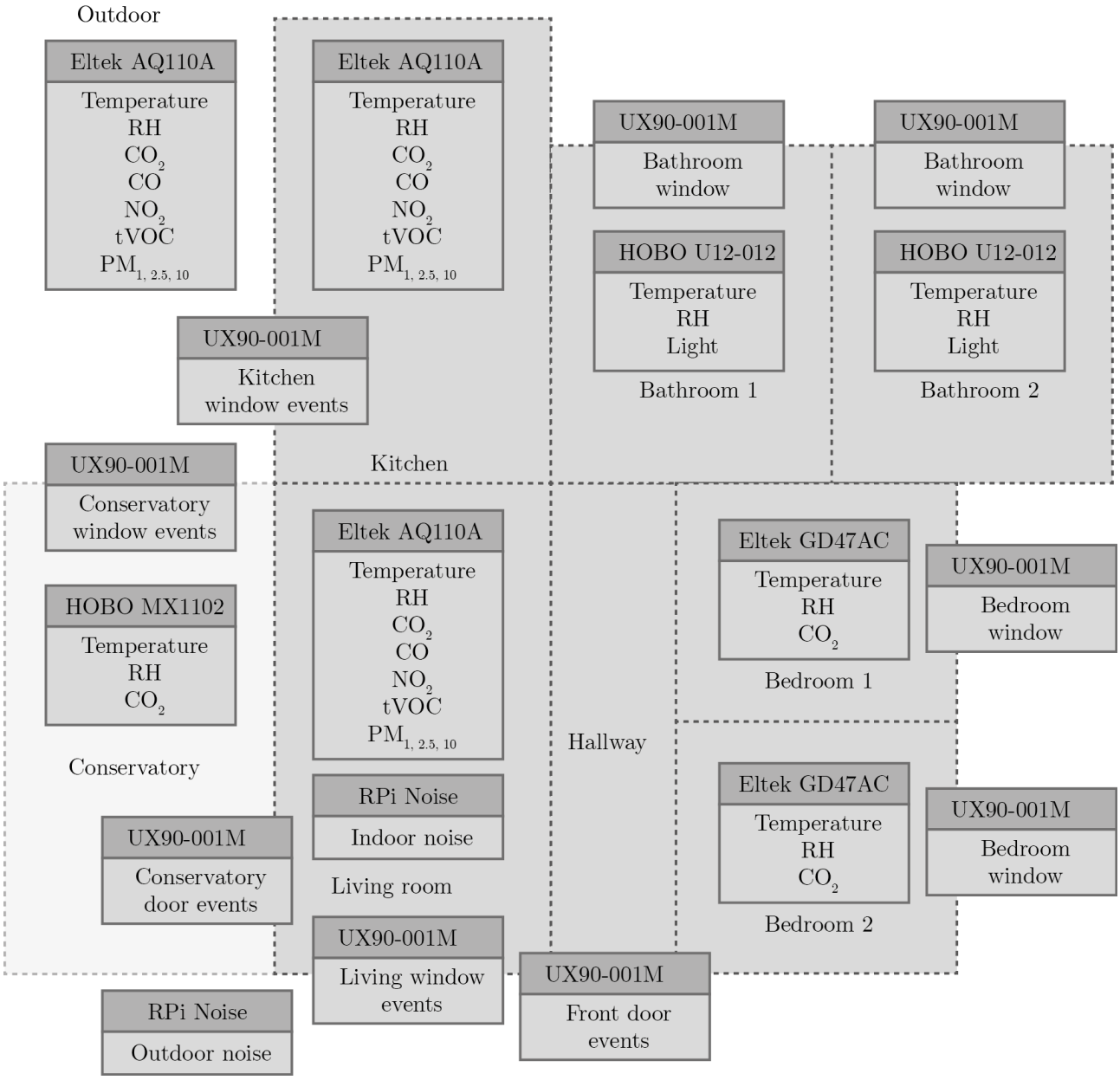


Figure E.4: Schematic diagram of case study P4, showing spaces inside and outside the dwelling, along with variables measured in each space.

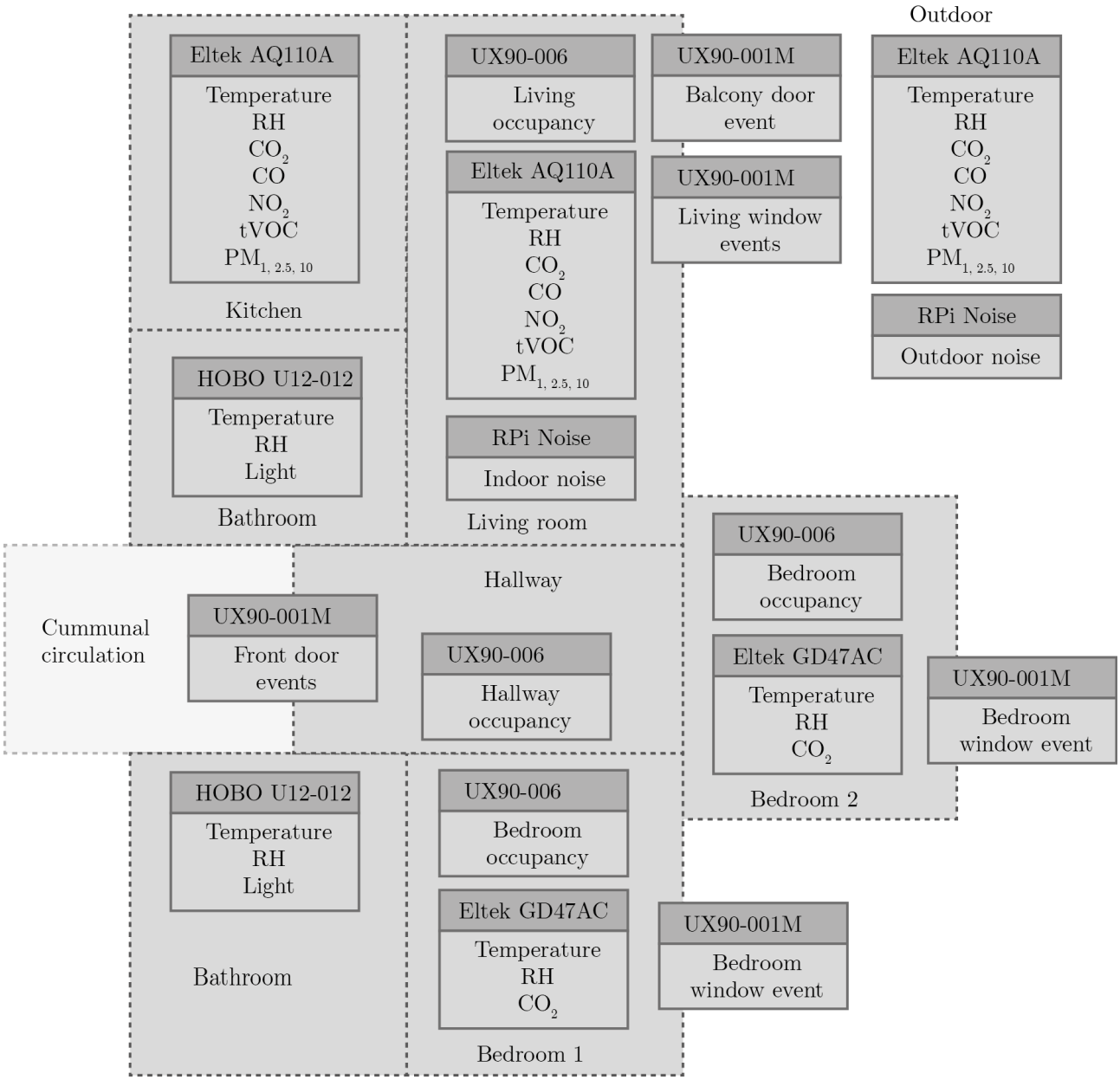


Figure E.5: Schematic diagram of case study P5, showing spaces inside and outside the dwelling, along with variables measured in each space.

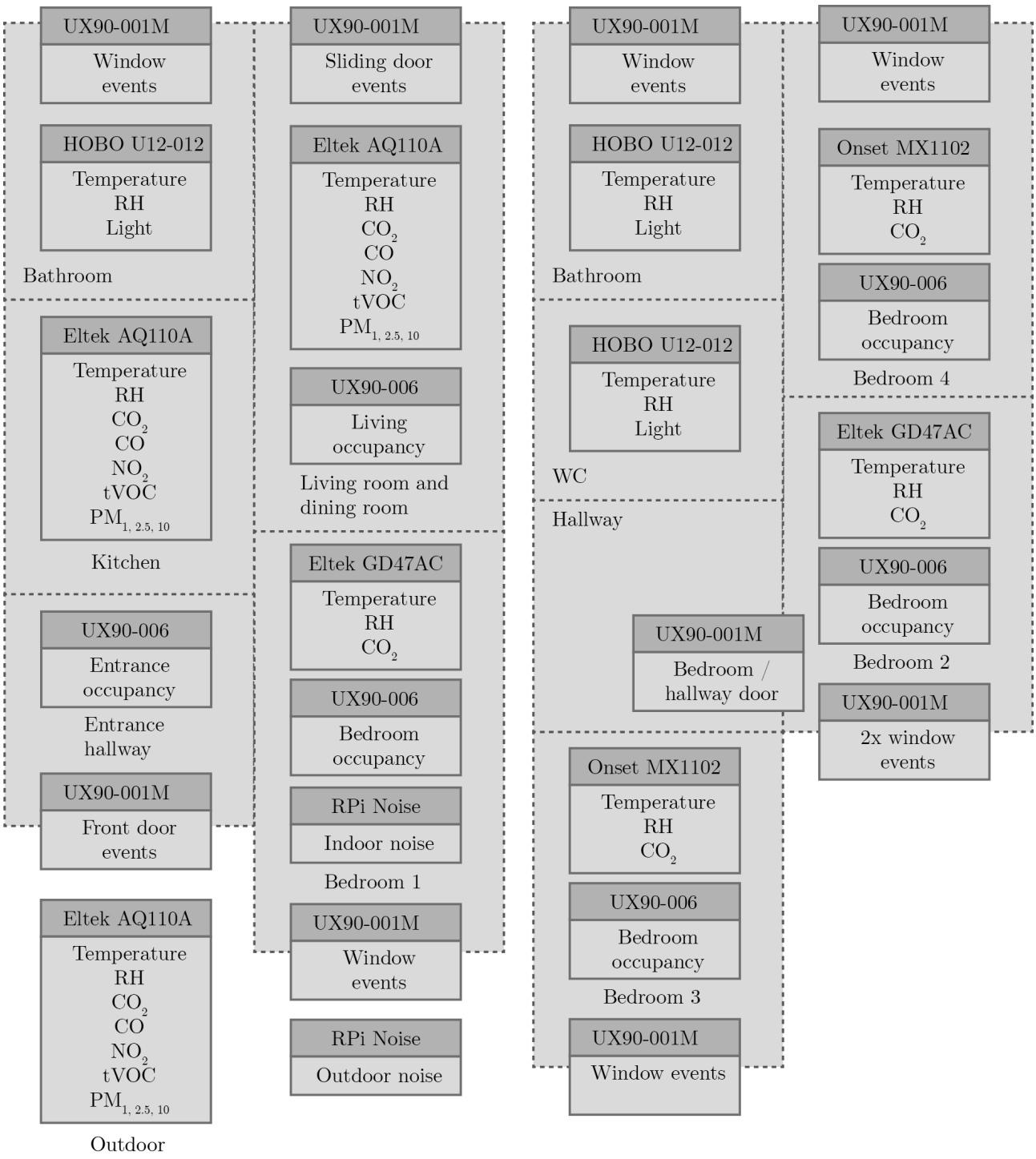


Figure E.6: Schematic diagram of case study P6, showing spaces inside and outside the dwelling, along with variables measured in each space.

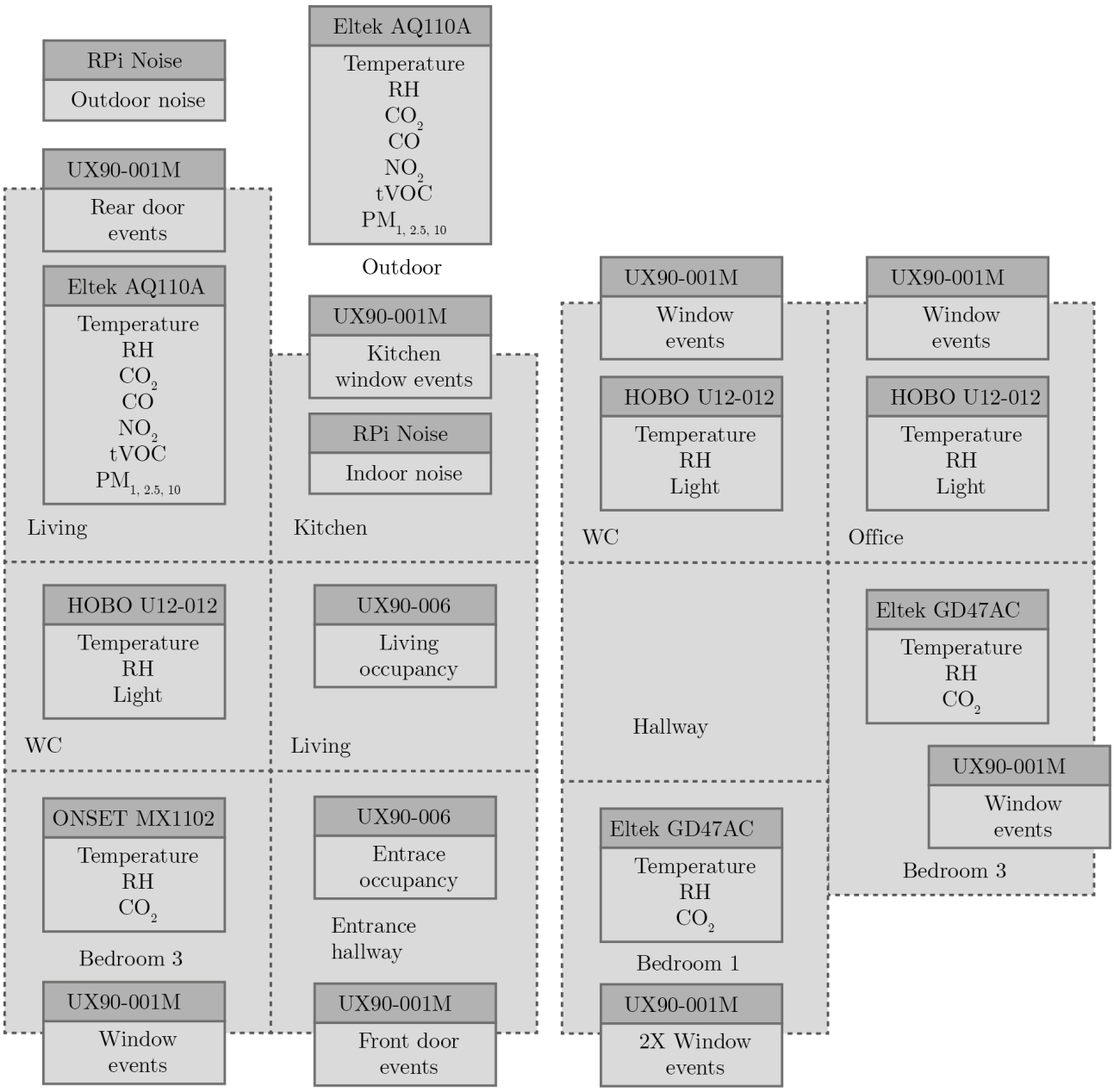


Figure E.7: Schematic diagram of case study P7, showing spaces inside and outside the dwelling, along with variables measured in each space.

F Results appendix

F.1 Results tables for Section 5.1 - participant ventilation practices when at home

Table F.1: Table showing the amount of time that the P1 is in each of the top 5 ventilation configurations when occupied.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All windows closed	24,269	63%	7,355	40%	16,914	82%
Balcony door open	50	0%	42	0%	8	0%
Living window open	7,768	20%	4,683	26%	3,085	15%
Living & bedroom window open	5,765	15%	5,511	30%	254	1%
Bedroom window open	856	2%	575	3%	281	1%
Total	38,708	100%	18,166	100%	20,542	100%

Table F.2: Table showing the amount of time that the P2 is in each of the top 7 (and all other) ventilation configurations when occupied.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	27,920	29%	1,395	4%	26,525	44%
Bedroom 1 window	16,111	17%	6,857	19%	9,254	15%
Bedroom 1 & bathroom window	9,713	10%	6,550	18%	3,163	5%
Kitchen window	5,382	6%	0	0%	5,382	9%
Bedroom 1,2,3 & bathroom window & sliding door	8,001	8%	7,064	19%	937	2%
Bedroom 1,3 and bathroom window	3,742	4%	920	3%	2,822	5%
Bedroom 1,3 & bathroom window & sliding door	4,837	5%	3,108	9%	1,729	3%
All other (n=78)	20,422	21%	10,394	29%	10,028	17%
Total	96,128	100%	36,288	100%	59,840	100%

Table F.3: Table showing the amount of time that the P3 is in each of the top 7 (and all other) ventilation configurations when occupied.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	26,844	57%	13,875	46%	12,969	76%
Bathroom window	7,412	16%	5,741	19%	1,671	10%
Bedroom 2 & bathroom window	3,734	8%	3,424	11%	310	2%
Bedroom 2 window	2,997	6%	2,002	7%	995	6%
Front door	1,201	3%	733	2%	468	3%
Bedroom 1 & bathroom window	1,082	2%	1,010	3%	72	0%
Bathroom window & front door	624	1%	450	2%	174	1%
All other (n=16)	3,125	7%	2,762	9%	363	2%
Total	47,019	100%	29,997	100%	17,022	100%

Table F.4: Table showing the amount of time that the P4 is in each of the top 7 (and all other) ventilation configurations when occupied.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	26,151	74%	11,528	67%	14,623	81%
Bathroom 1 window	5,677	16%	3,351	20%	2,326	13%
Bedroom 2 window	413	1%	30	0%	383	2%
Bathroom 2 window	712	2%	449	3%	263	1%
Kitchen window	510	1%	318	2%	192	1%
Kitchen and bathroom 1 window	697	2%	667	4%	30	0%
Bathroom 1&2 and kitchen window	340	1%	340	2%	0	0%
All other (n=?)	707	2%	453	3%	254	1%
Total	35,207	100%	17,136	100%	18,071	100%

Table F.5: Table showing the amount of time that the P5 is in each of the top 6 (and all other) ventilation configurations when occupied.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	19,887	83%	9,355	76%	10,532	90%
Balcony door	1,863	8%	1,222	10%	641	5%
Bedroom 1 window	1,664	7%	1,176	10%	488	4%
Balcony door and bedroom 1 window	546	2%	513	4%	33	0%
Balcony door, bedroom 1 & living window	59	0%	59	0%	0	0%
Balcony door and living window	10	0%	10	0%	0	0%
All other (n=1)	1	0%	1	0%	0	0%
Total	24,030	100%	12,336	100%	11,694	100%

Table F.6: Table showing the amount of time that the P6 is in each of the top 7 (and all other) ventilation configurations when occupied. Note: the monitoring campaign was limited in duration and only covered a short amount of the summer season.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	31,326	67%	0	0%	31,326	69%
FF bathroom window	6,355	14%	244	18%	6,111	13%
GF bathroom window	2,414	5%	0	0%	2,414	5%
GF & FF bathroom & bedroom 2 window	424	1%	21	2%	403	1%
GF & FF bathroom window	1,583	3%	651	48%	932	2%
Bedroom 1 window	374	1%	0	0%	374	1%
Bedroom 4 window	727	2%	0	0%	727	2%
All other (n=44)	3,505	8%	449	33%	3,056	7%
Total	46,708	100%	1,365	100%	45,343	100%

Table F.7: Table showing the amount of time that the P7 is in each of the top 7 (and all other) ventilation configurations when occupied. Note: the monitoring campaign was limited in duration and only covered a short amount of the summer season.

Ventilation configuration	All		Summer (& half Autumn)		Winter (& other half Autumn)	
	Count	Percent	Count	Percent	Count	Percent
All closed	30,213	65%	3,035	40%	27,178	70%
Kitchen window	11,066	24%	1,811	24%	9,255	24%
Bathroom window	2,663	6%	1,749	23%	914	2%
Living sliding door	300	1%	19	0%	281	1%
Bedroom 3 and kitchen window	252	1%	13	0%	239	1%
Bedroom 2 and bathroom window	393	1%	279	4%	114	0%
Bedroom 1 (window 2) and bathroom window	242	1%	76	1%	166	0%
All other (n=50)	1,400	3%	591	8%	809	2%
Total	46,529	100%	7,573	100%	38,956	100%

F.2 Results tables for Section 5.1.3 - comparing questionnaire responses with measured ventilation practices

The results tables below compare monitored data (M) with questionnaire responses (Q) for each participant, grouped by room type. The tables show the percentage of all occupied day and night periods when a window was opened in each of the respective rooms. The definition of a day and night period was a 12 hour period from 8am and 8pm and it was defined as occupied if the dwelling was occupied for more than 40% of that 12 hour period. These percentages from the questionnaires are compared with the monitored data to determine if they agree. A 10 % permissible margin is allowed between the questionnaire and measurements.

Table F.8: Table comparing questionnaire responses for each participant (Q) with the monitored data (M). The monitored data represents the average amount of occupied days and nights (12-hour periods) that a window was opened in the main bedroom during the summer and winter. This table also provides an indication of agreement between the questionnaire and monitored data (10% margin allowed).

Bedroom

Season	Time	P1			P2		
		M	Q	Agree	M	Q	Agree
Summer	Day	46%	100%	No	100%	100%	Yes
	Night	53%	100%	No	97%	40%	No
Winter	Day	16%	100%	No	85%	40%	No
	Night	17%	40%	No	44%	2%	No
		P3			P4		
		M	Q	Agree	M	Q	Agree
Summer	Day	53%	100%	No	30%	40%	Yes
	Night	32%	0%	No	22%	40%	No
Winter	Day	16%	13%	Yes	11%	3%	Yes
	Night	0%	0%	Yes	21%	2%	No
		P5			P6		
		M	Q	Agree	M	Q	Agree
Summer	Day	69%	100%	No	67%	100%	No
	Night	26%	40%	No	40%	0%	No
Winter	Day	51%	100%	No	28%	100%	No
	Night	20%	0%	No	0%	0%	Yes
		P7			Summary		
		M	Q	Agree	$\bar{M}$		
Summer	Day	23%	100%	No	55%	2 of 7 agree	
	Night	13%	3%	Yes	40%	1 of 7 agree	
Winter	Day	22%	40%	No	33%	2 of 7 agree	
	Night	5%	0%	Yes	15%	3 of 7 agree	

Table F.9: Table comparing questionnaire responses for each participant (Q) with the monitored data (M). The monitored data represents the average amount of occupied days and nights (12-hour periods) that a window was opened in the living room during the summer and winter. This table also provides an indication of agreement between the questionnaire and monitored data (10% margin allowed).

Living

Season	Time	P1			P2		
		M	Q	Agree	M	Q	Agree
Summer	Day	65%	100%	No	32%	40%	Yes
	Night	67%	100%	No	22%	0%	No
Winter	Day	32%	100%	No	6%	2%	Yes
	Night	41%	40%	Yes	1%	0%	Yes
		P3			P4		
		M	Q	Agree	M	Q	Agree
Summer	Day	6%	100%	No	13%	40%	No
	Night	3%	0%	Yes	18%	13%	Yes
Winter	Day	10%	13%	Yes	2%	7%	Yes
	Night	0%	0%	Yes	0%	0%	Yes
		P5			P6		
		M	Q	Agree	M	Q	Agree
Summer	Day	4%	40%	No	100%	100%	Yes
	Night	0%	2%	Yes	100%	0%	No
Winter	Day	0%	40%	No	60%	40%	No
	Night	0%	0%	Yes	30%	0%	No
		P7			Summary		
		M	Q	Agree	$\bar{M}$		
Summer	Day	70%	100%	No	41%	2 of 7 agree	
	Night	30%	0%	No	34%	3 of 7 agree	
Winter	Day	25%	40%	No	19%	3 of 7 agree	
	Night	31%	0%	No	15%	5 of 7 agree	

Table F.10: Table comparing questionnaire responses for each participant (Q) with the monitored data (M). The monitored data represents the average amount of occupied days and nights (12-hour periods) that a window was opened in the kitchen during the summer and winter. This table also provides an indication of agreement between the questionnaire and monitored data (10% margin allowed).

Kitchen

Season	Time	P1			P2		
		M	Q	Agree	M	Q	Agree
Summer	Day	NA	NA	NA	7%	100%	No
	Night	NA	NA	NA	4%	0%	Yes
Winter	Day	NA	NA	NA	13%	100%	No
	Night	NA	NA	NA	14%	0%	No
		P3			P4		
		M	Q	Agree	M	Q	Agree
Summer	Day	NA	NA	NA	24%	40%	No
	Night	NA	NA	NA	15%	13%	Yes
Winter	Day	NA	NA	NA	8%	7%	Yes
	Night	NA	NA	NA	11%	0%	No
		P5			P6		
		M	Q	Agree	M	Q	Agree
Summer	Day	NA	NA	NA	NA	NA	NA
	Night	NA	NA	NA	NA	NA	NA
Winter	Day	NA	NA	NA	NA	NA	NA
	Night	NA	NA	NA	NA	NA	NA
		P7			Summary		
		M	Q	Agree	$\bar{M}$		
Summer	Day	37%	40%	Yes	23%	1 of 3 agree	
	Night	30%	40%	Yes	16%	3 of 3 agree	
Winter	Day	28%	40%	No	16%	1 of 3 agree	
	Night	25%	0%	No	17%	0 of 3 agree	

Table F.11: Table presenting the average amount of day and nights (12-hour periods) that a window was open in the bathroom or sliding door in living room during the summer and winter.

		Bathroom							
Season	Time	P1	P2	P3	P4	P5	P6	P7	$\bar{x}$
Summer	Day	NA	100%	80%	75%	NA	100%	77%	86%
	Night	NA	86%	51%	51%	NA	100%	43%	66%
Winter	Day	NA	95%	84%	77%	NA	37%	44%	67%
	Night	NA	25%	42%	39%	NA	34%	5%	29%
		Balcony/sliding							
Season	Time	P1	P2	P3	P4	P5	P6	P7	$\bar{x}$
Summer	Day	25%	100%	NA	NA	69%	100%	70%	85%
	Night	24%	93%	NA	NA	26%	100%	30%	62%
Winter	Day	8%	97%	NA	NA	44%	60%	25%	57%
	Night	12%	56%	NA	NA	17%	30%	31%	34%

F.3 Results tables for Section 5.3 - ventilation practices and IEQ

The tables in each of the following sections show the results of the analysis for the change in each IEQ variable after each window and door in all case studies opens and closes. This includes the individual room AER and whole house AER for each respective room and for when the window or door was open and closed, the number of times each window and door opened and closed that were used in this analysis, the median indoor to outdoor ratio of each variable (IOR) before each window and door was opened and closed, the median value for each variable before each window and door was opened and closed, the median change in each IEQ variable ($\tilde{x}$) and the IQR of change in each IEQ variable when each window and door was opened and closed, and finally the results showing if there was a statistically significant difference between the summer and winter (S vs W) distributions of each IEQ variable. Bold results indicate where there is a statistically significant difference between the distribution of each IEQ variable after a window/door was opened and closed.

As mentioned in Section 3.2.4.4, $\tilde{x}$ represents the median difference between each IEQ variable after each window and door opens and closes (event), where the initial value (before each event) is the median value in the hour before the event and the final value (after the event) is the value between 45 minutes and 60 minutes after the event. The final value is based on either the value before the next event (if between 45 and 60 minutes after the event in question) or the value at 60 minutes after the event in question. This gives an estimate of the amount of change over roughly a one hour period, which can be related to AER.

F.3.1 Results tables for ventilation practices and temperature

Table F.12: Table showing the change in temperature after opening and closing different windows and doors in the bedrooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	57	-	24.60	0.02	0.28	57	-	24.47	0.03	0.21
P1	bedroom window	57	1.39	25.63	**-0.17**	0.43	54	1.45	24.34	**0.14**	0.38
P2	bedroom 1 window	23	1.73	21.28	**-0.20**	0.29	22	1.42	20.24	**0.33**	1.35
P3	bedroom 1 int door	177	-	20.05	0.03	0.52	145	-	20.28	0.05	0.42
P3	bedroom 1 window	80	1.18	20.84	**-0.15**	0.55	109	1.16	20.66	**0.19**	0.49
P3	bedroom 2 int door	181	1.24	20.39	**-0.03**	0.34	151	1.41	20.42	**0.00**	0.33
P3	bedroom 2 window	95	1.24	20.50	**-0.07**	0.32	112	1.22	20.41	**-0.01**	0.24
P4	bedroom 1 window	5	1.38	23.84	0.04	0.15	7	1.24	22.70	0.21	0.59
P5	bedroom 1 window	28	1.89	22.97	**-0.70**	1.11	53	1.87	22.72	**0.12**	0.71
P6	bedroom 1 window	2	1.25	20.02	-0.05	0.11	3	1.08	20.06	0.10	0.20
P6	bedroom 2 int door	6	-	21.05	0.09	0.26	7	-	20.11	0.05	0.17
P7	bedroom 1 window 1	8	1.41	23.44	-0.19	0.27	9	1.38	22.95	-0.09	0.12
P7	bedroom 1 window 2	15	1.39	23.14	0.01	0.29	14	1.33	23.22	0.06	0.23
	Average	-	1.41	22.13	-0.11	-	-	1.36	21.74	0.09	-

Table F.13: Table showing the change in temperature after opening and closing different windows and doors in the bedrooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	25	-	20.87	**0.13**	0.42	29	-	21.12	**-0.08**	0.28
P1	bedroom window	15	2.32	21.10	**-0.24**	0.37	20	2.31	21.03	**-0.02**	0.46
P2	bedroom 1 window	156	3.05	20.43	**-0.26**	0.52	164	2.22	19.38	**0.29**	0.98
P3	bedroom 1 int door	128	-	18.52	0.15	0.74	145	-	18.71	0.11	0.67
P3	bedroom 1 window	10	2.42	18.19	**-0.74**	0.89	25	1.98	17.96	**0.12**	0.64
P3	bedroom 2 int door	128	2.63	19.66	**-0.33**	0.78	111	2.88	19.79	**0.20**	0.58
P3	bedroom 2 window	43	3.07	19.79	-0.15	1.23	81	2.49	19.72	0.04	0.68
P4	bedroom 1 window	7	3.06	20.92	-0.07	0.08	14	2.32	20.03	-0.06	0.20
P5	bedroom 1 window	10	2.54	22.30	**-0.67**	1.07	54	2.42	21.73	**0.06**	0.34
P6	bedroom 1 window	44	1.96	19.76	**-0.15**	0.65	50	1.77	19.19	**0.21**	0.63
P6	bedroom 2 int door	196	-	19.80	**0.07**	0.58	468	-	20.85	-0.03	0.44
P7	bedroom 1 window 1	27	2.14	21.44	0.00	0.78	44	1.84	21.39	0.01	0.39
P7	bedroom 1 window 2	20	2.04	21.75	-0.04	0.63	33	1.87	21.42	0.00	0.39
	Average	-	2.52	20.35	-0.18	-	-	2.21	20.18	0.07	-

Table F.14: Table showing AER for bedrooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in temperature after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	Yes
P1	bedroom window	-	0.29	-	0.23	No	No
P2	bedroom 1 window	**0.66**	**0.49**	0.66	0.53	No	No
P3	bedroom 1 int door	-	-	0.77	0.50	No	No
P3	bedroom 1 window	-	0.53	0.92	0.51	No	No
P3	bedroom 2 int door	-	-	0.52	0.47	Yes	Yes
P3	bedroom 2 window	-	-	1.00	0.50	No	No
P4	bedroom 1 window	-	0.36	-	0.30	No	No
P5	bedroom 1 window	-	0.38	-	0.26	No	No
P6	bedroom 1 window	0.46	0.39	0.37	0.28	No	No
P6	bedroom 2 int door	-	-	-	-	-	-
P7	bedroom 1 window 1	**1.29**	**0.27**	0.94	0.26	No	No
P7	bedroom 1 window 2	**0.87**	**0.27**	0.67	0.26	No	No
	Average	0.82	0.37	0.73	0.37	-	-

Table F.15: Table showing the change in temperature after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	57	-	24.60	0.02	0.28	57	-	24.47	0.03	0.21
P1	window	57	1.39	25.63	**-0.17**	0.43	54	1.45	24.34	**0.14**	0.38
P2	bedroom 1 window	23	1.73	21.28	**-0.20**	0.29	22	1.42	20.24	**0.33**	1.35
P3	bedroom 1 int door	177	-	20.05	0.03	0.52	145	-	20.28	0.05	0.42
P3	bedroom 1 window	80	1.18	20.84	**-0.15**	0.55	109	1.16	20.66	**0.19**	0.49
P3	bedroom 2 int door	181	1.24	20.39	**-0.03**	0.34	151	1.41	20.42	**0.00**	0.33
P3	bedroom 2 window	95	1.24	20.50	**-0.07**	0.32	112	1.22	20.41	**-0.01**	0.24
P4	bedroom 1 window	5	1.38	23.84	0.04	0.15	7	1.24	22.70	0.21	0.59
P5	bedroom 1 window	28	1.89	22.97	**-0.70**	1.11	53	1.87	22.72	**0.12**	0.71
P6	bedroom 1 window	2	1.25	20.02	-0.05	0.11	3	1.08	20.06	0.10	0.20
P6	bedroom 2 int door	6	-	21.05	0.09	0.26	7	-	20.11	0.05	0.17
P7	bedroom 1 window 1	8	1.41	23.44	-0.19	0.27	9	1.38	22.95	-0.09	0.12
P7	bedroom 1 window 2	15	1.39	23.14	0.01	0.29	14	1.33	23.22	0.06	0.23
	Average	-	1.41	22.13	-0.11	-	-	1.36	21.74	0.09	-

Table F.16: Table showing the change in temperature after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	25	-	20.87	**0.13**	0.42	29	-	21.12	**-0.08**	0.28
P1	window	15	2.32	21.10	**-0.24**	0.37	20	2.31	21.03	**-0.02**	0.46
P2	bedroom 1 window	156	3.05	20.43	**-0.26**	0.52	164	2.22	19.38	**0.29**	0.98
P3	bedroom 1 int door	128	-	18.52	0.15	0.74	145	-	18.71	0.11	0.67
P3	bedroom 1 window	10	2.42	18.19	**-0.74**	0.89	25	1.98	17.96	**0.12**	0.64
P3	bedroom 2 int door	128	2.63	19.66	**-0.33**	0.78	111	2.88	19.79	**0.20**	0.58
P3	bedroom 2 window	43	3.07	19.79	-0.15	1.23	81	2.49	19.72	0.04	0.68
P4	bedroom 1 window	7	3.06	20.92	-0.07	0.08	14	2.32	20.03	-0.06	0.20
P5	bedroom 1 window	10	2.54	22.30	**-0.67**	1.07	54	2.42	21.73	**0.06**	0.34
P6	bedroom 1 window	44	1.96	19.76	**-0.15**	0.65	50	1.77	19.19	**0.21**	0.63
P6	bedroom 2 int door	196	-	19.80	**0.07**	0.58	468	-	20.85	-0.03	0.44
P7	bedroom 1 window 1	27	2.14	21.44	0.00	0.78	44	1.84	21.39	0.01	0.39
P7	bedroom 1 window 2	20	2.04	21.75	-0.04	0.63	33	1.87	21.42	0.00	0.39
	Average	-	2.52	20.35	-0.18	-	-	2.21	20.18	0.07	-

Table F.17: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in temperature after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	Yes
P1	window	-	0.29	-	0.23	No	No
P2	bedroom 1 window	**0.66**	**0.49**	0.66	0.53	No	No
P3	bedroom 1 int door	-	-	0.77	0.50	No	No
P3	bedroom 1 window	-	0.53	0.92	0.51	No	No
P3	bedroom 2 int door	-	-	0.52	0.47	Yes	Yes
P3	bedroom 2 window	-	-	1.00	0.50	No	No
P4	bedroom 1 window	-	0.36	-	0.30	No	No
P5	bedroom 1 window	-	0.38	-	0.26	No	No
P6	bedroom 1 window	0.46	0.39	0.37	0.28	No	No
P6	bedroom 2 int door	-	-	-	-	-	-
P7	bedroom 1 window 1	**1.29**	**0.27**	0.94	0.26	No	No
P7	bedroom 1 window 2	**0.87**	**0.27**	0.67	0.26	No	No
	Average	0.82	0.37	0.73	0.37	-	-

Table F.18: Table showing the change in temperature after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	25.38	0.04	0.34	40	-	25.73	-0.01	0.32
P1	living window	76	1.45	26.06	**-0.05**	0.41	58	1.68	25.32	**0.23**	0.37
P1	balc door	32	1.28	26.91	**-0.39**	0.68	118	1.42	25.89	**0.04**	0.36
P2	kitchen window	11	1.29	20.19	0.07	0.43	13	1.12	20.99	-0.31	0.77
P2	sliding door	316	1.41	20.42	**-0.13**	0.54	355	1.32	20.51	**0.17**	0.52
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	1.30	23.08	-0.15	0.49	22	1.28	22.82	0.08	0.28
P5	balc door	23	1.95	24.52	-0.09	0.24	65	2.16	24.42	-0.01	0.25
P6	sliding door	9	1.23	19.34	0.02	0.30	17	1.28	19.07	0.14	0.53
P7	kitchen window	4	1.40	22.86	-0.16	0.40	3	1.40	23.32	0.06	0.08
	Average	-	1.41	23.20	-0.09	-	-	1.46	23.12	0.04	-

Table F.19: Table showing the change in temperature after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	22.99	0.02	0.34	16	-	22.84	0.06	0.28
P1	living window	9	2.50	22.72	**-0.16**	0.45	22	2.52	22.40	**0.14**	0.61
P1	balc door	0	-	-	**-**	-	20	2.76	22.70	**-0.06**	0.37
P2	kitchen window	0	-	-	-	-	2	2.41	18.64	-0.05	0.22
P2	sliding door	234	2.11	18.97	-0.08	0.81	756	2.31	18.66	0.02	1.01
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	1.63	19.07	-0.24	0.41	13	1.60	18.99	0.30	0.63
P5	balc door	13	2.58	23.22	-0.18	0.46	45	2.82	22.88	-0.02	0.40
P6	sliding door	50	1.59	18.80	**-0.42**	0.78	439	2.29	20.06	**0.20**	0.80
P7	kitchen window	2	2.74	22.15	0.62	1.01	5	3.46	22.89	-0.26	0.43
	Average	-	2.19	21.13	-0.06	-	-	2.52	21.12	0.04	-

Table F.20: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in temperature after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	living window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P1	balc door	-	0.24	-	0.23	-	-
P2	kitchen window	0.69	0.57	0.85	0.58	-	-
P2	sliding door	1.19	0.58	-	-	Yes	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	-	-	1.64	0.29	No	No
P5	balc door	-	-	-	0.26	No	No
P6	sliding door	-	-	0.35	0.29	No	No
P7	kitchen window	-	-	0.25	0.27	No	No
	Average	0.83	0.41	0.77	0.31	-	-

Table F.21: Table showing the change in temperature after opening and closing different windows and doors in the bathrooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	92	-	26.70	**-0.07**	0.17	185	-	26.40	**0.04**	0.10
P2	bathroom window	86	1.81	19.61	0.01	1.81	82	1.45	19.68	-0.01	1.31
P3	int door	324	1.26	19.40	0.02	0.32	3	0.86	20.80	-0.23	0.34
P3	bathroom window	129	1.21	19.83	0.00	0.23	105	1.20	19.55	0.27	1.20
P4	bathroom 1 window	61	1.41	20.84	-0.01	0.22	76	1.29	21.13	0.01	0.29
P5	-	-	-	-	-	-	-	-	-	-	-
P6	gf bathroom window	4	1.66	18.68	-0.32	0.56	3	1.42	19.25	-0.27	0.37
P7	bathroom window	23	1.34	20.20	0.22	0.53	18	1.34	19.27	0.13	0.43
	Average	-	1.45	20.75	-0.02	-	-	1.26	20.87	-0.01	-

Table F.22: Table showing the change in temperature after opening and closing different windows and doors in the bathrooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median temperature change, IQR = interquartile range, before = median temperature before opening/closing. Bold results indicate where the temperature change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	0	-		-	-	0	-		-	-
P2	bathroom window	239	2.87	19.50	0.57	2.18	235	2.11	18.29	0.35	1.76
P3	int door	294	2.33	18.72	0.09	0.78	2	2.60	17.47	0.51	0.42
P3	bathroom window	85	2.42	18.64	**-0.15**	0.86	110	2.17	18.27	**0.22**	0.87
P4	bathroom 1 window	69	2.08	17.43	0.18	0.80	99	1.90	17.44	0.14	0.75
P5	-	-	-	-	-	-	-	-	-	-	-
P6	gf bathroom window	77	1.83	17.91	**-0.39**	1.20	81	1.69	18.75	**0.19**	0.69
P7	bathroom window	54	2.29	18.86	-0.09	0.79	73	2.05	18.91	-0.06	0.54
	Average	-	2.30	18.51	0.04	-	-	2.09	18.19	0.23	-

Table F.23: Table showing AER for bathrooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in temperature after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	-	-
P2	bathroom window	-	-	-	-	No	No
P3	int door	-	-	-	-	No	No
P3	bathroom window	-	-	-	-	Yes	Yes
P4	bathroom 1 window	-	-	-	-	No	No
P5	-	-	-	-	-	-	-
P6	gf bathroom window	-	-	-	-	No	No
P7	bathroom window	-	-	-	-	Yes	Yes
	Average	-	-	-	-	-	-

F.3.2 Results tables for ventilation practices and absolute humidity

Table F.24: Table showing the change in absolute humidity after opening and closing different windows and doors in the bedrooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	57	1.14	11.73	0	0.58	57	1.13	11.61	0.09	0.31
P1	window	57	1.08	11.66	**-0.16**	0.78	54	1.03	11.22	**0.28**	0.48
P2	bedroom 1 window	23	1.24	11.34	**-0.24**	0.41	22	1.16	10.30	**0.34**	0.41
P3	bedroom 1 int door	177	1.12	10.94	**0.04**	0.54	145	1.14	11.28	**0.11**	0.26
P3	bedroom 1 window	80	1.11	12.22	**-0.47**	0.88	109	1.07	11.79	**0.17**	0.63
P3	bedroom 2 int door	181	1.15	11.73	0.01	0.26	151	1.16	12.00	0.03	0.26
P3	bedroom 2 window	95	1.13	12.07	**-0.07**	0.69	112	1.14	11.74	**0.07**	0.3
P4	bedroom 1 window	5	1.28	12.28	-0.09	0.08	7	1.15	10.09	-0.35	0.92
P5	bedroom 1 window	28	1.21	9.19	**-1.35**	1.53	53	1.23	8.42	**0.25**	0.76
P6	bedroom 1 window	2	1.1	7.15	-0.53	0.15	3	1.1	6.36	0.06	0.26
P6	bedroom 2 int door	6	1.16	8.47	-0.1	0.42	7	1.16	7.70	0.27	0.25
P7	bedroom 1 window 1	8	1.22	14.00	**-0.39**	0.64	9	1.28	12.61	**0.1**	0.16
P7	bedroom 1 window 2	15	1.28	13.97	**-0.3**	0.57	14	1.24	13.34	**0.26**	0.27
	Average	-	1.17	11.29	-0.28	-	-	1.15	10.65	0.13	-

Table F.25: Table showing the change in absolute humidity after opening and closing different windows and doors in the bedrooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	25	1.51	10.77	**0.27**	0.78	29	1.49	10.72	**0.02**	0.37
P1	window	15	1.45	10.69	**-0.4**	0.52	20	1.41	9.88	**0.05**	0.38
P2	bedroom 1 window	156	1.45	8.77	**-0.15**	0.32	164	1.33	8.17	**0.23**	0.48
P3	bedroom 1 int door	128	1.39	7.70	0.09	0.69	145	1.43	7.59	0.09	0.29
P3	bedroom 1 window	10	1.26	7.28	**-0.87**	0.86	25	1.24	7.52	**-0.08**	0.94
P3	bedroom 2 int door	128	1.6	8.65	**-0.48**	1.52	111	1.57	8.81	**0.52**	0.85
P3	bedroom 2 window	43	1.7	8.74	**-0.62**	2.22	81	1.54	8.10	**0.24**	1
P4	bedroom 1 window	7	1.69	10.15	-0.24	0.76	14	1.64	9.94	-0.02	0.38
P5	bedroom 1 window	10	1.44	8.07	**-0.96**	0.97	54	1.32	8.08	**0**	0.55
P6	bedroom 1 window	44	1.17	8.12	**-0.26**	0.57	50	1.11	7.69	**0.14**	0.47
P6	bedroom 2 int door	139	1.29	8.38	0.06	0.53	468	1.44	8.83	-0.01	0.4
P7	bedroom 1 window 1	27	1.79	11.46	**-0.73**	0.58	44	1.58	10.59	**0.23**	0.59
P7	bedroom 1 window 2	20	1.53	11.48	**-0.82**	0.69	33	1.52	10.89	**0.32**	0.63
	Average	-	1.48	9.25	-0.39	-	-	1.43	8.99	0.13	-

Table F.26: Table showing AER for bedrooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in absolute humidity after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	Yes	Yes
P1	window	-	0.29	-	0.23	No	No
P2	bedroom 1 window	**0.66**	**0.49**	0.66	0.53	No	No
P3	bedroom 1 int door	-	-	0.77	0.50	No	No
P3	bedroom 1 window	-	0.53	0.92	0.51	No	No
P3	bedroom 2 int door	-	-	0.52	0.47	Yes	Yes
P3	bedroom 2 window	-	-	1.00	0.50	Yes	No
P4	bedroom 1 window	-	0.36	-	0.30	No	No
P5	bedroom 1 window	-	0.38	-	0.26	No	No
P6	bedroom 1 window	0.46	0.39	0.37	0.28	No	No
P6	bedroom 2 int door	-	-	-	-	No	No
P7	bedroom 1 window 1	**1.29**	**0.27**	0.94	0.26	No	No
P7	bedroom 1 window 2	**0.87**	**0.27**	0.67	0.26	Yes	No
	Average	0.82	0.37	0.73	0.37	-	-

Table F.27: Table showing the change in absolute humidity after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	1.16	11.33	0.07	0.52	40	1.11	11.34	0.07	0.38
P1	window	76	1.13	11.40	**-0.07**	0.61	58	1.17	10.66	**0.25**	0.61
P1	balc door	32	1.06	11.32	**-0.55**	1.37	118	1.08	11.12	**0.21**	0.65
P2	living window	58	1.1	12.11	**-0.06**	0.41	59	1.1	11.87	**0.06**	0.29
P3	living window 2	13	1.09	12.40	**-0.18**	0.64	21	1.07	12.33	**0.12**	0.52
P3	front door	104	1.1	11.67	**-0.32**	1.09	606	1.14	11.22	**0.17**	0.66
P4	living window	5	1.12	13.94	-0.9	1.86	4	1.01	11.41	0.66	0.45
P5	living window	1	1.52	7.55	-0.94	0	1	1.25	6.60	1.24	0
P5	balc door	23	1.18	9.26	-0.06	0.26	65	1.33	7.86	-0.05	0.37
P6	sliding door	9	1.15	8.24	**-0.69**	0.57	17	1.13	7.52	**0.53**	0.78
P7	sliding door	8	1.19	13.80	**-0.7**	0.65	89	1.32	13.08	**0.08**	0.64
	Average	-	1.30	9.67	0.21	-	-	1.16	10.46	0.30	-

Table F.28: Table showing the change in absolute humidity after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	1.4	10.53	0.12	0.63	16	1.33	10.54	0.13	0.3
P1	window	9	1.33	10.94	**-0.71**	0.71	22	1.27	9.62	**0.28**	0.41
P1	balc door	0	-	-	-	-	20	1.47	9.89	-0.05	0.45
P2	living window	14	1.35	7.97	**-0.39**	0.34	14	1.26	7.50	**0.13**	0.35
P3	living window 2	5	1.35	8.24	**-1.42**	0.24	16	1.32	8.01	**-0.21**	1.8
P3	front door	26	1.31	8.22	**-0.92**	1.2	371	1.37	8.11	**0.2**	0.79
P4	living window	0	-	-	-	-	1	2.08	11.78	-1.78	0
P5	living window	0	-	-	-	-	1	1.48	8.17	0.42	0
P5	balc door	13	1.49	7.49	**-0.35**	0.79	45	1.39	7.43	**0.01**	0.33
P6	sliding door	50	1.18	8.63	**-1.01**	0.93	439	1.28	8.19	**0.18**	0.6
P7	sliding door	8	1.9	10.32	-0.17	0.12	259	1.75	11.52	-0.12	0.3
	Average	-	1.41	9.04	-0.61	-	-	1.45	9.16	-0.07	-

Table F.29: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in absolute humidity after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	window	**0.67**	**0.22**	**0.75**	**0.23**	Yes	No
P1	balc door	-	0.47	-	0.23	-	-
P2	living window	-	-	0.69	0.59	Yes	No
P3	living window 2	-	0.52	-	0.52	No	No
P3	front door	-	-	0.95	0.51	Yes	No
P4	living window	-	0.31	-	0.30	-	-
P5	living window	-	0.28	-	0.26	-	-
P5	balc door	-	0.28	-	0.26	No	No
P6	sliding door	-	0.39	0.35	0.29	No	Yes
P7	sliding door	-	0.25	0.69	0.26	Yes	Yes
	Average	19.45	0.93	7.34	-0.14	-	-

Table F.30: Table showing the change in absolute humidity after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	1.16	11.35	0.04	0.61	40	1.13	11.61	0.05	0.39
P1	living window	76	1.13	11.39	**-0.03**	0.68	58	1.17	10.62	**0.22**	0.43
P1	balc door	32	1.07	11.33	**-0.5**	1.42	118	1.08	11.26	**0.17**	0.58
P2	kitchen window	11	1.16	10.80	**-0.32**	0.19	13	1.17	10.51	**0.06**	0.57
P2	sliding door	316	1.17	11.42	**-0.11**	0.67	355	1.16	10.82	**0.3**	0.61
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	1.16	13.51	**-0.24**	1.59	22	1.18	12.92	**0.5**	0.36
P5	balc door	23	1.19	9.38	-0.04	0.45	65	1.34	8.01	-0.04	0.44
P6	sliding door	9	1.16	8.29	**-0.3**	0.48	17	1.17	7.80	**0.2**	0.65
P7	kitchen window	4	1.12	13.45	**-0.4**	0.66	3	1.2	13.48	**0.28**	0.14
	Average	-	1.33	10.02	0.05	-	-	1.18	10.78	0.19	-

Table F.31: Table showing the change in absolute humidity after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	1.39	10.68	0.11	0.44	16	1.32	10.44	0.12	0.25
P1	living window	9	1.32	10.88	**-0.75**	0.58	22	1.29	9.65	**0.28**	0.44
P1	balc door	0	-	-	-	-	20	1.47	10.08	0.07	0.6
P2	kitchen window	0	-	-	-	-	2	1.4	9.55	-0.23	0
P2	sliding door	234	1.3	8.90	**-0.03**	0.73	756	1.46	8.71	**0.02**	0.71
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	1.43	12.55	-0.88	1.14	13	1.69	11.68	0.49	0.37
P5	balc door	13	1.52	7.78	**-0.4**	0.87	45	1.43	7.75	**0.02**	0.52
P6	sliding door	50	1.19	8.83	**-0.68**	0.75	439	1.33	8.47	**0.17**	0.75
P7	kitchen window	2	1.93	11.41	-1.71	1.2	5	1.9	11.74	-0.2	0.69
	Average	-	1.44	10.15	-0.62	-	-	1.48	9.79	0.08	-

Table F.32: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in absolute humidity after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	living window	**0.60**	**0.23**	**0.75**	**0.23**	Yes	No
P1	balc door	-	0.24	-	0.23	-	-
P2	kitchen window	0.69	0.57	0.85	0.58	-	-
P2	sliding door	1.19	0.58	-	-	Yes	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	-	-	1.64	0.29	No	No
P5	balc door	-	-	-	0.26	No	No
P6	sliding door	-	-	0.35	0.29	No	No
P7	kitchen window	-	-	0.25	0.27	No	No
	Average	41.50	1.13	8.52	-0.19	-	-

Table F.33: Table showing the change in absolute humidity after opening and closing different windows and doors in the bathrooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	92	1.32	12.59	**-0.23**	0.72	185	1.34	12.41	**0.17**	0.4
P2	bathroom window	86	1.33	10.66	0.1	1.15	82	1.31	10.09	0.08	0.64
P3	int door	324	1.19	11.36	0.07	0.8	3	1.47	10.30	-0.56	0.58
P3	bathroom window	129	1.13	11.82	0.02	0.83	105	1.2	11.43	0.02	1
P4	bathroom 1 window	61	1.25	12.64	-0.01	0.56	76	1.28	12.31	0.04	0.42
P5	-	-	-	-	-	-	-	-	-	-	-
P6	gf bathroom window	4	1.65	10.57	-1.74	1.56	3	1.48	9.37	0	1.3
P7	bathroom window	23	1.36	13.81	0.85	1.31	18	1.32	12.60	0.49	1.08
	Average	-	1.38	10.31	0.08	-	-	1.34	11.22	0.03	-

Table F.34: Table showing the change in absolute humidity after opening and closing different windows and doors in the bathrooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median absolute humidity change, IQR = interquartile range, before = median absolute humidity before opening/closing. Bold results indicate where the absolute humidity change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	0	-	-	-	-	0	-	-	-	-
P2	bathroom window	239	1.59	9.37	**0.96**	2.53	235	1.45	8.72	**0.23**	0.7
P3	int door	294	1.71	9.73	0.12	1.04	2	1.64	10.00	0.39	0.09
P3	bathroom window	85	1.74	10.26	**-0.38**	1.78	110	1.65	9.11	**0.41**	1.41
P4	bathroom 1 window	69	1.7	10.51	**0.89**	1.75	99	1.54	10.22	**0.28**	1.05
P5	-	-	-	-	-	-	-	-	-	-	-
P6	gf bathroom window	77	1.56	10.64	**-1.59**	2.21	81	1.38	9.63	**0.12**	0.68
P7	bathroom window	54	2.03	12.84	**-0.82**	1.4	73	1.9	12.02	**-0.34**	1.28
	Average	-	1.72	10.56	-0.14	-	-	1.59	9.95	0.18	-

Table F.35: Table showing AER for bathrooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in absolute humidity after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	-	-
P2	bathroom window	-	-	-	-	Yes	Yes
P3	int door	-	-	-	-	No	No
P3	bathroom window	-	-	-	-	Yes	Yes
P4	bathroom 1 window	-	-	-	-	Yes	Yes
P5	-	-	-	-	-	-	-
P6	gf bathroom window	-	-	-	-	No	No
P7	bathroom window	-	-	-	-	Yes	Yes
	Average	116.86	1.72	10.56	-0.14	-	-

F.3.3 Results tables for ventilation practices and carbon dioxide

Table F.36: Table showing the change in CO_2 after opening and closing different windows and doors in the bedrooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	57	-	1084	**-84**	**310**	57	-	879	**138**	**291**
P1	window	57	1.48	593	**-75**	**220**	54	1.28	503	**167**	**173**
P2	bedroom 1 window	23	1.74	882	**-111**	**77**	22	1.12	528	**106**	**135**
P3	bedroom 1 int door	177	-	877	**-45**	**401**	145	-	786	**185**	**307**
P3	bedroom 1 window	80	1.7	785	**-155**	**420**	109	1.24	560	**26**	**204**
P3	bedroom 2 int door	181	1.57	713	**-1**	**178**	151	1.7	792	**12**	**279**
P3	bedroom 2 window	95	1.47	681	**-59**	**426**	112	1.42	654	**47**	**397**
P4	bedroom 1 window	5	1.6	779	-106	237	7	1.33	718	-87	208
P5	bedroom 1 window	28	1.95	901	**-219**	**297**	53	1.73	782	**17**	**222**
P6	bedroom 1 window	2	1.55	577	-37	65	3	1.32	475	9	41
P6	bedroom 2 int door	6	-	632	**-46**	**106**	7	2	746	**123**	**112**
P7	bedroom 1 window 1	8	2.9	1368	**-311**	**460**	9	1.59	720	**43**	**111**
P7	bedroom 1 window 2	15	2.42	1171	**-148**	**188**	14	1.61	740	**82**	**101**
	Average	-	1.84	849	-107	-	-	1.49	683	67	-

Table F.37: Table showing the change in CO_2 after opening and closing different windows and doors in the bedrooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	25	-	1518	**-95**	**702**	29	-	1284	**117**	**412**
P1	window	15	2.8	1243	**-214**	**421**	20	2.2	920	**51**	**304**
P2	bedroom 1 window	156	1.68	795	**-66**	**143**	164	1.3	614	**44**	**88**
P3	bedroom 1 int door	128	-	967	**-40**	**262**	145	-	860	**153**	**295**
P3	bedroom 1 window	10	1.66	708	-200	313	25	1.86	1036	-139	396
P3	bedroom 2 int door	128	2.57	1157	**-237**	**1146**	111	2.32	1043	**372**	**645**
P3	bedroom 2 window	43	1.82	802	**-85**	**686**	81	1.77	805	**47**	**449**
P4	bedroom 1 window	7	2.35	1140	134	218	14	2.31	1104	-29	305
P5	bedroom 1 window	10	2.01	936	**-194**	**187**	54	1.86	857	**-8**	**98**
P6	bedroom 1 window	44	1.89	713	**-85**	**104**	50	1.49	562	**45**	**82**
P6	bedroom 2 int door	196	-	806	**-57**	**180**	468	2.22	863	**24**	**157**
P7	bedroom 1 window 1	27	2.28	1177	**-290**	**166**	44	1.62	759	**55**	**144**
P7	bedroom 1 window 2	20	2.41	1186	**-298**	**154**	33	1.56	762	**69**	**88**
	Average	-	2.15	1011	-133	-	-	1.86	882	62	-

Table F.38: Table showing AER for bedrooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in CO_2 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	window	-	0.29	-	0.23	Yes	No
P2	bedroom 1 window	**0.66**	**0.49**	0.66	0.53	Yes	Yes
P3	bedroom 1 int door	-	-	0.77	0.50	No	No
P3	bedroom 1 window	-	0.53	0.92	0.51	No	Yes
P3	bedroom 2 int door	-	-	0.52	0.47	Yes	Yes
P3	bedroom 2 window	-	-	1.00	0.50	No	No
P4	bedroom 1 window	-	0.36	-	0.30	No	No
P5	bedroom 1 window	-	0.38	-	0.26	No	No
P6	bedroom 1 window	0.46	0.39	0.37	0.28	No	No
P6	bedroom 2 int door	-	-	-	-	-	-
P7	bedroom 1 window 1	**1.29**	**0.27**	0.94	0.26	No	No
P7	bedroom 1 window 2	**0.87**	**0.27**	0.67	0.26	Yes	No
	Average	0.82	0.37	0.73	0.37	-	-

Table F.39: Table showing the change in CO_2 after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	703	**10**	**117**	40	-	1041	**54**	**112**
P1	window	76	1.55	630	**-2**	**156**	58	1.38	546	**114**	**124**
P1	balc door	32	1.15	461	**-36**	**133**	118	1.39	552	**27**	**114**
P2	living window	58	1.05	490	**-25**	**62**	59	0.99	457	**26**	**457**
P3	living window 2	13	1.22	562	**-42**	**111**	21	1.12	511	**60**	**86**
P3	front door	104	1.29	615	**-85**	**207**	606	1.35	624	**31**	**155**
P4	living window	5	1.07	488	22	105	4	1.02	493	51	23
P5	living window	1	1.92	854	-12	0	1	1.82	835	256	0
P5	balc door	23	1.54	707	-19	73	65	1.59	745	-2	72
P6	sliding door	9	1.5	549	**-40**	**67**	17	1.48	529	**40**	**68**
P7	sliding door	8	1.84	862	**-228**	**150**	89	2.08	965	**13**	**240**
	Average	-	1.66	782	62	-	-	1.42	663	61	-

Table F.40: Table showing the change in CO_2 after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	733	-17	238	16	-	1017	146	134
P1	window	9	2.48	1030	-269	200	22	1.59	698	83	148
P1	balc door	0	-	-	-	-	20	2.21	912	53	249
P2	living window	14	1.25	588	-44	69	14	1.18	556	16	75
P3	living window 2	5	1.47	657	-54	183)	16	1.48	650	-37	231
P3	front door	26	1.46	666	-92	256	371	1.72	774	45	197
P4	living window	0	-	-	-	-	1	3.52	1680	-780	0
P5	living window	0	-	-	-	-	1	1.79	801	62	0
P5	balc door	13	1.62	755	-71	201	45	1.56	729	16	90
P6	sliding door	50	1.74	680	-122	170	439	1.7	642	25	117
P7	sliding door	8	2.07	1036	-62	111	259	2.03	988	-38	93
	Average	-	1.73	768	-91	-	-	1.88	859	-37	-

Table F.41: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in CO_2 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	window	**0.67**	**0.22**	**0.75**	**0.23**	Yes	No
P1	balc door	-	0.47	-	0.23	-	-
P2	living window	-	-	0.69	0.59	No	No
P3	living window 2	-	0.52	-	0.52	No	Yes
P3	front door	-	-	0.95	0.51	No	No
P4	living window	-	0.31	-	0.30	-	-
P5	living window	-	0.28	-	0.26	-	-
P5	balc door	-	0.28	-	0.26	No	No
P6	sliding door	-	0.39	0.35	0.29	Yes	No
P7	sliding door	-	0.25	0.69	0.26	Yes	Yes
	Average	0.67	0.34	0.69	0.35	-	-

Table F.42: Table showing the change in CO_2 after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	679	**6**	**123**	40	-	724	**66**	**110**
P1	living window	76	1.49	590	**-2**	**132**	58	1.36	543	**94**	**100**
P1	balc door	32	1.18	469	**-29**	**116**	118	1.35	533	**20**	**95**
P2	kitchen window	11	1.11	502	-45	61	13	1.06	479	2	85
P2	sliding door	316	1.13	530	**-7**	**76)**	355	1.11	508	**34**	**75**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	1.52	734	**-65**	**205**	22	1.29	604	**89**	**140**
P5	balc door	23	1.51	688	-11	67	65	1.56	723	-4	79
P6	sliding door	9	1.39	537	**-34**	**62**	17	1.48	531	**23**	**80**
P7	kitchen window	4	1.72	841	**-172**	**166**	3	1.4	626	**-20**	**148**
	Average	-	1.66	748	-3	-	-	1.33	586	34	-

Table F.43: Table showing the change in CO_2 after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median CO_2 change, IQR = interquartile range, before = median CO_2 before opening/closing. Bold results indicate where the CO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	1083	**-15**	**208**	16	-	946	**112**	**128**
P1	living window	9	2.32	964	**-250**	**269**	22	1.58	686	**82**	**141**
P1	balc door	0	-	-	-	-	20	2.22	895	58	208
P2	kitchen window	0	-	-	-	-	2	1.63	707	60	26
P2	sliding door	234	1.4	641	-6	120	756	1.46	669	7	159
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	2.99	1428	-284	378	13	2.47	1186	91	244
P5	balc door	13	1.61	754	**-65**	**157**	45	1.54	723	**10**	**82**
P6	sliding door	50	1.77	688	**-121**	**208**	439	1.78	680	**23**	**162**
P7	kitchen window	2	2.33	1220	-344	45	5	2.06	1000	-18	70
	Average	-	2.07	968	-155	-	-	1.84	832	47	-

Table F.44: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in CO_2 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	-	-	-	No	No
P1	living window	**0.60**	**0.23**	**0.75**	**0.23**	Yes	No
P1	balc door	-	0.24	-	0.23	-	-
P2	kitchen window	0.69	0.57	0.85	0.58	-	-
P2	sliding door	1.19	0.58	-	-	No	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	-	-	1.64	0.29	No	No
P5	balc door	-	-	-	0.26	Yes	No
P6	sliding door	-	-	0.35	0.29	Yes	No
P7	kitchen window	-	-	0.25	0.27	No	No
	Average	0.83	0.41	0.77	0.31	-	-

F.3.4 Results tables for ventilation practices and particulate matter

Table F.45: Table showing the change in PM_1 after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_1 change, IQR = interquartile range, before = median PM_1 before opening/closing. Bold results indicate where the PM_1 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	12	-	3.28	0.1	1.16	5	-	-	-0.02	2.47
P1	window	12	1.24	3.15	0.68	3.51	15	1.32	3.2	0.05	2.34
P1	balc door	4	1.25	2.72	0.72	1.23	33	1.62	1.96	0.4	4.04
P2	living window	58	0.54	2.46	0.17	1.41	59	0.68	2.18	-0.03	0.65
P3	living window 2	13	2.08	2.79	1.08	5.44	21	2.49	4.13	-0.02	4.88
P3	front door	104	2.72	4.34	0.21	6.5	606	2.34	3.84	0.03	3.39
P4	living window	5	1.03	1	0.72	0.3	4	1.17	1.69	0.07	0.34
P5	living window	1	-	-	-	-	-	-	-	-	-
P5	balc door	23	1.2	3.28	-0.01	1.43	65	1.18	2.09	0.2	0.73
P6	sliding door	9	1.44	3.86	1	9.4	17	2.62	4.72	-0.62	5.07
P7	sliding door	8	0.71	1.92	0.85	1.45	89	0.74	1.51	0.14	0.48
	Average	-	1.36	2.88	0.55	-	-	1.57	2.81	0.02	-

Table F.46: Table showing the change in PM_1 after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_1 change, IQR = interquartile range, before = median PM_1 before opening/closing. Bold results indicate where the PM_1 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	0	-	-	-	-	0	-	-	-	-
P1	window	0	-	-	-	-	0	-	-	-	-
P1	balc door	0	-	-	-	-	0	-	-	-	-
P2	living window	14	0.32	2.7	**0.45**	**0.78**	14	0.52	2.44	**-0.17**	**0.28**
P3	living window 2	5	0.62	2.4	1.33	0.85	16	0.83	3.82	0.68	2.2
P3	front door	26	0.8	3.37	0.27	1.52	371	1.36	5.02	0.06	4.46
P4	living window	0	-	-	-	-	1	2.05	1.1	0.33	0
P5	living window	0	-	-	-	-	1	-	-	-	0
P5	balc door	13	1.56	5	0.15	1.91	45	1.27	4.36	-0.03	2.92
P6	sliding door	50	1.81	4.67	**0.39**	**4.2**	439	1.64	4.32	**0.04**	**1.81**
P7	sliding door	8	0.16	2.45	-0.11	0.43	259	0.3	1.31	-0.04	0.25
	Average	-	0.88	3.43	0.41	-	-	1.14	3.20	0.12	-

Table F.47: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in PM_1 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	No	No
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	Yes
P7	sliding door	-	-	0.95	0.51	No	Yes
	Average	0.82	0.36	0.73	0.36	-	-

Table F.48: Table showing the change in PM_1 after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_1 change, IQR = interquartile range, before = median PM_1 before opening/closing. Bold results indicate where the PM_1 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	3.74	-0.05	3.26	40	-	3.98	-0.19	1.2
P1	living window	76	1.43	3.55	0.26	2.79	58	1.35	3.24	-0.23	2.09
P1	balc door	32	1.45	2.95	0.42	2.53	118	1.46	3.19	0.12	1.68
P2	kitchen window	11	0.74	3.07	0.42	1.52	13	0.84	3.9	-0.69	1.88
P2	sliding door	316	0.49	1.77	**1.02**	**2.39**	355	0.77	2.71	**-0.3**	**1.02**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	0.76	1.36	**0.4**	**1.35**	22	1.01	1	**-0.11**	**0.44**
P5	balc door	23	1.02	2.79	-0.1	0.98	65	0.84	1.57	0.14	0.63
P6	sliding door	9	1.1	3.01	**0.6**	**3.04**	17	2.03	4.41	**-0.86**	**2.65**
P7	kitchen window	4	0.93	2.13	-0.14	0.32	3	0.79	1.73	-0.13	0.17
	Average	-	0.99	2.71	0.31	-	-	1.14	2.86	-0.25	-

Table F.49: Table showing the change in PM_1 after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_1 change, IQR = interquartile range, before = median PM_1 before opening/closing. Bold results indicate where the PM_1 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	4.42	0.34	5.1	16	-	3.24	-0.01	2.54
P1	living window	9	1.13	4.54	1.1	11.39	22	1.06	4.87	-0.21	1.15
P1	balc door	0	-	-	-	-	20	1.21	5.85	0	1.5
P2	kitchen window	0	-	-	-	-	2	0.13	2.34	2.31	2.2
P2	sliding door	234	0.37	1.93	**1.11**	**2.85**	756	0.48	2.7	**-0.05**	**1.23**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	1.67	1.42	-0.41	0.54	13	1.44	1.72	0.18	0.6
P5	balc door	13	1.17	4.13	0	1.87	45	1.03	3.65	-0.06	2.27
P6	sliding door	50	1.63	3.81	0.27	2.15	439	1.39	3.74	0.03	1.7
P7	kitchen window	2	0.51	1.93	1.83	1.12	5	0.56	2.84	-0.17	1.01
	Average	-	1.08	3.17	0.61	-	-	0.91	3.44	0.22	-

Table F.50: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in PM_1 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	No	No
P1	living window	-	0.28	-	0.26	No	No
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					No	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	No
P6	sliding door	0.69	0.57	0.85	0.58	No	Yes
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

Table F.51: Table showing the change in $PM_{2.5}$ after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median $PM_{2.5}$ change, IQR = interquartile range, before = median $PM_{2.5}$ before opening/closing. Bold results indicate where the $PM_{2.5}$ change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	12	-	4.46	0.73	1.94	5	-	6.64	0.03	3.95
P1	window	15	1.43	4.49	0.26	3.89	12	2.45	5.61	8.38	20.49
P1	balc door	4	1.34	4.41	1.35	1.7	33	1.75	10.84	1.39	7.18
P2	living window	58	0.53	3.36	0.19	2.59	59	0.71	3.2	0.02	1
P3	living window 2	13	1.99	6.57	2.83	8.47	21	2.74	6.95	-0.47	9.66
P3	front door	104	2.79	7.56	0.44	12.62	606	2.44	7.25	0.12	7.1
P4	living window	5	0.98	1.51	0.98	1.51	4	1.68	3.47	0.07	0.83
P5	living window	1	-	-	-	-	1	-	-	-	-
P5	balc door	23	1.3	4.38	0.11	2.02	65	1.09	3.05	0.36	0.94
P6	sliding door	9	1.45	5.39	**1.16**	**10.5**	17	2.67	6.95	**-1.44**	**5.57**
P7	sliding door	8	0.92	5.7	0.84	3	89	1.01	5.79	1.5	3.94
	Average	-	1.41	4.78	0.89	-	-	1.84	5.98	1.00	-

Table F.52: Table showing the change in $PM_{2.5}$ after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median $PM_{2.5}$ change, IQR = interquartile range, before = median $PM_{2.5}$ before opening/closing. Bold results indicate where the $PM_{2.5}$ change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	0	-	-	-	-	0	-	-	-	-
P1	window	0	-	-	-	-	0	-	-	-	-
P1	balc door	0	-	-	-	-	0	-	-	-	-
P2	living window	14	0.31	4.16	**0.78**	**1.07**	14	0.53	3.36	**-0.22**	**0.44**
P3	living window 2	5	0.43	5.59	3.88	3.31	16	0.87	10.77	2.89	7.07
P3	front door	26	0.78	7.56	0.49	4.47	371	1.08	10.38	0.07	8.51
P4	living window	0	-	-	-	-	1	1.8	4.16	2	0
P5	living window	0	-	-	-	-	1	-	-	-	-
P5	balc door	13	1.57	7.04	0.18	2.69	45	1.19	5.72	-0.06	4.18
P6	sliding door	50	2	6.28	**0.83**	**6.3**	439	1.73	6.62	**0.03**	**2.98**
P7	sliding door	8	0.15	4.92	-0.57	1.02	259	0.3	4.01	-0.21	1.49
	Average	-	0.87	5.93	0.93	-	-	1.07	6.43	0.64	-

Table F.53: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in $PM_{2.5}$ after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	No	No
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	Yes
P7	sliding door	-	-	0.95	0.51	No	Yes
	Average	0.82	0.36	0.73	0.36	-	-

Table F.54: Table showing the change in $PM_{2.5}$ after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median $PM_{2.5}$ change, IQR = interquartile range, before = median $PM_{2.5}$ before opening/closing. Bold results indicate where the $PM_{2.5}$ change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	5.4	0.57	4.65	40	-	5.81	0.08	1.76
P1	living window	76	1.42	4.87	0.68	3.82	58	1.32	4.97	-0.17	3.68
P1	balc door	32	1.51	4.49	0.62	3.2	118	1.49	4.67	0.38	2.77
P2	kitchen window	11	0.78	3.36	0.71	1.75	13	0.85	4.77	-0.99	2.26
P2	sliding door	316	0.42	2.27	**1.58**	**3.21**	355	0.76	3.78	**-0.47**	**1.38**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	0.87	2.54	**0.56**	**3.69**	22	1.02	2.27	**-0.17**	**1.04**
P5	balc door	23	1.11	3.6	-0.13	1.64	65	0.84	2.22	0.24	0.91
P6	sliding door	9	1.1	4.19	**1.46**	**3.75**	17	2.04	6.24	**-1.11**	**3.05**
P7	kitchen window	4	0.95	5.96	-0.34	3.64	3	0.9	5.39	0.22	0.58
	Average	-	1.02	4.08	0.63	-	-	1.15	4.46	-0.22	-

Table F.55: Table showing the change in $PM_{2.5}$ after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median $PM_{2.5}$ change, IQR = interquartile range, before = median $PM_{2.5}$ before opening/closing. Bold results indicate where the $PM_{2.5}$ change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	5.74	0.68	6.93	16	-	4.78	0.11	3.93
P1	living window	9	1.09	6.13	2.26	13.84	22	1.06	6.22	-0.15	2.17
P1	balc door	0	-	-	-	-	20	1.14	8.36	0.39	1.85
P2	kitchen window	0	-	-	-	-	2	0.16	3.3	2.97	2.74
P2	sliding door	234	0.33	2.59	**1.68**	**3.81**	756	0.44	3.64	**-0.05**	**1.77**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	1.87	4.1	-1.25	2.76	13	1.9	4.05	-0.13	2.08
P5	balc door	13	1.17	5.8	0.32	1.58	45	0.92	4.71	-0.03	3.3
P6	sliding door	50	1.71	5.35	0.45	3.18	439	1.48	5.67	0.11	2.94
P7	kitchen window	2	0.78	9.85	2.65	2.45	5	0.63	10.39	-0.84	1.95
	Average	-	1.16	5.65	0.97	-	-	0.97	5.68	0.26	-

Table F.56: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in $PM_{2.5}$ after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	No	No
P1	living window	-	0.28	-	0.26	No	No
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					No	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	No
P6	sliding door	0.69	0.57	0.85	0.58	No	Yes
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

Table F.57: Table showing the change in PM_{10} after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_{10} change, IQR = interquartile range, before = median PM_{10} before opening/closing. Bold results indicate where the PM_{10} change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	12	-	10.06	6.96	23.62	0	-	15.39	-	-
P1	window	12	2.45	9.04	8.38	20.49	15	4.38	18.9	2.51	24.07
P1	balc door	4	4	18.78	1.29	5.06	33	5.89	-	0.87	33.48
P2	living window	58	0.64	5.69	2.05	9.08	59	0.94	6.64	1.77	4.66
P3	living window 2	13	3.27	19.79	15.43	25.89	21	5.02	20.58	-2.38	18.27
P3	front door	104	5.78	18.07	1.24	22.77	606	4.29	18.23	-0.17	20.18
P4	living window	5	1.96	5.53	0.27	8.86	4	3.82	10.65	1.87	4.93
P5	living window	1	-	-	-	-	1	-	-	-	-
P5	balc door	23	2.48	6.62	-0.32	6.61	65	1.5	4.24	1.85	4.99
P6	sliding door	9	1.39	13.12	2.19	20.91	17	3.48	15.53	-1.69	6.89
P7	sliding door	8	2.2	33.4	2.55	32.36	89	3.38	33.54	9.48	39.57
	Average	-	2.69	14.01	4.00	-	-	3.63	15.97	1.57	-

Table F.58: Table showing the change in PM_{10} after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_{10} change, IQR = interquartile range, before = median PM_{10} before opening/closing. Bold results indicate where the PM_{10} change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	5	-	-	-1.15	8.9	0	-	-	-	-
P1	window	0	-	-	-	-	0	-	-	-	-
P1	balc door	0	-	-	-	-	0	-	-	-	-
P2	living window	14	0.44	10.06	2.93	8.64	14	0.74	5.21	1.1	6.03
P3	living window 2	5	0.35	7.02	18.98	10.84	16	1.21	25.07	8.75	26.56
P3	front door	26	1.74	20.87	1.26	27.47	371	1.82	24.87	-0.4	1.82
P4	living window	0	-	-	-	-	1	-	-	-	0
P5	living window	0	-	-	-	-	1	-	-	-	0
P5	balc door	13	2.24	14.03	-2.53	11.18	45	1.62	10.18	1.24	8.81
P6	sliding door	50	4.12	25.4	**-3.46**	**24.92**	439	3.78	19.54	**0.56**	**19.79**
P7	sliding door	8	0.17	10.65	-1.97	5.02	259	0.44	11.73	-0.67	7.88
	Average	-	1.51	14.67	2.01	-	-	1.60	16.10	1.76	-

Table F.59: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in PM_{10} after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	No	No
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	No
P7	sliding door	-	-	0.95	0.51	No	Yes
	Average	0.82	0.36	0.73	0.36	-	-

Table F.60: Table showing the change in PM_{10} after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_{10} change, IQR = interquartile range, before = median PM_{10} before opening/closing. Bold results indicate where the PM_{10} change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	22.37	8.33	37.32	40	-	20.03	1.77	34.98
P1	living window	76	3.48	17.27	12.88	42.36	58	4.26	17.84	5.87	28.5
P1	balc door	32	4.96	24.47	3.62	42.55	118	4.43	21.06	4.05	24.12
P2	kitchen window	11	1.57	8.28	-1.56	6.13	13	1.22	7.84	-0.61	20.8
P2	sliding door	316	0.36	3.08	**8.6**	**11.9**	355	1.11	9.24	**-2.12**	**6.94**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	1.28	5.64	1.16	9.34	22	2.19	6.31	0.81	5.4
P5	balc door	23	2.37	5.91	**0.43**	**6.16**	65	1.11	3.4	**1.79**	**5.32**
P6	sliding door	9	1.02	11.63	**9.32**	**12.8**	17	3.9	17.15	**-1.79**	**4.53**
P7	kitchen window	4	1.59	18.84	-3.85	14.97	3	1.55	26.77	-0.57	9.31
	Average	-	2.08	13.05	4.33	-	-	2.47	14.40	1.02	-

Table F.61: Table showing the change in PM_{10} after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median PM_{10} change, IQR = interquartile range, before = median PM_{10} before opening/closing. Bold results indicate where the PM_{10} change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	16.48	19.32	29.16	16	-	16.03	1.64	13.76
P1	living window	9	3.24	24.99	6.74	29.76	22	1.81	16.76	6.07	13.39
P1	balc door	0	-	-	-	-	20	4.84	31.69	4.41	17.45
P2	kitchen window	0	-	-	-	-	2	0.75	14.37	7.13	5.83
P2	sliding door	234	0.34	4.04	**5.46**	**7.95**	756	0.66	7.49	**0.33**	**6.43**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	2.92	8.61	6.71	10.21	13	4.48	13.59	-4.78	20.03
P5	balc door	13	1.53	7.92	0.28	4.16	45	1.32	7.67	1.43	6.15
P6	sliding door	50	3.22	20.45	-2.84	21.28	439	3.73	17.23	1.08	19.17
P7	kitchen window	2	2.82	84.64	-15.2	16.95	5	1.11	45.42	-0.74	12.89
	Average	-	2.35	23.88	2.92	-	-	2.34	18.92	1.84	-

Table F.62: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in PM_{10} after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	No	No
P1	living window	-	0.28	-	0.26	No	No
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					Yes	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	Yes
P6	sliding door	0.69	0.57	0.85	0.58	No	No
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

F.3.5 Results tables for ventilation practices and nitrogen dioxide

Table F.63: Table showing the change in NO_2 after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median NO_2 change, IQR = interquartile range, before = median NO_2 before opening/closing. Bold results indicate where the NO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	living window	58	0.19	8.92	2.12	10.56	59	0.19	14.93	0.97	6.61
P3	living window 2	13	1.29	17.96	1.31	12.89	21	0.83	19.35	-1.62	12.74
P3	front door	104	0.8	17.95	**2.37**	**13.99**	606	0.89	17.51	**0.23**	**9.12**
P4	living window	5	0.62	15.44	1.03	7.45	4	0.34	24.99	6.47	13.29
P5	living window	1	-	-	-	-	1	-	-	-	-
P5	balc door	23	0.35	10.25	0.5	3.48	65	0.34	8	1.14	3.15
P6	sliding door	9	1	10.85	-3.12	6.94	17	0.65	16.54	1.71	12.29
P7	sliding door	8	0.71	25.23	0.63	14.33	89	0.59	20.5	0.77	9.08
	Average	-	0.71	15.23	0.69	-	-	0.55	17.40	1.38	-

Table F.64: Table showing the change in NO_2 after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median NO_2 change, IQR = interquartile range, before = median NO_2 before opening/closing. Bold results indicate where the NO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	living window	14	0.25	12.76	-0.33	7.36	14	0.16	12.99	2.39	6.04
P3	living window 2	5	1.37	28.03	6.13	9.45	16	1.09	20.66	8.33	25.82
P3	front door	26	1.04	31.2	4.32	23.36	371	0.92	24.34	0.4	15.56
P4	living window	0	-	-	-	-	1	-	-	-	-
P5	living window	0	-	-	-	-	1	-	-	-	-
P5	balc door	13	0.54	12.69	-0.72	10.87	45	0.45	9.71	0.98	3.64
P6	sliding door	50	0.49	18.71	1.13	12.02	439	0.42	15.17	1.01	9.41
P7	sliding door	8	0.45	15.33	0.31	4.02	259	0.43	13.01	0.17	4.32
	Average	-	0.69	19.79	1.81	-	-	0.58	15.98	2.21	-

Table F.65: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in NO_2 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	No	No
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	No
P7	sliding door	-	-	0.95	0.51	No	No
	Average	0.82	0.36	0.73	0.36	-	-

Table F.66: Table showing the change in NO_2 after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median NO_2 change, IQR = interquartile range, before = median NO_2 before opening/closing. Bold results indicate where the NO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	living window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	kitchen window	11	0.12	4.73	-0.36	4.23	13	0.17	11.76	-3.18	36.28
P2	sliding door	316	0.09	5.72	**3.12**	**13.79**	355	0.15	10.46	**-0.4**	**8.13**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	1.45	16.86	0.44	25.13	22	0.54	19.18	-0.53	9.41
P5	balc door	23	0.56	17.32	2.1	11.36	65	0.81	17.21	1.24	6.25
P6	sliding door	9	0.85	17.93	-0.13	8.35	17	1.16	26.73	3.89	7.53
P7	kitchen window	4	0.61	14.88	5.94	7.26	3	0.71	26.48	-2.71	11.07
	Average	-	0.61	12.91	1.85	-	-	0.59	18.64	-0.28	-

Table F.67: Table showing the change in NO_2 after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median NO_2 change, IQR = interquartile range, before = median NO_2 before opening/closing. Bold results indicate where the NO_2 change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	living window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	kitchen window	0	-	-	-	-	2	-	-	-	-
P2	sliding door	234	0.17	10.51	**3.28**	**25.57**	756	0.34	16.46	**-0.13**	**13.78**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	0.34	3.96	-2.97	16.51	13	0.86	28.03	1.21	68.48
P5	balc door	13	1.04	17.79	6.32	17.07	45	0.78	18.18	2.36	10.72
P6	sliding door	50	0.48	21.83	**-3.83**	**20.23**	439	0.5	17.82	**1.56**	**16.46**
P7	kitchen window	2	-	-	-	-	5	0.42	21.01	-1.21	7.55
	Average	-	0.51	13.52	0.70	-	-	0.58	20.30	0.76	-

Table F.68: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in NO_2 after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	-	-
P1	living window	-	0.28	-	0.26	-	-
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					No	No
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	No
P6	sliding door	0.69	0.57	0.85	0.58	No	No
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

F.3.6 Results tables for ventilation practices and carbon monoxide

Table F.69: Table showing the change in carbon monoxide after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median carbon monoxide change, IQR = interquartile range, before = median carbon monoxide before opening/closing. Bold results indicate where the carbon monoxide change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	12	-	396	21	176	5	-	114	-2	41
P1	window	12	1.61	268	**-3**	75	15	0.92	93	**45**	57
P1	balc door	4	0.21	59	-57	39	33	1.99	320	8	111
P2	living window	58	1.72	162	**-17**	56	59	1.28	146	**10**	55
P3	living window 2	13	0.87	437	**-171**	438	21	0.31	171	**42**	262
P3	front door	104	0.59	389	**-116**	393	606	0.72	365	**67**	446
P4	living window	5	0.86	452	-58	395	4	0.67	436	58	146
P5	living window	1	-	-	-	-	1	-	-	-	-
P5	balc door	23	2.81	454	-8	890	65	1.14	266	-10	101
P6	sliding door	9	3.81	81	**-54**	69	17	0.38	31	**12**	80
P7	sliding door	8	1.36	740	**-395**	363	89	1.08	508	**2**	267
	Average	-	1.54	344	-86	-	-	0.94	245	23	-

Table F.70: Table showing the change in carbon monoxide after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median carbon monoxide change, IQR = interquartile range, before = median carbon monoxide before opening/closing. Bold results indicate where the carbon monoxide change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	0	-	-	-	-	0	-	-	-	-
P1	window	0	-	-	-	-	0	-	-	-	-
P1	balc door	0	-	-	-	-	0	-	-	-	-
P2	living window	14	0.35	152	-19	87	14	0.27	57	17	36
P3	living window 2	5	4.32	590	**-500**	677	16	2.21	338	**5**	460
P3	front door	26	1.76	533	**-171**	487	371	3.47	520	**59**	535
P4	living window	0	-	-	-	-	1	-	-	-	0
P5	living window	0	-	-	-	-	1	-	-	-	0
P5	balc door	13	2.11	392	-22	183	45	1.45	299	-45	150
P6	sliding door	50	1.22	282	**-107**	165	439	0.53	173	**18**	118
P7	sliding door	8	2.4	390	-37	36	259	2.12	421	-42	101
	Average	-	2.03	390	-143	-	-	1.68	301	2	-

Table F.71: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in carbon monoxide after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	No	No
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	No
P7	sliding door	-	-	0.95	0.51	No	No
	Average	0.82	0.36	0.73	0.36	-	-

Table F.72: Table showing the change in carbon monoxide after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median carbon monoxide change, IQR = interquartile range, before = median carbon monoxide before opening/closing. Bold results indicate where the carbon monoxide change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	49	-	363	**-30**	268	40	-	312	**21**	134
P1	living window	76	1.89	247	**-35**	185	58	1.04	152	**62**	108
P1	balc door	32	0.77	122	**-52**	128	118	1.29	145	**18**	139
P2	kitchen window	11	0.42	182	-10	79	13	0.45	159	-16	84
P2	sliding door	316	0.76	168	20	124	355	0.9	202	16	97
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	0.97	545	1	232	22	0.76	420	39	95
P5	balc door	23	3.15	503	-14	812	65	1.35	279	-15	114
P6	sliding door	9	6.79	258	-42	78	17	-	277	17	231
P7	kitchen window	4	1.08	589	**-221**	110	3	0.69	361	**-3**	110
	Average	-	1.98	331	-42	-	-	0.93	256	15	-

Table F.73: Table showing the change in carbon monoxide after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median carbon monoxide change, IQR = interquartile range, before = median carbon monoxide before opening/closing. Bold results indicate where the carbon monoxide change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	18	-	679	-30	190	16	-	665	50	85
P1	living window	9	5.47	1232	**-318**	483	22	1.85	326	**32**	86
P1	balc door	0	-	-	-	-	20	1.63	328	-20	345
P2	kitchen window	0	-	-	-	-	2	0.12	90	3	6
P2	sliding door	234	0.29	146	**40**	184	756	0.3	184	**0**	184
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	1.6	374	-15	452	13	2.95	400	131	479
P5	balc door	13	1.7	316	0	203	45	1.03	260	-22	149
P6	sliding door	50	2.53	426	**-87**	239	439	1.51	481	**17**	288
P7	kitchen window	2	-	-	-	-	5	3.73	592	69	2516
	Average	-	2.32	529	-68	-	-	1.64	370	29	-

Table F.74: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in carbon monoxide after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	No	No
P1	living window	-	0.28	-	0.26	Yes	No
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					No	No
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	No
P6	sliding door	0.69	0.57	0.85	0.58	No	No
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

F.3.7 Results tables for ventilation practices and TVOC

Table F.75: Table showing the change in VOC after opening and closing different windows and doors in the living rooms of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median VOC change, IQR = interquartile range, before = median VOC before opening/closing. Bold results indicate where the VOC change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	living window	-	-	-	-	-	-	-	-	-	-
P3	living window 2	13	1.84	0.21	**-0.04**	**0.03**	21	1.49	0.21	**0.00**	**0.05**
P3	front door	104	1.84	0.26	**-0.04**	**0.09**	606	1.98	0.25	**0.01**	**0.09**
P4	living window	5	3.23	0.43	-0.02	0.05	4	3.02	0.37	0.02	0.04
P5	living window	1	-	-	-	-	1	-	-	-	-
P5	balc door	23	1.83	0.21	-0.01	0.05	65	1.92	0.20	0.00	0.02
P6	sliding door	9	1.26	0.10	**-0.02**	**0.02**	17	1.00	0.07	**0.01**	**0.02**
P7	sliding door	8	2.84	0.38	**-0.07**	**0.05**	89	4.60	0.41	**0.00**	**0.05**
	Average	-	2.14	0.27	-0.03	-	-	2.34	0.25	0.01	-

Table F.76: Table showing the change in VOC after opening and closing different windows and doors in the living rooms of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median VOC change, IQR = interquartile range, before = median VOC before opening/closing. Bold results indicate where the VOC change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	living window	-	-	-	-	-	-	-	-	-	-
P3	living window 2	5	3.37	0.39	**-0.17**	**0.12**	16	4.95	0.38	-0.01	0.3
P3	front door	26	3.97	0.36	**-0.04**	**0.15**	371	5.06	0.41	**0.00**	**0.09**
P4	living window	0	-	-	-	-	1	-	-	-	-
P5	living window	0	-	-	-	-	1	-	-	-	-
P5	balc door	13	1.83	0.20	-0.01	0.06	45	2.12	0.18	0.00	0.02
P6	sliding door	50	1.15	0.10	**-0.02**	**0.02**	439	1.09	0.10	**0.00**	**0.02**
P7	sliding door	8	2.21	0.28	0.00	0.00	259	4.69	0.35	0.00	0.01
	Average	-	2.51	0.27	-0.05	-	-	3.58	0.28	0.00	-

Table F.77: Table showing AER for living rooms in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in VOC after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	0.46	0.39	0.37	0.28	-	-
P1	window	-	-	-	-	-	-
P1	balc door	**1.29**	**0.27**	0.94	0.26	-	-
P2	living window	**0.87**	**0.27**	0.67	0.26	-	-
P3	living window 2					No	No
P3	front door	-	-	-	-	No	No
P4	living window	**0.67**	**0.22**	**0.75**	**0.23**	-	-
P5	living window	-	0.47	-	0.23	-	-
P5	balc door	-	-	0.69	0.59	No	No
P6	sliding door	-	0.52	-	0.52	No	No
P7	sliding door	-	-	0.95	0.51	Yes	No
	Average	0.82	0.36	0.73	0.36	-	-

Table F.78: Table showing the change in VOC after opening and closing different windows and doors in the kitchens of all case studies during the summer. n = number of observations, IOR = indoor to outdoor ratio, x = median VOC change, IQR = interquartile range, before = median VOC before opening/closing. Bold results indicate where the VOC change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	living window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	kitchen window	11	-	0.15	**-0.02**	**0.01**	13	9.00	0.13	**0.00**	**0.01**
P2	sliding door	316	-	0.14	**0.00**	**0.02**	355	-	0.13	**0.01**	**0.02**
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	19	5.82	0.47	**-0.03**	**0.07**	22	5.03	0.36	**0.02**	**0.03**
P5	balc door	23	2.51	0.25	-0.01	0.13	65	2.54	0.26	0.00	0.03
P6	sliding door	9	1.83	0.15	-0.01	0.01	17	1.94	0.13	0.00	0.01
P7	kitchen window	4	3.85	0.44	-0.08	0.33	3	3.43	0.38	0.01	0.03
	Average	-	3.50	0.27	-0.03	-	-	4.39	0.23	0.01	-

Table F.79: Table showing the change in VOC after opening and closing different windows and doors in the kitchens of all case studies during the winter. n = number of observations, IOR = indoor to outdoor ratio, x = median VOC change, IQR = interquartile range, before = median VOC before opening/closing. Bold results indicate where the VOC change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	IOR	Before	$\tilde{x}$	IQR	n	IOR	Before	$\tilde{x}$	IQR
P1	int door	-	-	-	-	-	-	-	-	-	-
P1	living window	-	-	-	-	-	-	-	-	-	-
P1	balc door	-	-	-	-	-	-	-	-	-	-
P2	kitchen window	0	-	-	-	-	2	-	0.11	0.02	0.01
P2	sliding door	234	-	0.14	0.00	0.03	756	-	0.15	0.00	0.03
P3	kitchen/living	-	-	-	-	-	-	-	-	-	-
P4	kitchen window	4	-	0.78	**-0.22**	**0.29**	13	11.06	0.49	**0.01**	**0.03**
P5	balc door	13	2.15	0.21	-0.01	0.07	45	2.33	0.20	0.00	0.02
P6	sliding door	50	1.33	0.13	**-0.01**	**0.05**	439	2.02	0.18	**0.00**	**0.04**
P7	kitchen window	2	7.12	0.37	-0.03	0.00	5	7.34	0.38	0.00	0.02
	Average	-	3.53	0.33	-0.05	-	-	5.69	0.25	0.01	-

Table F.80: Table showing AER for kitchens in different case studies with certain windows and doors open and closed. Table also shows results of statistical analysis for significant differences between summer and winter for the difference in VOC after opening and closing windows and doors.

		AER				Summer vs Winter	
		Room		Whole house		Significantly different	
		Open	Closed	Open	Closed	Opening	Closing
P1	int door	-	0.28	-	0.26	-	-
P1	living window	-	0.28	-	0.26	-	-
P1	balc door	-	0.39	0.35	0.29	-	-
P2	kitchen window	-	0.25	0.69	0.26	-	-
P2	sliding door					Yes	Yes
P3	kitchen/living	-	-	-	-	-	-
P4	kitchen window	**0.60**	**0.23**	**0.75**	**0.23**	No	No
P5	balc door	-	0.24	-	0.23	No	No
P6	sliding door	0.69	0.57	0.85	0.58	No	No
P7	kitchen window	1.19	0.58	-	-	No	No
	Average	0.83	0.35	0.66	0.30	-	-

F.3.8 Results tables for ventilation practices and noise

Table F.81: Table showing the change in noise levels after opening and closing different windows and doors in the different rooms of all case studies during the summer. n = number of observations, Out = median outdoor noise before opening/closing (dB(A)), In = median indoor noise before opening/closing (dB(A)), x = median noise change, IQR = interquartile range. Bold results indicate where the noise change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	Out	In	$\tilde{x}$	IQR	n	Out	In	$\tilde{x}$	IQR
P1 living	int door	37	-	64.1	**2.5**	14.6	35	-	61.9	**0.0**	15.2
P1 living	window	63	64.0	61.5	1.1	11.5	42	61.8	61.4	0.1	7.9
P1 living	balc door	28	64.3	62.8	**6.4**	8.1	85	63.5	64.8	**-2.4**	12.1
P2 kitchen	window	11	59.8	58.2	**11.0**	10.5	13	61.8	72.0	**1.2**	5.5
P2 kitchen	sliding door	316	59.9	56.8	2.4	12.7	355	60.6	68.6	1.4	10.9
P2 bed 3	window	144	71.2	44.1	**5.3**	7.8	128	71.2	58.5	**0.0**	1.7
P4 living	window	5	59.0	62.6	5.8	8.1	4	57.1	72.5	0.0	3.5
P5 living	balc door	23	68.8	56.9	0.2	7.5	65	66.8	50.3	3.8	8.9
Average	-	-	63.8	58.4	4.3	-	-	63.3	63.8	0.5	-

Table F.82: Table showing the change in noise levels after opening and closing different windows and doors in the different rooms of all case studies during the winter. n = number of observations, Out = median outdoor noise before opening/closing (dB(A)), In = median indoor noise before opening/closing (dB(A)), x = median noise change, IQR = interquartile range. Bold results indicate where the noise change for opening vs closing is statistically significantly different.

		Opening					Closing				
		n	Out	In	$\tilde{x}$	IQR	n	Out	In	$\tilde{x}$	IQR
P1 living	int door	25	-	66.47	-1.89	10.67	21	-	64.83	-1.85	5.95
P1 living	window	15	61.33	72.47	-7.32	18.26	29	59.82	64.00	-5.22	12.72
P1 living	balc door	0	-	-	-	-	24	62.10	65.65	-3.49	8.00
P2 kitchen	window	0	-	-	-	-	1	-	-	-	-
P2 kitchen	sliding door	209	62.66	64.96	**4.20**	14.89	654	62.50	71.50	**-0.41**	8.86
P2 bedroom 3	window	147	73.28	51.49	**8.19**	8.78	158	73.16	60.26	**-7.11**	10.02
P4 living	window	0	-	-	-	-	1	-	-	-	-
P5 living	balc door	13	66.95	57.07	1.60	11.72	45	66.74	52.80	1.20	9.85
Average		-	66.06	62.49	0.96	-	-	64.86	63.17	-2.81	-

Table F.83: Table showing results of statistical analysis for significant differences between summer and winter for the difference in noise after opening and closing windows and doors.

		S vs W	
		Opening	Closing
P1 living	int door	Yes	No
P1 living	window	No	Yes
P1 living	balc door	-	-
P2 kitchen	window	-	-
P2 kitchen	sliding door	Yes	Yes
P2 bedroom 3	window	Yes	Yes
P4 living	window	-	-
P5 living	balc door	No	No

F.4 Results of sorbent tube laboratory analysis

Table F.84: Table showing the results of the laboratory analysis of the sorbent tube installed in the living room of P1 for 14 days (20,160 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
2,2,4-Trimethyl-1,3-pentanediol diisobutyrate	-	110.1	2.7	31.2
Nonanal	-	52.6	1.3	7.4
Decanal	-	36.6	0.9	5.7
2,6-Diphenyl-p-benzoquinone	-	34.8	0.9	9
Benzaldehyde	-	29.8	0.7	3.1
alpha-Pinene	-	25	0.6	3.4
Acetic acid	-	22.1	0.5	1.3
Toluene	-	19.5	0.5	1.8
1-Hexanol, 2-ethyl-	-	16.9	0.4	2.2
Propylene glycol	-	16.5	0.4	1.2

Table F.85: Table showing the results of the laboratory analysis of the sorbent tube installed in the living room of P2 for 19 days (27,360 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Hexanedioic acid, bis(2-ethylhexyl) ester	96	662	12	179
1,3-Dioxolane-4-methanol, 2,2-dimethyl-	83	140	2.6	14
Nonanal	90	90	1.7	9.4
Tetradecane	98	83	1.5	12
Limonene	99	78	1.4	7.7
Dipropylene glycol methyl ether Isomer 1		73	1.3	19
Cyclopentasiloxane, decamethyl-	91	70	1.3	19
Several compounds. Identity not confirmed		50	0.9	
Decanal	94	48	0.9	5.5
Dipropylene glycol methyl ether Isomer 2		48	0.9	5.2

Table F.86: Table showing the results of the laboratory analysis of the sorbent tube installed in the bedroom of P2 for 19 days (27,360 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Tetradecane	98	253	4.6	37
Cyclopentasiloxane, decamethyl-	90	206	3.8	56
Pentadecane	97	133	2.4	21
Dipropylene glycol methyl ether Isomer 1		111	2	12
Limonene	98	98	1.8	9.7
1,3-Dioxolane-4-methanol, 2,2-dimethyl-	83	98	1.8	9.4
Hexanedioic acid, bis(2-ethylhexyl) ester	84	93	1.7	25
Nonanal	81	90	1.6	9.4
Decanal	90	80	1.5	9.1
Dipropylene glycol methyl ether Isomer 2		80	1.5	8.6

Table F.87: Table showing the results of the laboratory analysis of the sorbent tube installed in the living room of P3 for 18 days (25,920 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Cyclopentasiloxane, decamethyl-	91	948	18	271
Limonene	99	118	2.3	12
Hexanedioic acid, bis(2-ethylhexyl) ester	81	113	2.2	32
Nonanal	91	81	1.6	8.8
Heptane, 2,2,4,6,6-pentamethyl-	83	58	1.1	7.6
3-Octanol, 3,7-dimethyl-	80	57	1.1	6.9
7-Octen-2-ol, 2,6-dimethyl-	90	54	1	6.5
Cyclohexanol, 2-(1,1-dimethylethyl)-	72	48	0.9	5.8
1-Hexanol, 2-ethyl-	90	46	0.9	4.6
Compoud A		32	0.6	

Table F.88: Table showing the results of the laboratory analysis of the sorbent tube installed in the bedroom of P3 for 18 days (25,920 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Cyclopentasiloxane, decamethyl-	93	2173	42	620
Hexanedioic acid, bis(2-ethylhexyl) ester	95	316	6.1	90
Several compounds. Identity not confirmed		204	3.9	
Heptane, 2,2,4,6,6-pentamethyl-	83	184	3.5	24
Limonene	99	153	2.9	16
Nonanal	90	131	2.5	14
Linalyl acetate	90	93	1.8	14
Tetrasiloxane, decamethyl-	91	92	1.8	22
3-Octanol, 3,7-dimethyl-	72	90	1.7	11
7-Octen-2-ol, 2,6-dimethyl-	90	89	1.7	11

Table F.89: Table showing the results of the laboratory analysis of the sorbent tube installed in the living room of P4 for 14 days (20,160 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Cyclopentasiloxane, decamethyl-	93	2173	42	620
Hexanedioic acid, bis(2-ethylhexyl) ester	95	316	6.1	90
Several compounds. Identity not confirmed		204	3.9	
Heptane, 2,2,4,6,6-pentamethyl-	83	184	3.5	24
Limonene	99	153	2.9	16
Nonanal	90	131	2.5	14
Linalyl acetate	90	93	1.8	14
Tetrasiloxane, decamethyl-	91	92	1.8	22
3-Octanol, 3,7-dimethyl-	72	90	1.7	11
7-Octen-2-ol, 2,6-dimethyl-	90	89	1.7	11

Table F.90: Table showing the results of the laboratory analysis of the sorbent tube installed in the bedroom of P4 for 14 days (20,160 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Hexanedioic acid, bis(2-ethylhexyl) ester	96	656	16	241
Cyclopentasiloxane, decamethyl-	91	124	3.1	46
Nonanal	98	79	2	11
Limonene	98	65	1.6	8.8
1-Hexanol, 2-ethyl-	90	47	1.2	6
Benzaldehyde	94	39	1	4.1
Acetic acid	90	34	0.9	2
Decanal	94	33	0.8	5.2
Benzothiazole	87	32	0.8	4.3
Benzene, 1,2,4-trimethyl-	95	27	0.7	3.3

Table F.91: Table showing the results of the laboratory analysis of the sorbent tube installed in the living room of P5 for 14 days (20,160 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	$\mu g.m^{-3}$
Hexanedioic acid, bis(2-ethylhexyl) ester	98	947	23	348
Limonene	98	114	2.8	15
Nonanal	90	103	2.6	15
2,2,4-Trimethyl-1,3-pentanediol diisobutyrate	72	81	2	23
1-Hexanol, 2-ethyl-	90	65	1.6	8
Propanoic acid, 2-methyl-, 3-hydroxy-2,2,4-trimethylpentyl ester	91	61	1.5	13
Cyclopentasiloxane, decamethyl-	90	50	1.2	18
Butanoic acid, 1-methylpropyl ester	50	47	1.2	6.7
Benzaldehyde	94	46	1.1	4.8
Benzene, 1-methyl-4-(1-methylethyl)-	93	42	1	5.5

Table F.92: Table showing the results of the laboratory analysis of the sorbent tube installed in the bedroom of P5 for 14 days (20,160 minutes). The results show the top 10 VOC's.

Top 10 VOC	NIST Library Quality Match	Estimated ng on tube	PPB in air	μg.m^{-3}
Hexanedioic acid, bis(2-ethylhexyl) ester	98	817	20	300
Methyl salicylate	97	202	5	30
Limonene	98	164	4.1	22
Nonanal	90	125	3.1	18
Levomenthol	91	114	2.8	18
Cyclopentasiloxane, decamethyl-	91	101	2.5	37
1-Hexanol, 2-ethyl-	90	93	2.3	12
Eucalyptol	98	66	1.6	10
Cyclohexane	50	58	1.4	4.8
Benzothiazole	93	56	1.4	7.5

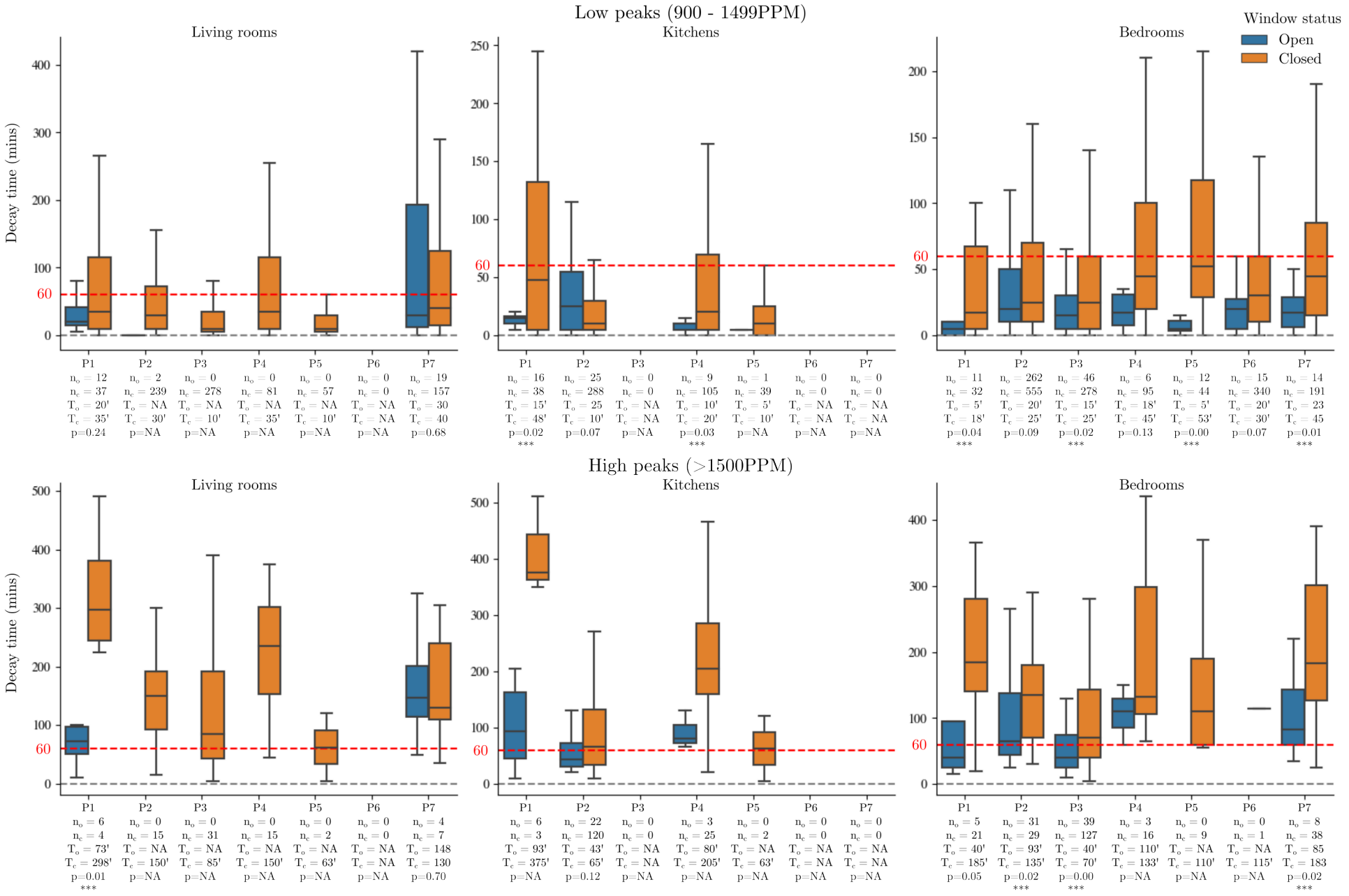


Figure F.1: Series of bar graphs showing the time for low (900-1500ppm) and high (>1500ppm) peaks of carbon dioxide to decay to the health threshold (900ppm) for each room in each participant, when windows were open (blue) and closed (orange). n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.

F.5 Results for Section 5.4 - Pollutant decays and health messaging

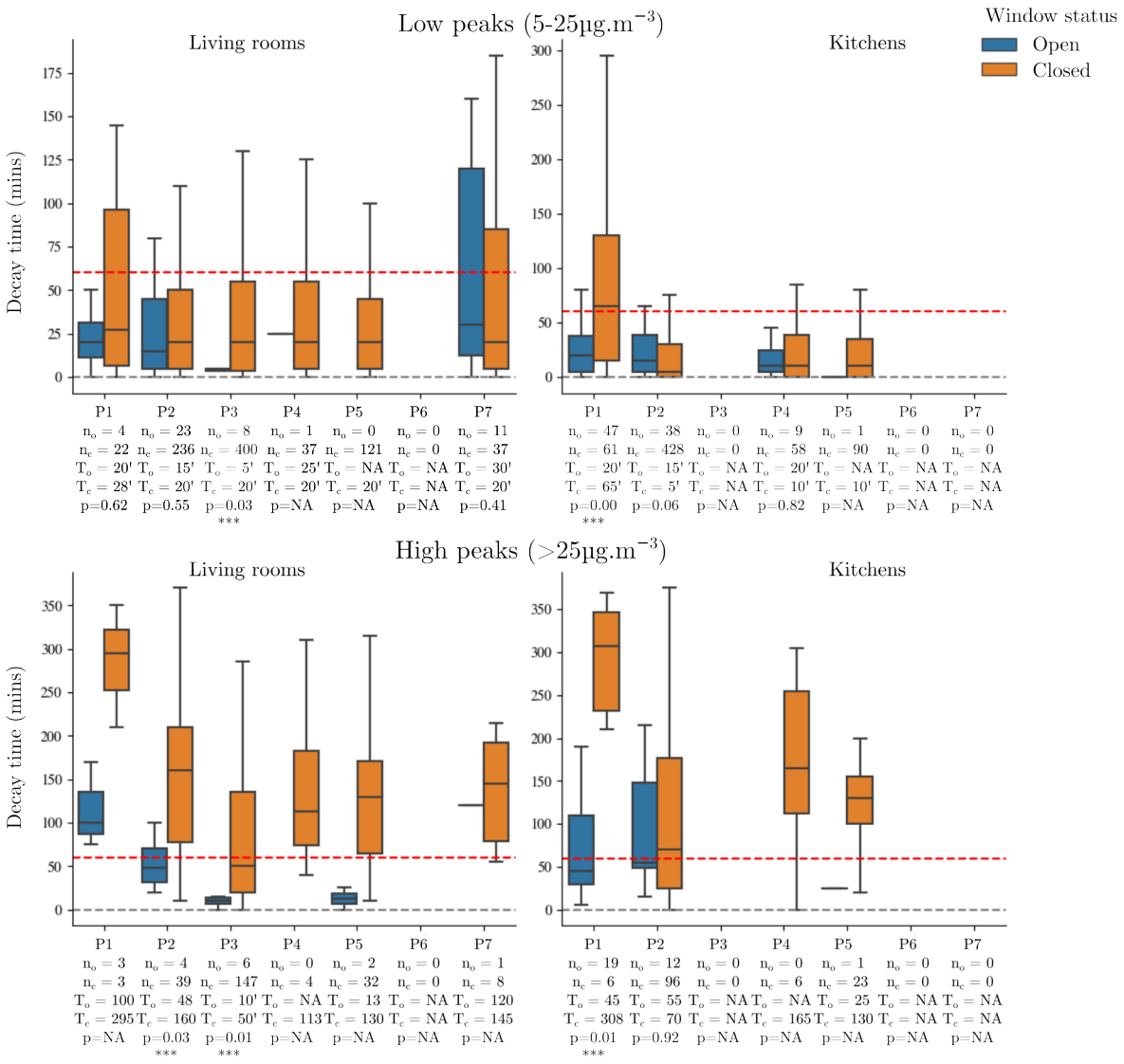


Figure F.2: Series of bar graphs showing the time for low (5-25μg.m^{-3}) and high (>25μg.m^{-3}) peaks of PM_1 to decay to the arbitrary threshold for each room in each participant, when windows were open (blue) and closed (orange).n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.

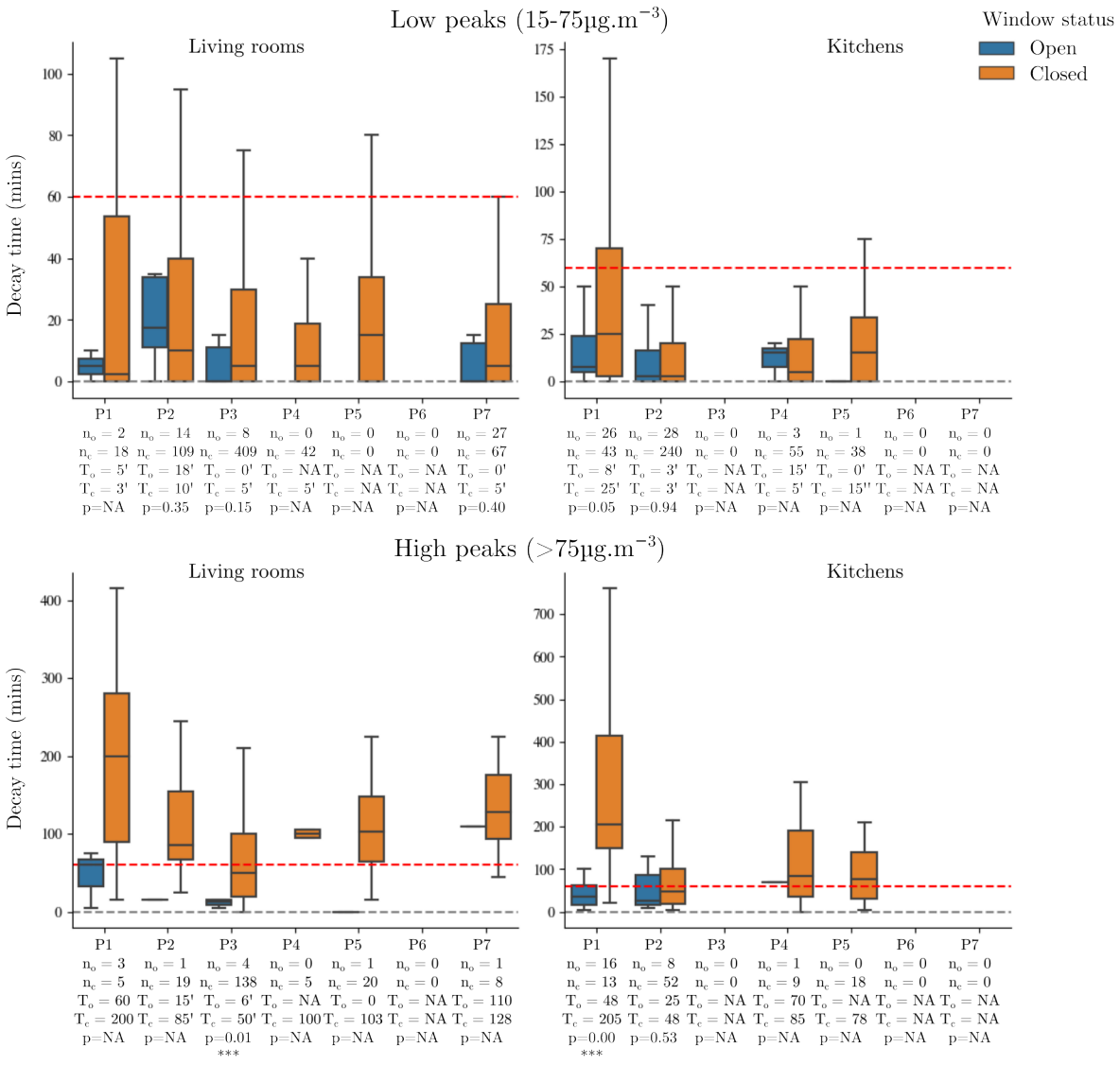


Figure F.3: Series of bar graphs showing the time for low (15-75μg.m^{-3}) and high (>75μg.m^{-3}) peaks of $PM_{2.5}$ to decay to the arbitrary threshold for each room in each participant, when windows were open (blue) and closed (orange).n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.

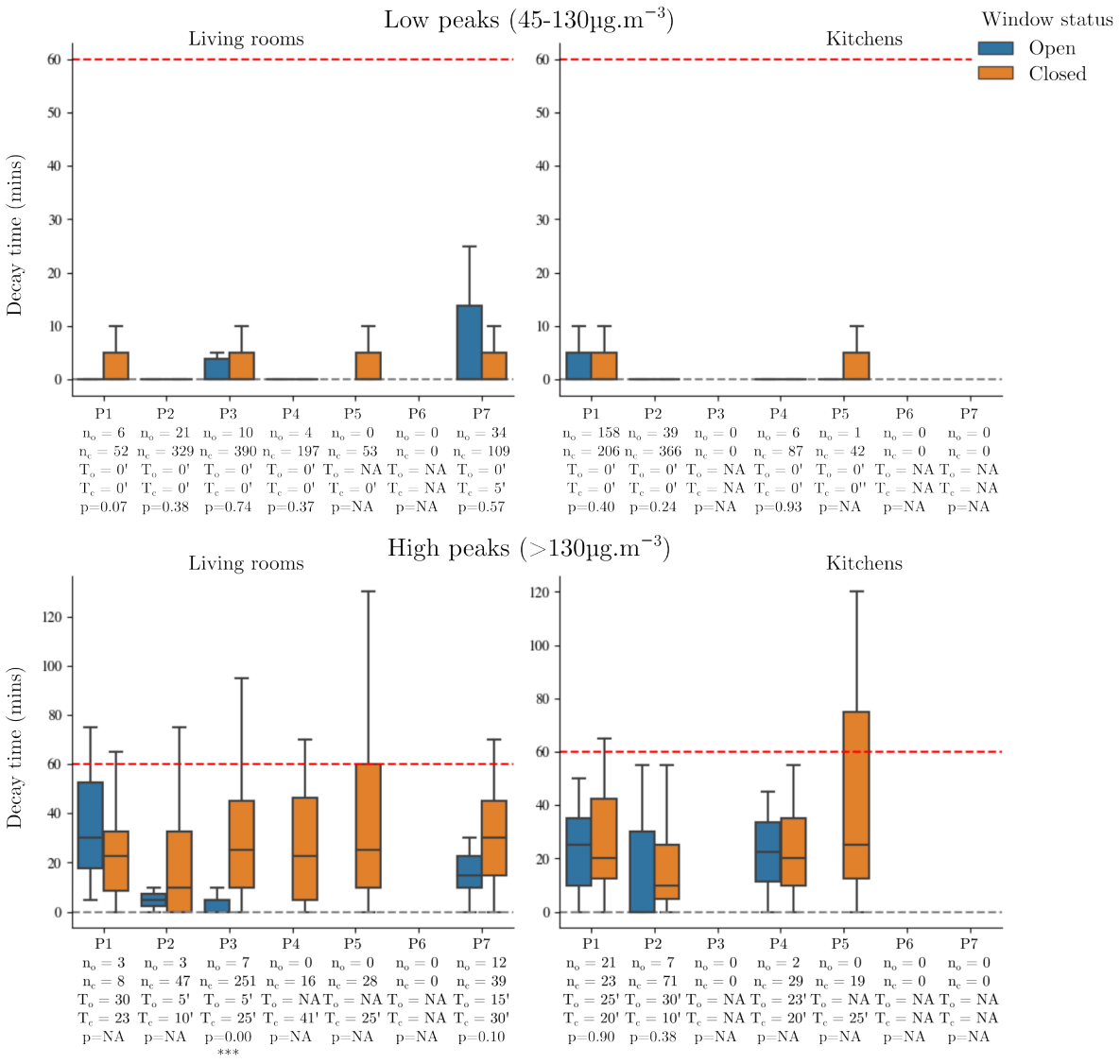


Figure F.4: Series of bar graphs showing the time for low (45-130μg.m^{-3}) and high (>130μg.m^{-3}) peaks of PM_{10} to decay to the arbitrary threshold for each room in each participant, when windows were open (blue) and closed (orange).n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.

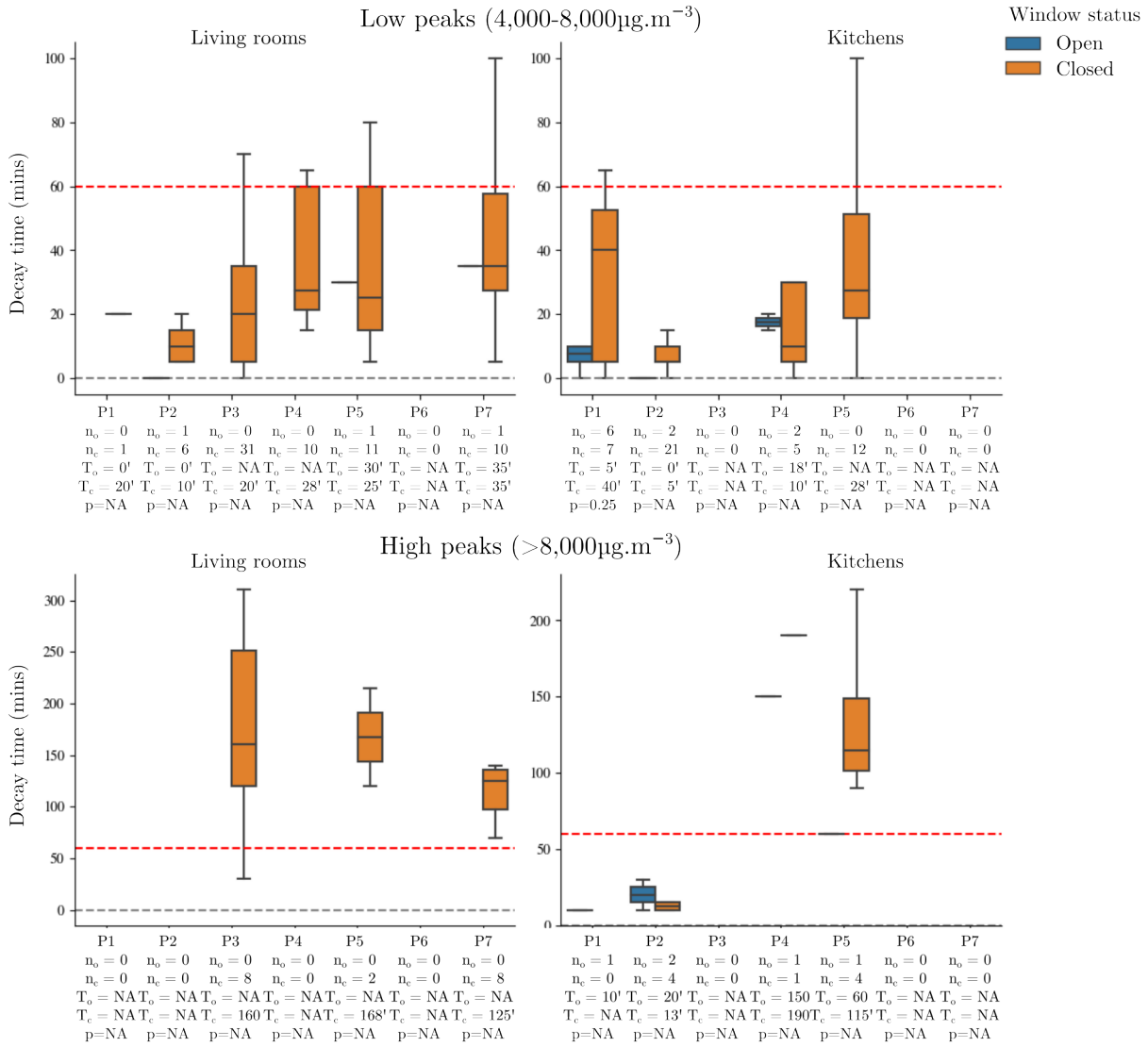


Figure F.5: Series of bar graphs showing the time for low (4,000-8,000μg.m^{-3}) and high (>8,000μg.m^{-3}) peaks of carbon monoxide to decay to the health threshold (4,000μg.m^{-3}) for each room in each participant, when windows were open (blue) and closed (orange).n_o = count windows open, n_c = count windows closed, T_o = median time for peak to decay to health threshold when windows were open, T_c = median time for peak to decay to health threshold when windows were closed, p = Kruskal-Wallis p-value for decay times when windows were open vs closed.