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Human Dimensions Of Building Performance: Sensing, Modeling, And Predicting Indoor Environmental Quality

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Abstract

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HUMAN DIMENSIONS OF BUILDING PERFORMANCE: SENSING, MODELING, AND PREDICTING INDOOR ENVIRONMENTAL QUALITY

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ABSTRACT

HUMAN DIMENSIONS OF BUILDING PERFORMANCE: SENSING, MODELING, AND PREDICTING INDOOR ENVIRONMENTAL QUALITY

Nan Ma

William W. Braham

The indoor environment critically affects occupant health and comfort, especially since humans spend most of the day indoors. Meanwhile, occupant activities, preferences, and behaviors may contribute to a significant amount of building energy consumption. The focus of environmental buildings shifted from automated systems to a paradigm of collective environmental design since the second half of the 20th century, emphasizing human dimensions in building performance, which allows occupants to participate as active/passive actuators and sensors. Concurrently, increased environmental awareness further spurred the green building movement intending to encourage more high-performance buildings. The question remains as to whether high-performance buildings are also healthy buildings. This dissertation aims to cast new light on how environmental design and building systems work for people as well as how building sensors and human senses work together to inform the organization and optimization of various performance targets such as sustainability, public health, and resiliency. Special attention is given to the non-visual environment attempting to facilitate human-in-the-loop of the building design and operation processes. In order to achieve this goal, environmental monitoring, data analysis, and human subject recruitments are developed to characterize the human dimension of building performance.

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CHAPTER 1: INTRODUCTION

1.1. On the Historical Context of the Built Environment and Health

Theories about how cities shape the health of residents have existed since ancient times. *Vitruvius* suggested that cities be founded so that they maximize their access to helpful sea breezes and minimize the health effects from foul-smelling swamps (Vitruvius 1960). In the 19th century, researchers paid increasing attention to the matter of health in the indoor environment and concluded that ventilation is an influential factor of environmental health (Bedford 1936; Janssen 1999). In the course of the 19th and 20th centuries, building systems such as heating, ventilation, air-conditioning (HVAC), and lighting have been developed to provide, control, and maintain a comfortable and healthy indoor environment (Fitch 1975; Cooper 1998). A remarkable study of the late 19th century revealed the importance of the indoor environments of homes on human health (Carnelley et al. 1887). The study in Scotland showed that living and sleeping in crowded rooms, with elevated levels of CO_2, microbes, and volatile organic compounds (VOCs), meant earlier death from diarrhea, measles, premature birth, bronchitis, pneumonia, and accidents. Since then, scientific discussions have been focusing on whether indoor air is an important route for the spread of infections. Many studies in the 1930s and 1940s demonstrated that airborne particles carried and transmitted the bacteria of measles, tuberculosis, chickenpox, anthrax, influenza, smallpox, to a large extent (Wells 1934; Riley, Murphy, and Riley 1978). IAQ and ventilation settings for health concerns attracted much attention up until 1950 (Sundell and för Miljömedicin 1994). In the London smog episode of 1952, the dwelling residents closed the windows to prevent bad air from getting in, but the indoor air caused significantly high mortality rate during this period of time. Since then, indoor air consequently received more attention than outdoor air (Bell, Davis, and Fletcher 2004).

The middle of the twentieth century was also an era where engineers believed that machines could solve and do everything. Typical buildings were constructed with large single-glazed windows, fully operated with mechanical systems, open plans, and high-ceilings leading to problems of thermal comfort and health (i.e., improper thermal controls among zones; heat gains in summer; heat losses in winter) (Bedford 1936; Janssen 1999). Many researchers in the field of thermal comfort have attempted to quantify the relationship among the physical parameters of the environment, the physiological parameters of people, and the perception of comfort expressed by people themselves. One of most influential models was developed by Povl Ole Fanger during this period of time (Fanger 1970).

In 1973, the energy crisis impacted energy consumption in buildings. In order to reduce energy consumption, fresh air supply volumes were minimized and building envelopes became tighter to reduce infiltration. This decrease in fresh air supply created problems with IAQ, especially in office buildings. It triggered the modern scientific history of studying indoor air which started in the 1970s with a question: "did indoor air pose a threat to health as did outdoor air?" Soon it was recognized that indoor air was a critical aspect of the built environment for health (including comfort) (Sundell 2017). From 1982, the World Health Organization (WHO) used the term Sick Building Syndrome (SBS) to label a range of human health symptoms associated with poor IAQ. Recently, the COVID-19 pandemic outbreak taught us again that buildings could increase the spread of infectious viruses due to spatial configuration, air circulation patterns, and human-building interactions. Understanding the relationship between the built environment and health risks can ensure better decision making when we design future indoor spaces, to be prepared for the next pandemic.

1.2. Two Kinds of Effects of Occupants on Building Performance

As architects, we design high-performance buildings to decrease building energy use and provide the benefits of greater comfort, health, and usability to occupants. In these buildings, control technologies have advanced over the past decades, and there has been a tendency for building designers to increase automation to mitigate energy inefficient occupant behaviors. However, overly automated buildings come at a great risk: occupant tolerance for discomfort is substantially reduced if occupants as actuators (controllers) are disabled. Recent work in social science and psychology and suggest that these theories could help us understand occupant behavior in buildings. In this section I bring together the related social science research to paint a picture of occupants as sensors and actuators in the built environment.

One theory in the social science literature that sheds light on the "occupant as actuator" is Robert White's *Motivation reconsidered: The concept of competence* (White 1959). White described a human motive to exercise control for its own sake. White further concluded that mankindhas an intrinsic need to obtain a sense of mastery over their environment. The notion that people are motivated to feel like effective agents capable of influencing the events in their environment was also promoted by Jerry M. Burger (Burger 1992). Burger called this kind of motive the "desire for control". Burger believes that mankind's desire for control is a general personality trait, but also acknowledges that this motive is not present to the same extent in all people. In the book, he explained that "....as we all know, someone who is highly motivated to make the decisions..., and to demonstrate his or her ability to conquer any and all challenging tasks. On the other hand, ... someone shows little of these inclinations and who seems more than willing to allow others to make decisions...” (p. 6). The book is devoted to the message that people generally prefer to have some ability to control what happens to them.

Putting Burger’s theory in the human-in-the-loop context, this is why many building managers implemented dummy controls to let the building occupants change the environment psychologically, particularly for the occupants who express high desire for control. This placebo effect provided the illusion of control to tenants without compromising on the system’s efficiency. Some building occupants are more inclined to adjust thermostats using more energy to meet their thermal comfort needs, while some building occupants drink cold or hot liquids to mitigate thermal discomfort. Hong et al. (Hong et al. 2017) observed these differences of energy-related adaptive and non-adaptive actions, and categorized these behaviors into three levels: 1) austerity – occupants are proactive in saving energy, 2) standard – average occupants, and 3) wasteful – occupants do not care about energy use. As explained by Nicol and Humphreys’ principle (Nicol and Humphreys) – ‘‘people react in ways which tend to restore their comfort’’. People naturally try to avoid unpleasant conditions and look for pleasant ones.

Michel Cabanac (Cabanac 1971) introduced the term “alliesthesia” in his publication of *Physiological role of pleasure* to explain human adaptation. “Alliesthesia” explains that “a given stimulus can induce a pleasant or unpleasant sensation depending on the subject’s internal state” (p. 1107). The term “alliesthesia” is composed of two words “allios” meaning “changed” and "esthesia" meaning “sensation”. In the article, Cabanac also believes that skin temperature is a human peripheral signal in thermal sensation and the skin detectors can “translate this thermal signal into a nervous message describing local temperature and its changes” (p. 1104). However, if we can also look at the extent to which people engage in active efforts to deal with the situation, many other external drivers such as economic, cultural, regulatory issues, people do not receive, perceive, and respond the same way owning to the physical, physiological, and psychological differences between people.

In summary, there is a general agreement that occupants are effective sensors and most of the time, we can sense temperature much better than a thermostat especially to decide the right temperature for themselves. On the other hand, occupants regularly behave as actuators to mitigate their thermal discomfort, such as opening/closing windows, adjusting thermostats, changing clothes, and so forth. The resultant actions could impact the indoor environment and building HVAC, and plug load system energy consumptions, while self-adaptive behaviors can lead to some energy conservation. No matter what the energy-using or non-energy-using behaviors that the occupants take, these kinds of occupants take an active role when they inhabit in the buildings. At the same time, occupant behavior has passive impacts on the building indoor environment by generating heat and CO2 which can indirectly affect building performance as well. By acknowledging these two effects and roles, occupant behavior is an important part of the social-technical system. Energy use in buildings should be considered a social problem as much as a technological one. Architects have to think not just how buildings should be designed, but also how buildings will be commissioned and used when they are occupied. Occupants behave in more complex ways than designers account for and machine learning models can capture, we have to ask and put insight into: what technologies and innovations we can encourage building occupants to be more environmentally engaged?

1.3. Variables and Modeling Techniques

Modeling and predicting environmental variables to characterize IAQ for occupants' health and thermal comfort has long been an important topic. Health and thermal comfort are commonly quantified using analytical models (Ma, Aviv, et al. 2021). Analytical models are those which are based on a mathematical solution of governing equations, including empirical and deterministic models. Empirical models are derived by fitting a stream of data to define the relationship between independent variables and outcome variables leading to an approximation to analytic formulae, including measurement and system noise. By contrast, deterministic models are exact solutions formulated from a hypothesis and one or more assumptions. This type of model supposes that the underlying mechanisms in the variability of parameters are well-defined such as thermodynamic and mass-transfer rules. In building science, developing a deterministic model necessitates detailed and complex input data such as characteristics of building envelope, building configurations, and outdoor levels of the target pollutants. Such models provide a reference to understand the underlying mechanisms, estimate their dependent relations, and identify related variables. One weakness of deterministic analysis is the difficulty of retrieving adequate information to assemble a model, particularly in complex buildings and especially when the interaction of occupants with the environment is included.

It is important to note that empirical and analytical models developed with machine learning techniques show a robust capacity for providing insights into setting environmental systems, taking multiple referred variables into account to audit building performance, allowing the occupant to adjust and make corresponding plans. Machine learning and statistical models that have been widely used include decision trees (classification and regression trees), random forests, support vector machine (SVM), various regression models, k-nearest neighbors (KNN), reinforcement learning (RL), and artificial neural networks (ANN). All of these studies showed promise, though the input variables and output variable might be chosen differently. However, it is worth noting that the uncertainty and stochasticity of occupant behavior can be troublesome and can limit predictive performance in practice. Previous studies found that the dynamic responses of occupants to indoor climates affect IAQ and thermal experience. Behavior has consequences for building performance, namely energy use and environmental quality in the buildings over time. Multiple studies have demonstrated that integrating occupant behavior such as thermostat adjustments (Ghahramani, Jazizadeh, and Becerik-Gerber 2014), personal comfort system control (Kim et al. 2018), and interaction with window systems (Tan and Deng 2020) provides more data points, captures an individual's distinctive thermal characteristics, and enhances the reliability and reproducibility of models.

In addition to the uncertainty of occupant behavior, many other sources of uncertainty contribute to the precision of thermal comfort and IAQ models. As concluded by Wang et al. (Wang et al. 2018), these sources include inter-individual and intra-individual differences, uncertainty in objective instrumental measurement, and subjective evaluation principles. Even further, many unmeasurable or indirect influencing factors are driving thermal comfort and IAQ. For example, occupants' social and cultural experiences, physical properties of the building design, and open plan office space configuration may not be universally quantifiable. All of these circumstances increase the prediction uncertainty of deterministic data-driven models. Bayesian computation can be more effective in calibrating thermal parameters, IAQ forecast, and building energy models. The Bayesian approach allows us to synthesize prior knowledge and available measurements into a unified modeling framework. Modeling methods such as Bayesian linear regression, Bayesian hierarchical modeling, and Bayesian neural network (Ma, Chen, et al. 2021) offer a way to express and quantify uncertainty. The models and methods described above will lay the foundations for this dissertation research methodology and enable the progress of the studies referring to healthy building, IEQ analysis, and energy system optimization.

1.4. Research Objectives: The Vision on the Four Parts

People are the central and fundamental measure in architecture and buildings are designed to fulfill people's biological needs (Olgyay 1963). Prior to technical solutions (i.e., environmental systems), the pre-modern buildings had very little alternatives but had to rely on building forms and materials against hostile climates (Fitch and Branch 1960). These passive/vernacular buildings mixed with man's inventiveness demonstrated a primitive approach to the climate response. These buildings are completely driven and operated by people. The dialogue between people and place was evoked (Figure 1. 1).

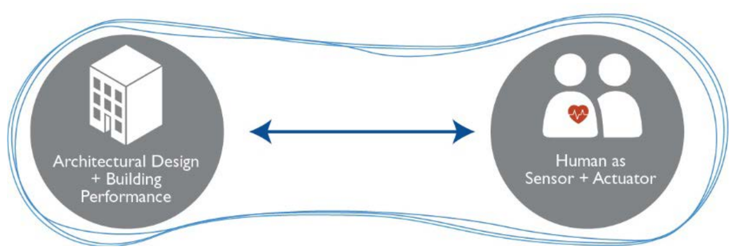

Figure 1. 1: The dialogue between people and buildings.

As HVAC took over the conditioning of the indoor spaces, the media of architecture and climate also began to shift (Barber 2020). The invention of control systems such as the thermostat that can automatically decide when to heat or when to cool became hugely important in lots of buildings designed in the mid-20th century. Architectural examples such as Seagram Building designed by Mies van der Roh and the United Nations

Headquarters developed by Oscar Niemeyer and Le Corbusier exemplify that people inside buildings are not favored and involved in the building management (Figure 1. 2). People cannot control and change the way that how the building is heated or cooled. The only intervention they can take is to adjust the shades. It turns out that people struggled with the physical environment and experienced uncomfortable a lot of the time. If this piece of history taught architects and designers any lessons, I believe it is rethinking and reflecting on this total relationship among people, building, and environmental system.

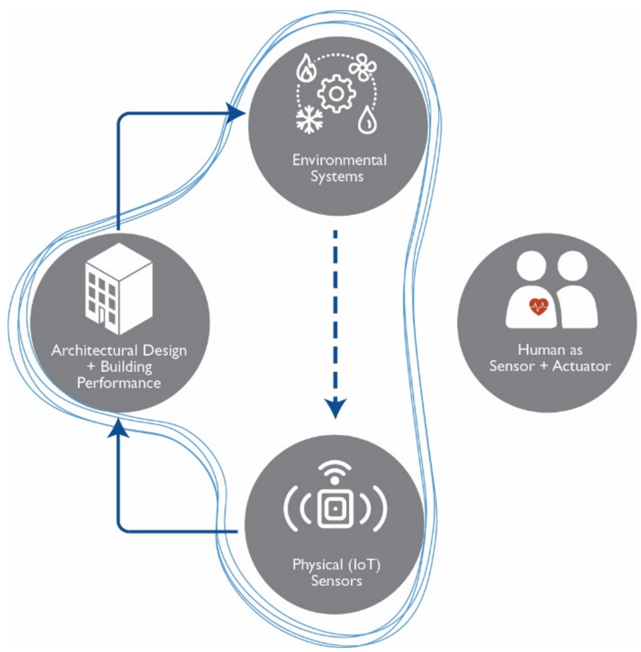

Figure 1. 2: People inside buildings are not involved in the building management.

While air conditioning has seemingly taken over the built environment, understanding the interactions of the four elements - building, people, environmental system, and sensors – appear to be particularly critical. The modeling methods, simulation tools, and diagnostic and sensing devices are advanced in the contemporary discourse. More efforts should be made to bring these different trajectories of research together.

Almost all buildings are expected to satisfy the often-divergent environmental requirements of the people and the necessities of shelter. We have to admit that there is no “one size fits all.” People’s desire for control (acting as an actuator) conflicts with the increased automation of the environmental system (cutting people out of the loop), making it difficult to reconcile contradictory requirements. Such conflicts must be studied, understood, and resolved, though they involve factors that are subjective and objective, dynamic and static, theoretical and practical. As illustrated in Figure 1. 3, the main goal of this dissertation is to get the human-system-building to work together better and when appropriate, to let sensors stand in for people. By monitoring the building and people, this doctoral dissertation aims to put more information here in order to bring people back to the loop and facilitate four parts working together in our contemporary architecture practice.

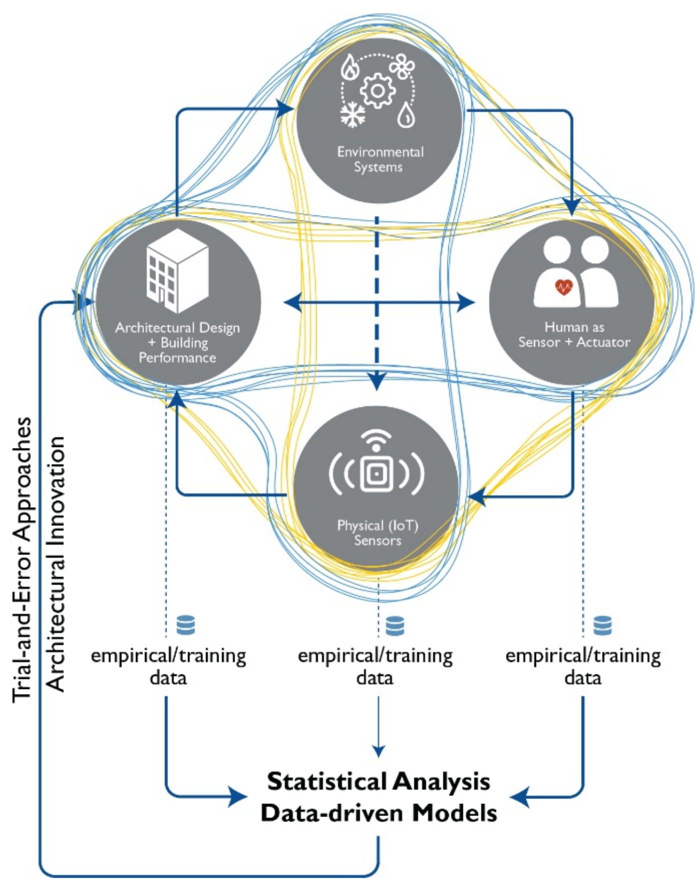

Figure 1. 3: A schematic overview of the dissertation research objectives.

1.5. Dissertation Chapter Overview

Chapter 1 introduces the dissertation. Chapter 2 examines what factors are worth measuring if we want the human-building-system to work together by performing a critical review on analytical models. Chapter 3 looks at different part of the loop illustrated in Figure 1. 1 and aims to examine how occupants as environmental controllers influence building performance and how to improve building thermal performance by quantifying the uncertainty of occupants' adaptive thermal behavior. Chapter 4 investigates how the physical IoT sensors could stand in for people to evaluate indoor health risks if people cannot sense the colorless and odorless air pollutants, such as ozone. This chapter also rethinks the role of the building envelope more than just separating the physical boundary between indoor and outdoor but preventing outdoor pollutant penetration. Chapter 5 focuses on how environmental parameters determine children's sleep quality using subjective questionnaires and polysomnographic measures. Chapter 6 reflects the general discussion on human dimensions of building performance and outlooks the future research directions.

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CHAPTER 2: MEASURING THE RIGHT FACTORS

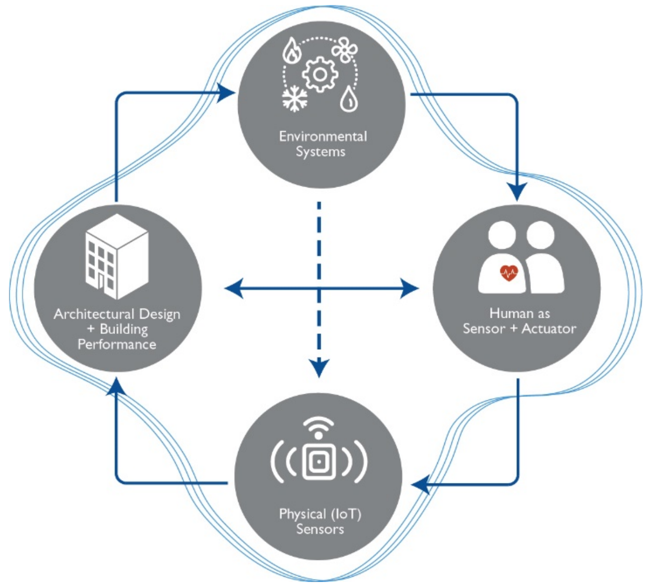

Figure 2. 1: An overview of human-building-and-system

Discussing the human dimensions of building performance starts with an exploration in fundamental models and variables, explored in this chapter and adapted from (Ma et al. 2021). As illustrated in Figure 2. 1, this chapter focuses on what factors are worth measuring if we want the human-building-and system work together. We can measure numerous factors in the buildings, but what are the variables that play a critical role in delivering thermal comfort and indoor air quality if we prioritize people’s needs and wellbeing in that loop. The summary and understanding presented in this chapter are the foundation for showing that indoor air quality (IAQ) has a powerful impact on human health and thermal comfort. This chapter is intended for practicing architects and engineers to determine what they need to measure when they carry out the field investigations.

Buildings determine the quality of the living environment, and thermal comfort and occupant wellbeing are primary indicators of their success (Mendell et al. 2002). In the indoor environment, ventilation systems play an important role in IAQ and reducing occupant discomfort. Their purpose is to remove airborne pollutants and/or dilute their concentration to acceptable levels (Y. Li, Leung, G. M., Tang, J. W., Yang, X. , Chao, C. Y., Lin, J. Z., Lu, J. W., Nielsen, P. V., Niu, J. , Qian, H. , Sleigh, A. C., Su, H. J., Sundell, J. , Wong, T. W. and Yuen, P. L. 2007; Chenari, Dias Carrilho, and Gameiro da Silva 2016). In many circumstances, ventilation is also used to maintain acceptable temperature and relative humidity (Carrer et al. 2015), which are among the largest energy consumers in buildings (d'Ambrosio Alfano et al. 2014). One way to increase energy efficiency and manage indoor health and comfort is through modeling and predicting the prevalence of indoor air pollutants while buildings are being designed. The problem is multidimensional and extremely complex, and it has attracted researchers from a variety of fields and disciplines to work on solutions; which nevertheless remain a challenge (Yin et al. 2010; Okochi and Yao 2016). Ventilation system modeling is generally covered in the field of building control. On the other hand, understanding occupant health and comfort is conducted by scientific communities focused on thermal comfort, epidemiology, and public health. Alignment of occupant health and comfort with ventilation control requires a synthesis between these two fields. Therefore, investigating what variables of occupant health and comfort are required in the modeling of ventilation systems is a critical step toward energy reduction and building control.

The reliance on heating, ventilation, and air conditioning (HVAC) systems in working, living, and learning environments have resulted in increased energy usage. Nearly 50% of building sector energy is used to maintain indoor health and thermal comfort conditions (L. Yang, Yan, and Lam 2014). Many articles in the literature assessed control strategies or building sensing systems on the performance of HVAC components. For example, Wang et al. (Wang, Kuckelkorn, and Liu 2017) presented diverse low energy methodologies on controlled components, controlled parameters, control mode, and control algorithms. Vakiloroaya et al. (Vakiloroaya et al. 2014) evaluated various technologies in modeling machinal configurations and component combinations to compare energy performance of HVAC systems and more recently, Afroz et al. (Afroz et al. 2018) summarized the implementation of state-of-the-art techniques in selecting appropriate modeling processes for HVAC control system. Due to the fuzzy nature of thermal comfort and indoor environmental quality, other studies investigated fuzzy logic controllers (Kolokotsa et al. 2006), fuzzy proportional integral derivative (PID) controllers (Carvajal, Chen, and Ogmen 2000), and adaptive fuzzy PD controller (Calvino et al. 2004) to maintain a thermally comfortable condition. However, these studies focused on energy conservation and standard variables, namely thermal comfort metrics and IAQ indices, as primary input and control variables. Occupant wellbeing is too often viewed as an energy cost and this means that occupant related variables and their associated building design variables remain negligible. This situation calls for a clarification of the effective variables.

2.1. Background

A number of recent review papers established the connection between ventilation for thermal comfort and ventilation for health outcomes. For example, Djongyang et al. (Djongyang, Tchinda, and Njomo 2010) reviewed ventilation systems designed for thermal comfort based on mathematical modeling of heat transfer. Park and Nagy (Park and Nagy 2018) identified a research gap between thermal comfort and building control (e.g. ventilation) through the historical development of current systems. Connecting ventilation and associated health problems, Fisk (Fisk 2017) argued that increased ventilation rates in schools accelerate variability of elevated indoor humidity levels, bringing higher risks of indoor mold growth and increasing thermal discomfort in hot and humid climates. Sundell et al.'s (Sundell et al. 2011) study indicated that inappropriately low ventilation rates are a contributing factor, raising risks for sick building syndrome (SBS) and respiratory infections. Li et al. (Y. Li, Leung, G. M., Tang, J. W., Yang, X. , Chao, C. Y., Lin, J. Z., Lu, J. W., Nielsen, P. V., Niu, J. , Qian, H. , Sleigh, A. C., Su, H. J., Sundell, J. , Wong, T. W. and Yuen, P. L. 2007) substantiated an association among ventilation rates, airflow, and the airborne transmission of infectious diseases. As demonstrated in numerous additional studies, ventilation systems are a critical means for governing IAQ and comfort management.

Further studies related to three main topics - wellbeing, energy, and building sensing systems – have developed different forms of physics-based models to approximate the behavior of environmental systems. Enescu (Enescu 2017) reviewed thermal comfort models and discussed the integrations of intelligent control methods such as fuzzy and hybrid control. The review study conducted by André et al. (André, De Vecchi, and Lamberts 2020), investigated personal comfort models for user-centered environmental control, considering energy impact and optimization algorithms. Jung and Jazizadeh (Jung and Jazizadeh 2019) proposed a review taxonomy for human-in-the-loop HVAC operations and summarized machine learning and probabilistic modeling for pattern recognition with respect to the dimensions of occupancy, comfort, and energy efficiency.

In addition to reviews on thermal comfort models, Wei et al. (Wei et al. 2019) reviewed state-of-the-art of IAQ predictions using statistical models such as partial least squares, generalized linear models, and Bayesian hierarchical models. Liu et al. (Zhe Liu, Ye, and Little 2013) assessed the existing physically based models for predicting the emission of organic compounds and the study results suggested that the application of these models require more reliable validation. Other than the physics-based models, Cheng et al.

(Cheng, Niu, and Gao 2012) coupled representative thermal comfort models to computational fluid dynamic (CFD) numerical simulation and evaluated the reliability and stability of determining thermal comfort in asymmetrical environments. They highlighted the challenge and complexity of coupling between the model and CFD simulation, which is usually reserved for specialized inquiries. It is notable that the deterministic models implemented through numerical simulation provide vital information on independent variables, and valuable feedback on system interactions during the design process. These are distinct from the modeling techniques used in environmental systems based on time-series of data. A holistic review of measuring right factors to improve the interaction of forecasting techniques, comfort, and IAQ is not yet available.

Health and thermal comfort are commonly measured using analytical models. Analytical models are those which are based on a mathematical solution of governing equations, including empirical and deterministic models. Empirical models are derived by fitting a stream of data to define the relationship between independent variables and outcome variables leading to an approximation to analytic formulae, including measurement and system noise. By contrast, deterministic models are exact solutions formulated from a hypothesis and one or more assumptions. This type of model supposes that the underlying mechanisms in variability of parameters is well-defined such as examples of thermodynamic and mass-transfer rules. In building science, developing a deterministic model necessitates detailed and complex input data such as characteristics of the building envelope, building configurations, and outdoor levels of the target pollutants. Such models provide a reference to understand the underlying mechanisms, estimate their dependent relations, and identify related variables. One weakness of deterministic analysis is the difficulty of retrieving adequate information to assemble a model, particularly in complex buildings and especially when the interaction of occupants with the environment is included (Carreira et al. 2018; Zhao et al. 2014). In the meantime, empirical models developed with machine learning (ML) techniques have a robust capacity for providing insights into controlling ventilation systems, taking multiple referred variables into account during the design stage and the auditing of building performance, allowing the occupant to adjust and make corresponding plans. Among many ML techniques, artificial neural network (ANN) has the advantage of mapping the non-linear dependency of inputs and outputs and performing well for continuous data. Reinforcement learning (RL) has substantiated the capacity of learning human responses and preferences with a great applicability in complex realistic environments (Dalamagkidis et al. 2007; Vázquez-Canteli and Nagy 2019).

Before ML techniques, the control system for guaranteeing thermal comfort in most buildings is the thermostat, which only measures sensible air temperature, neglecting humidity, contaminant concentrations, air speed, and other environmental factors. More recent buildings have added the CO_2 sensor, which serves as a proxy measurement of occupancy and air exchange rates. In other words, most of the buildings are dumb and only are able to measure a few variables. ML techniques can interact with more datapoints and process more measurements of indoor environments. This raises the key question of this study, which variables are worth measuring?

2.2. Analytical Models of Thermal Comfort

Currently, there are two major thermal metrics that researchers and standards use to determine a proper thermal environment for occupants: steady-state approach (Section 2.2.1) and adaptive comfort approach (Section 2.2.2). Fanger’s steady-state model derived from experimental data of college-age students collected in a climate chamber based on the principle of heat balance, which is now the default model of assessing occupants' thermal comfort for building design and operation. The temperature fluctuation was minimized in the chamber and the experiment was conducted for a 3-hour period in winter. Participants wore standardized clothing and performed standardized activities. Using a different approach, the adaptive models were developed from field study data and are expressed in a linear regression that relates supply air temperature to outdoor temperature or outdoor meteorological variables. They provide an alternate comfort model for naturally ventilated buildings.

2.2.1. Overview of Steady-state Models

For indoor thermal comfort, Fanger's steady-state model is widely accepted for describing thermal perception of near-sedentary occupants in air-conditioned spaces (Van Hoof 2008). Fanger assumed that the human body strives towards thermal equilibrium between the heat generated, consumed, and transferred to the environment. The general aim of Fanger's model is to predict the mean thermal sensation and the percentage of dissatisfaction of a given group of people in the environment, represented through the indices Predicted Mean Vote-Predicted Percentage Dissatisfied (PMV–PPD) in accordance with a seven-point scale of thermal sensation (P.O. Fanger 1970; P. Fanger 1967). The PMV model encompasses the most important variables that affect the thermal comfort state: four measurable environment variables (dry-bulb air temperature T_{db}, air velocity v_a, air humidity H, and mean radiant temperature T_{MR}) and two personal variables (metabolic rate and clothing insulation). This chapter focuses on the IAQ-related variables and their impacts on thermal comfort and health. Therefore the human parameters put forward by Fanger will not be analyzed.

The purpose of introducing T_{MR} is to quantify the equivalent temperature of radiant fluxes of the indoor environment received by the human body (Guo et al. 2020; 2013). It is worth noting that Fanger's computation of T_{MR} only reports thermal radiation transferred by the walls and T_{MR} is oversimplified by averaging the temperatures taken at different surfaces in an unchanging condition:

$$T_{MR} = \left(\sum_{i=1}^{n} T_i \cdot S_i\right)\left(\sum_{i=1}^{n} S_i\right)^{-1}$$

(**Error! Bookmark not defined.**2.1)

where:

T_i = simulated or measured surface i temperature, °C;

S_i = surface i areas, m².

In addition, the expression of the PMV index shown in the standard (2005) is contingent on the following quantities. All the related quantities are visualized in Figure 2. 2.

$$PMV = f(\dot{M}, \dot{W}, f_{cl}, p_a, T_{db}, T_{cl}, h_c)$$

(**Error! Bookmark not defined.**2.2)

where:

$\dot{M}$ = the metabolic rate, W/m²;

$\dot{W}$ = effective mechanical work/power, W/m²;

f_{cl} = the ratio of clothing surface area to the exposed surface area;

p_a = vapor pressure of water;

T_{cl} = the clothing surface temperature, °C;

T_{db} = dry bulb temperature, °C;

h_c = the heat exchange by evaporation on the skin, °C;

The extended explanation and formulation of the PMV index are elucidated in (Croitoru et al. 2015). The PMV index is also approximated and derived empirically by accounting for the occupant exposure time (2013):

$$PMV = \alpha_p \cdot T_{db} + \beta_p \cdot p_a + \delta_p \tag{2.3}$$

where:

α_p, β_p, δ_p = the correlative coefficients for indoor environments.

Other than T_{MR}, the rationale for including the rest of the ambient parameters proposed by Fanger such as air temperature T_a, air speed v_a, humidity H (sometimes captured with relative humidity RH) is that the human thermoregulatory system maintains thermal equilibrium with multiple pathways of heat exchange. The air velocity v_a [m/s] is the distance that air flows per unit time. The air velocity has a considerable effect on discomfort conditions, especially when it is higher than 40 ft/min (0.203 m/s) (Singh et al. 2002). Moreover, the air velocity across the building material surface will affect the convective mass transfer coefficient of formaldehyde and other organic compounds (Ye, Won, and Zhang 2015).

The relative humidity RH is the ratio of water vapor pressure to maximal quantity of water vapor pressure embodied in the air at a given temperature (Singh et al. 2002), which is regularly expressed in percentage. In the indoor environment, RH is dependent on T_a and the quantity of water vapor contained in the air. For human comfort the building system control must maintain RH within a moderate range, low enough to be comfortable but high enough to avoid the effects of very dry air on skin and respiration. A number of research outcomes showed that RH can strongly affect thermal comfort (2013; Wolkoff 2018; P.O. Fanger 1970), IAQ perception (Rupp, Vásquez, and Lamberts 2015; Fang et al. 2004), occupant health (Wolkoff 2018; Fang et al. 2004), and energy usage (L. Yang, Yan, and Lam 2014; Wan et al. 2009). These scientific studies indicated that ventilation control plays an important role in striking a balance between humidity and air temperature to deliver comfort for the occupants.

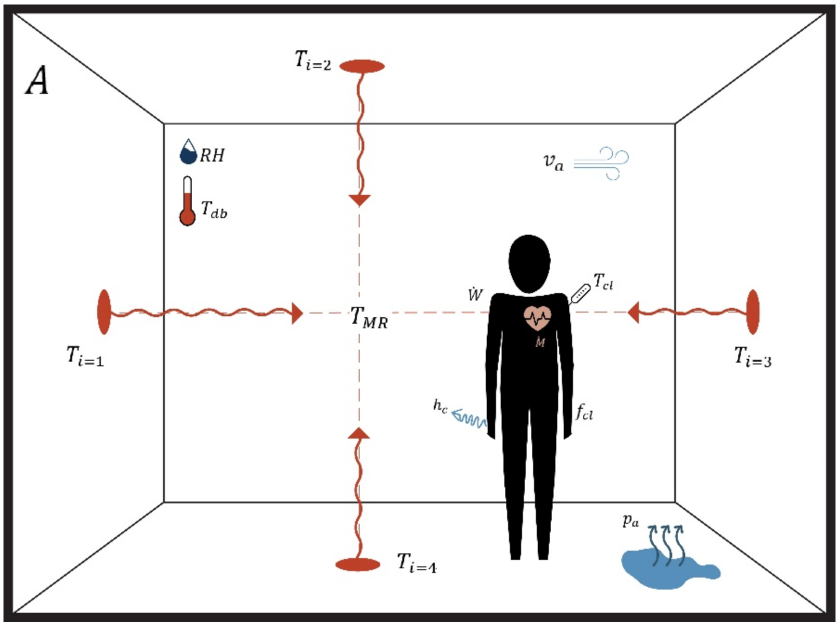

Figure 2. 2: Variables identified from Fanger's steady-state model.

2.2.2. Overview of Adaptive Models

Adaptive models are derived from field studies that determine the actual acceptability of the thermal environment. These have shown that the PMV index is not recommended for the prediction of mean thermal comfort when occupants are under spatially non-uniform thermal conditions such as naturally ventilated buildings, due to a large discrepancy between the predicted PMV and actual thermal sensation votes (X. Yang et al. 2015; Ioannou, Itard, and Agarwal 2018). The calculated PMV likely underestimates or overestimates the performance of thermal environment for its occupants (Han et al. 2007; Ioannou, Itard, and Agarwal 2018; Gilani, Khan, and Pao 2015). One way to explain the discrepancy is that the description of thermal comfort often conforms with physiological acclimatization (B. Li et al. 2010). These physiological changes occur within an individual, modifying thermoregulatory system settings to respond to continuous exposure caused by environmental heat stress (Prek 2005).

Modified PMV indices were then introduced and called Adaptive Predicted Mean Vote ($aPMV$). The $aPMV$ method addresses the thermal comfort in a warm environment and essentially computes "the same optimum operative temperature as the analytic PMV approach, but uses mean outdoor effective temperature as the only input instead of the usual four inputs (RH, v_a, clothing insulation, metabolic rate,) required by the analytic PMV method" (de Dear, Brager, and Cooper 1997). Yao et al. (Yao, Li, and Liu 2009) investigated and developed the correlative relation between $aPMV$ and PMV in the case of buildings with natural ventilation:

$$aPMV = (PMV^{-1} + \beta)^{-1} \tag{2.4}$$

The term β in Eq. (2.4) is recognized as "adaptive coefficient" in buildings with natural ventilation, and stands for the ratio of impact between psychology, behavior, and the physical stimulus. The implementation of adaptive coefficient β aims to correct and adjust the PMV model itself to reduce overestimations and/or underestimations (Holopainen et al. 2014). Other field studies further determined β to be more specific by taking consideration of cold (Yao, Li, and Liu 2009) and warm conditions (Gao, Wang, and Wargocki 2015), buildings in free-running period of time (Baker and Standeven 1996), or buildings in a hot and humid climate region (Han et al. 2007).

Another adaptive model is the New Predicted Mean Vote ($nPMV$) introduced by Humphreys and Nicol (Humphreys and Fergus Nicol 2002), which aims to match the predicted PMV results with actual thermal sensation voted by occupants in air-conditioned buildings (Rupp, Vásquez, and Lamberts 2015). The $nPMV$ model expressed in (Humphreys and Fergus Nicol 2002) is shown as:

$$nPMV = \gamma \cdot f_{PMV\_ASHRAE} \tag{2.5}$$

where f_{PMV_ASHRAE} is an empirically fit model defined as:

$$f_{PMV_{A}SHRAE} = -4.03 + 0.0949 \cdot T_{op} + 0.00584 \cdot RH\% + 1.201 \cdot \dot{M} \cdot f_{cl} + 0.000838 \cdot T_{out}^{2} \tag{2.6}$$

This model assesses the relation among the operation temperature T_{op}, relative humidity $RH\%$, metabolic rate $\dot{M}$, the ratio of clothing surface area to the exposed surface area f_{cl}, and the outdoor mean air temperature T_{out}. The operative temperature is determined and affected by the mean radiant temperature T_{MR} and air temperature T_{a} (Atmaca, Kaynakli, and Yigit 2007). Study in (Butera 1998) expresses the relation of these three parameters into a mathematical equation, if T_{MR} is less than 4 °C apart from T_a and airflow is lower than 0.2m/s:

$$T_{op} = (T_a + T_{MR})/2 \tag{2.7}$$

Another equation to establish the relationship among T_{MR}, T_a and T_{op} is presented in (d'Ambrosio Alfano et al. 2014) and this model is included in the ASHRAE 55 standards (American Society of Heating, Refrigerating and Air-Conditioning Engineers) as well (2013):

$$T_{op} = \alpha T_a + (1 - \alpha) T_{MR} \tag{2.8}$$

where α is a correction coefficient dependent on the air speed.

Apart from the aforementioned models, Nicol and Humphreys (Nicol and Humphreys 2002) included exposure time as a factor as well as occupants' actions to specify thermally comfortable temperature, for example opening a window and taking off clothes. The equation for the exponentially weighted running mean at time t is written as:

$$T_{a(t)} = (1 - \alpha)(T_{t-1} + \alpha T_{t-2} + \alpha^2 T_{t-3} \ldots) \tag{2.9}$$

where α is a constant ($\alpha \in [0,1)$), $T_{a(t)}$ represents the running mean temperature at time t, T_t is collected as the mean temperature in a time-series t at equal intervals. T_{t-n} is the instantaneous temperature at previous n time-intervals. Figure 2. 3 diagrammatically illustrates the key variables used in adaptive models.

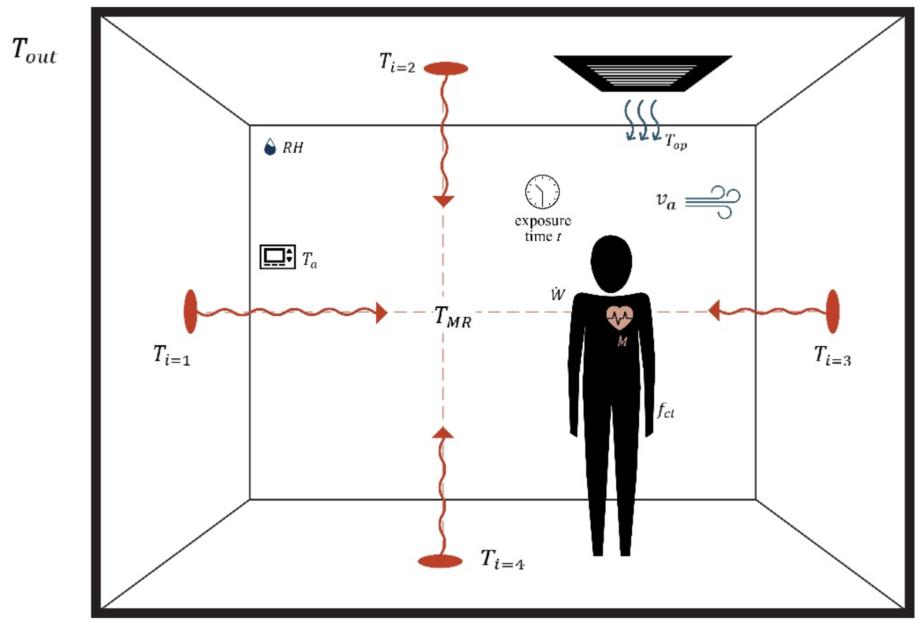

Figure 2. 3: Variables identified from adaptive comfort models.

2.2.3. Application and Limitations

Fanger's method became the basis of the ISO 7730 (2005), still used in practice , and of the ASHRAE 55 standard (2013). Table 2. 1 and Table 2. 2 present the permissible range of operative temperature that concluded from the steady-state studies.

Table 2. 1**.** ISO 7730 recommended T_{op} for occupants doing sedentary activity.

Season	Clothing insulation	Metabolic rate	Optimal T_{op} (°C)	T_{op} ranges (°C)
Summer	0.5	1.2	24.5	23-26
Winter	1.0	1.2	22	20-24

Table 2. 2. ASHRAE 55 recommended T_{op} for occupants doing sedentary activity at 50% RH and average v_a less than 0.15 m/s.

Season	Clothing insulation	Metabolic rate	Optimal T_{op} (°C)	T_{op} ranges (°C)
Summer	0.5	1.2	24.5	23-26
Winter	0.9	1.2	22	20-23.5

Both steady-state and adaptive models have limitations. The steady-state models have high uncertainty of thermal comfort predictions even if air temperature, air velocity and relative humidity are measured, due to the inaccurate estimation on occupants' clothing insulation and metabolic rate. Up to this point, the table-lookup method is the most used approach to approximate these factors. This can introduce severely biased estimates, since the calculated value of clothing insulation differs if different methods were used to measure clothing area, the body surface area and clothing circumference and then infer the insulation value. Moreover, Kingma and van Marken Lichtenbelt (Kingma and van Marken Lichtenbelt 2015) claimed that the enumerated metabolic rate in the standards badly needs to be recalibrated. For practical applications, Gilani et al. (Gilani, Khan, and Pao 2015) compared validation of the steady-state model in air-conditioned and naturally ventilated buildings and found that the model underestimates thermal sensation by 13% in summer and overestimates by 35% in winter.

The simplicity of adaptive comfort models gives rise to the concerns of oversimplifying inter-individual variability of adaption and the validation of models was supported by data acquired from occupants in naturally ventilated buildings. Moreover, the impacts of other environmental factors on human adaptability were neglected. Nguyen et al.

(Nguyen, Singh, and Reiter 2012) conducted field surveys and found that the adaptive model introduced a large bias of indoor temperature setting due to the ignorance of air velocity and humidity. Halawa and Van Hoof (Halawa and Van Hoof 2012) stated that the adaptive comfort metric is not accurate when T_{out} is colder than 10 °C and hotter than 33 °C.

2.3. Analytical Models of Indoor Air Quality

The gold standards of healthy IAQ were challenged by researchers from time to time. Many countries' national organizations and authentic agencies have stipulated guidelines. A comprehensive summary of standards and guidelines as developed by various worldwide organizations is presented in Abdul-Wahab et al.'s review study (Abdul-Wahab et al. 2015). World Health Organization (WHO) and the United States' key standards involved in setting IAQ will be summarized in this section as well (Table 2. 3). As noted above, this study focuses on the typical contaminants which exist in a majority of indoor environments and poses the greatest risk to health. Contaminants like carbon monoxide and Radon are not covered because they usually accumulate at high levels in particular spaces (e.g., kitchen and basement). Other contaminates such as mold are not discussed in this study since they are difficult to detect with environmental monitoring and require daily observations to measure.

Table 2. 3. The primary IAQ standards and guidelines stipulated by WHO and the United States' authentic agencies.

Organization	Reference
American Society of Heating, Refrigerating and Air Conditioning Engineer (ASHRAE)	("American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)" 2016)
Occupational Safety and Health Administration (OSHA)	("Occupational Safety Health Administration (OSHA)" 2014; "United States Environmental Protection Agency (EPA)" 2010)
US Environmental Protection Agency (EPA)	("United States Environmental Protection Agency (EPA)" 2010; "United States Environmental Protection Agency (EPA)" 2004)

World Health Organization (WHO)	("World Health Organization (WHO)" 2010; "World Health Organization (WHO)" 2006)

2.3.1. Models of Determining Carbon Dioxide Concentrations

Carbon Dioxide (CO_2) level is of great importance in the IAQ and is often used as the proxy for ventilation rates (Fisk 2017). CO_2 concentrations indicate IAQ acceptability, air exchange suitability, and whether adequate fresh air is being supplied to the indoor spaces in buildings (Apte 2000). The concentration of CO_2 in buildings can be higher than outdoors in magnitude, typically ranging from 350 to 2,500 parts per million (ppm) (Seppänen, Fisk, and Mendell 1999), but in some cases reaching 4,000–4,500 ppm or even higher (Bekö et al. 2010; Shaughnessy et al. 2006). Sick building syndrome (SBS) symptoms correlated by elevated CO_2 levels include headache (Dan Norbäck and Nordström 2008; Azuma et al. 2015), fatigue (X. Zhang et al. 2017), eye irritation symptoms (Azuma et al. 2015), neuro-physiologic symptoms (i.e. lack of concentration (Muscatiello et al. 2015), cognitive performance (Allen et al. 2016), decision-making (Satish et al. 2012)), upper and lower respiratory tract symptoms (Mentese et al. 2015). WHO and different organizations in the United States have suggested different limit values as listed in Table 2. 4.

Table 2. 4. Standards and guidelines for limiting values of CO_2.

Organization	Value	Ref
ASHRAE	No more than 700 ppm above outdoor concentration 600 ppm (high level of comfort)	("American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)" 2016)
OSHA	600-1,000 ppm (preferred)	("Occupational Safety Health Administration (OSHA)" 2014)
EPA	800 ppm (acceptable)	("United States Environmental Protection Agency (EPA)" 2010; "United States Environmental Protection Agency (EPA)" 2004)
WHO	1,000 ppm	("World Health Organization (WHO)" 2010)

From a practical point of view, CO_2 concentration is often taken as an approximate surrogate for levels of occupant-generated pollutants (X. Zhang et al. 2017), and for estimating a proper ventilation rate per occupant (Apte 2000). There are a variety of methods for the CO_2 concentration estimations in a well-mixed space, as described in some studies (T. Lu et al. 2010; Griffiths and Eftekhari 2008; Ng et al. 2011):

$$C_{CO_2}(t) = C_0 + \frac{G}{Q} + (C_0 - C_{out} - \frac{G}{Q})\, e^{-\frac{Q}{V}t} \tag{2.10}$$

where:

G = the generation rate of CO_2, m^3/s;

C_{out} = outdoor CO_2 concentrations, ppm;

C_0 = indoor CO_2 concentrations at time 0, ppm;

Q = the volume of air flows into a space per unit time, m^3/s;

V = the volume of indoor air, m^3;

t = time, s.

The exponential term in Eq.10 is neglectable when CO_2 concentration ultimately reaches a steady state (Eq. 2.11). The system then can be simplified and computed to approximate a building ventilation operation as:

$$C_{CO_2}(t) = \frac{N(t)G(t)}{1.8Q(t)} + C_{out}(t) \tag{2.11}$$

where:

$G(t)$ = CO_2 generated by each occupant at time t;

Q = the volume of air flows into a space per unit time, m^3/s;

$N(t)$ = a number of occupants in the space at time t;

$C_{out}(t)$ = outdoor CO_2 concentration at time t.

Eq. 10 and 11 model the temporal evolution of CO_2 concentration and capture a general trend to reflect future fluctuations. However, these two models require multiple observations recorded sequentially over time, for example, real-time occupancy monitoring. Apart from that, Chan et al. (Chan et al. 2015) used the following equation to predict the steady-state indoor CO_2 concentrations, C_{in} [ppm]2., given the CO_2 generation rate G [L/s-person]. The equation introduced by Chan el al. uses similar factors but without the time evolution.

$$C_{in} = C_{out} + \frac{G \cdot N}{Q} \tag{2.12}$$

where:

C_{out} = the outdoor CO_2 concentrations, ppm;

Q = the outdoor airflow rate, m^3/h;

N = the number of occupants in the space.

To summarize, studies on computing and modeling CO_2 concentration in the built environment identified a number of variables (Figure 2. 4), such as CO_2 generation rate G, outdoor CO_2 concentrations C_{out}, the volume flow rate Q, room volume V and number of occupants in a room N. The concentration of CO_2 is rarely constant in an indoor environment and must be evaluated regularly, since the occupancy (CO_2 generation rate) varies. The effectiveness of ventilation is the same as the dilution of CO_2 (Seppänen, Fisk, and Mendell 1999). Other than investigations on CO_2 concentration and its impact on occupants' wellbeing, Ramalho et al.'s (Ramalho et al. 2015) study results indicated that CO_2 concentration could be used as an IAQ proxy and averaged concentration of CO_2 had a positive and significant association with $PM_{2.5}$ and PM_{10} levels.

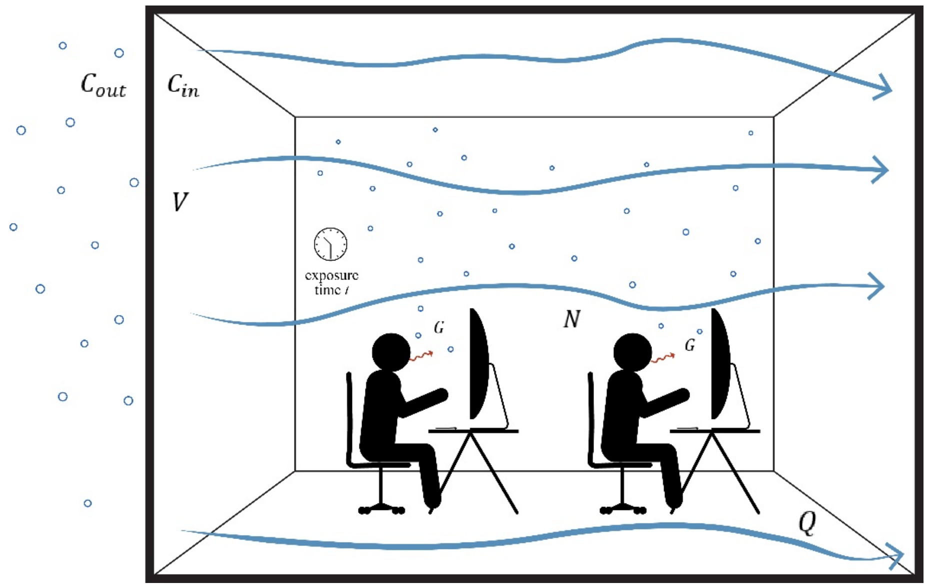

Figure 2. 4: Variables identified from models of CO_2 concentration computation.

2.3.2. Indoor Airborne Contaminants

Indoor air pollution and its adverse health effects attracted much attention from the late 1960s (Samet, Marbury, and Spengler 1987). Reduced ventilation rates and airtight buildings for the sake of energy conservation resulted in building-related illness and other adverse effects on human health (Sundell 2004). Although the impact of indoor air pollution on many health effects remains controversial, epidemiologic and clinical research has identified some health problems closely related to the common pollutants found in indoor environments, particularly particulate matter (PM), nitrogen dioxide (NO_2), ozone and volatile organic compounds (VOCs).

Models of Determining Particulate Matter Concentrations

Airborne PM has been recognized as one of the most health-relevant air contaminants. PM is a complex mixture of solid and/or liquid particles suspended in air and varies in size, shape and composition ("United Nations Environment Programme and the World Health Organization" 2013; R. Zhang et al. 2015; "World Health Organization (WHO)"

2013). Kim et al.'s (K.-H. Kim, Kabir, and Kabir 2015) extensive review analyzed a number of epidemiological studies and consistently suggested a strong association between exposure to ambient PM, and diminished total lung capacity and increased risks of chronic obstructive pulmonary diseases. EPA regulated particles mainly in two sizes following their predicted penetration capacity into healthy lung tissue as either: 1) coarse inhalable particles (PM_{10}) with an aerodynamic diameter of 10 micrometers and smaller, or 2) fine inhalable particles ($PM_{2.5}$) with an aerodynamic diameter of 2.5 micrometers and smaller ("United States Environmental Protection Agency (EPA)" 2010). Given that there is a significant inter-individual difference in responding to a given exposure, it appears unlikely that any guidelines would provide complete protection for every individual. The guideline values recommended by WHO and the US agencies listed in Table 2. 5.

Table 2. 5. Standards for guidance values of $PM_{2.5}$.

Organization	PM2.5 Value	PM10 Value	Ref
ASHRAE	3,000 μg/m^3 for a 8h average at ceiling height 65 μg/m^3 for a 24h average in breathing zone	150 μg/m^3 for a 24h average	("American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)" 2016)
OSHA	5,000 μg/m^3 for a 8h average	150 μg/m^3 for a 24h average	("Occupational Safety Health Administration (OSHA)" 2014)
EPA	60 μg/m^3 for a 24h average	150 μg/m^3 for a 24h average	("United States Environmental Protection Agency (EPA)" 2004)
WHO	25 μg/m^3 for a 24h average	50 μg/m^3 for a 24h average	("World Health Organization (WHO)" 2006)

There is no single model well-suited for addressing all issues of concerns due to the essentially complicated system of particles, although all deterministic methods were developed on the basis of a fundamental principle - mass conservation. According to

(Nazaroff 2004), Figure 2. 5 diagrammatically illustrates the material-balance approach and depicts some processes that determine indoor particle concentrations associated with the effectiveness of ventilation or air transportation capacity.

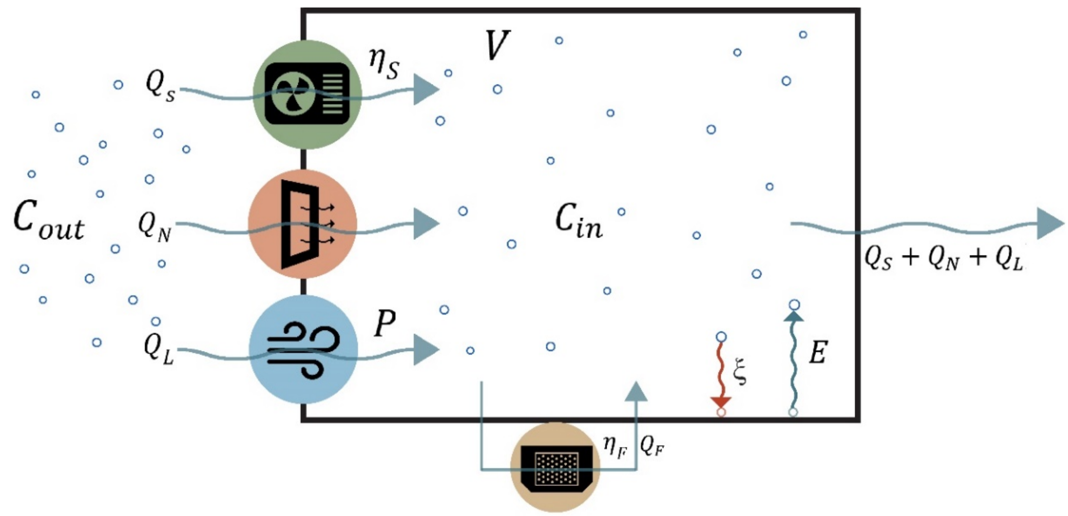

Figure 2. 5: Reproduced schematic representation of indoor particle dynamic processes from (Nazaroff 2004).

As suggested by Figure 4, it is assumed that mechanical supply, natural ventilation, and infiltration are the only pathways that affect indoor particle levels and the particles are attributed uniformly throughout the indoor space, sequentially mass conservation would be written into this governing equation for the concentration of indoor particles:

$$\frac{d(C_{in}V)}{dt} = E + \ C_{out}[Q_s(1-\eta_s) + Q_N + Q_L P] - C_{in}[Q_F\eta_F + \xi V + (Q_S + Q_N + Q_L)] \tag{2.13}$$

where:

C_{out} = outdoor particles concentrations, μg/m^3;

Q_S = the flow rate of mechanical supply, m^3/h;

Q_N = the flow rate of natural ventilation, m^3/h;

Q_L = the flow rate of leakage (infiltration), m^3/h;

P = the penetration rate of leakage flow path;

η_S = single-pass removal efficiency filtered by mechanically operated supply;

Q_F = the flow rate of a particle-control filter, m^3/h;

η_F = single-pass removal efficiency of a particle-control filter;

E = emission source rate, μg/h;

ξ = a deposition rate of particles onto room surfaces, h^{-1};

V = space volume, m^3;

C_{in} = indoor particles concentrations, $\mu g/m^3$.

Eq. 2.13 is the most widely used model to estimate indoor particle levels in typical processes, since it directly solves the net rate of particle accumulation by subdividing particle behaviors into different pathways. On the other hand, it assumes these are the only pathways that transport particles. The calculated results are highly contingent on η_S, η_F, P, E, and β and may vary largely with different particle size. Therefore, Eq. 13 is not a direct representation of the entire particle mass in the air. To eliminate such concern, Madureira et al.'s study (Madureira, Paciência, and De Oliveira Fernandes 2012) focused on PM_{10} dose rates which were calculated using the following model to assess health risks and this equation was validated in other published studies as well (Castro et al. 2011; Fonseca et al. 2014; Kalaiarasan et al. 2009):

$$D = \frac{BR_{WA}}{BW} \cdot C_{WA} \cdot OF \cdot N_t \tag{2.14}$$

where:

D = age-dependent dose rate, μg/kg/day;

BR_{WA} = age-dependent weighted average breathing rate, L/min;

BW = age-dependent body weight, kg;

C_{WA} = weighted average values of PM_{10} concentrations, μg/L;

OF = occupancy factor for effective dose;

N_t = the total amount of minutes spent indoors per day, min/day.

The model concluded in Madureira et al.'s study also indicated the need to collect occupant data and then established the corresponding profile to better offer health and comfort centered building control system (Naylor, Gillott, and Lau 2018).

Models of Determining Nitrogen Dioxide Concentrations

Nitrogen Dioxide (NO_2) is a well-known air pollutant with evidence of adverse health effects independent of other common pollutants such as PM. Since NO_2 is the pollutant negatively associated with wind speed, some studies have shown that NO_2 level may be used as an indicator of air stagnation in a local microclimate (Dan Norbäck et al. 2017; Ito, Thurston, and Silverman 2007). Ito et al. (Ito, Thurston, and Silverman 2007; Cesaroni et al. 2013) further posited that NO_2 can be a surrogate marker of the outdoor air contaminants concentration, particularly for the buildings located in traffic-related areas. Norback et al. (D. Norbäck et al. 2000) investigated the respiratory health aspects of NO_2 in twelve primary schools in central Sweden and reported the statistical significance of nasal congestion and mucosal inflammation. They claimed that the ventilation flow rate was the leading cause of such problems. The setting for the flow rates should be lower than the hygienic standards in the classrooms. In general, inconsistencies and uncertainties remain in the NO_2 epidemiology, with reported studies of respiratory-associated health outcomes ranging both positive and negative associations (Faustini, Rapp, and Forastiere 2014). WHO and the US have issued the limit values of NO_2 (Table 2. 6) and established requirements for the time duration.

A number of studies analyzed how the outdoor NO_2 penetrated into the indoor environment and investigated indoor to outdoor (I/O) NO_2 ratios. Challoner and Gill (Avril Challoner and Gill 2014) found that the indoor NO_2 concentration is mainly determined by the surface removal rate and outdoor level of NO_2 if there is no indoor NO_2 source and derived a model as:

$$\frac{I}{O} = \frac{E_X}{E_X + K_{NO2}} \tag{2.15}$$

where:

E_X = air exchange rate, h^{-1};

K_{NO2} = the constant removal rate of the surface.

K_{NO2} is material-dependent and its value ranges from 0.80 to 1.45 h^{-1}. Challoner and Gill further observed that the I/O ratio is significantly large overnight, even the nighttime outdoor concentrations decreased dramatically. This indicated that the benefit of increasing E_X at night flushes out indoor NO_2. Other than that, more specific relationship between ventilation control and NO_2 distribution is under development, given the restrictions where level of NO_2 is significantly correlated with other pollutants such as PM, ozone, and carbon monoxide. Available deterministic analysis on indoor NO_2 concentrations is drawn from the multi-pollutant models (Hesterberg et al. 2009; Faustini, Rapp, and Forastiere 2014).

Table 2. 6. Standards for guidance values of NO_2

Organization	Value	Ref
ASHRAE	3 ppm for a 8h average	("American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)" 2016)
OSHA	5 ppm at ceiling level	("Occupational Safety Health Administration (OSHA)" 2014)
EPA	5,600 $\mu g/m^3$ for a 8h average	("United States Environmental Protection Agency (EPA)" 2004)

WHO	200 μg/m^3 for a 1h average	("World Health Organization (WHO)" 2010)

Models of Determining Ozone Concentrations

Out of numerous air contaminates, ozone tends to have the most significant health effects and a wide array of recent works has focused on the role of ozone in the indoor climate (Apte, Buchanan, and Mendell 2008; Walker and Sherman 2013). The primary source of ozone in the indoor environment is ascribed to the outdoor ozone penetration through the building envelope (Walker and Sherman 2013). The entry of outdoor ozone into the indoors depends on a number of factors, including the outdoor ozone variations, airflow velocity, air exchange rates, surface removal rates, and chemical reaction probabilities on the surfaces or in the air (Lai, Karava, and Chen 2015; Chan et al. 2015). Weschler (C. J. Weschler 2000) quantified the ratio between indoor and outdoor ozone concentration at a constant air exchange rate as:

$$\frac{I}{O} = \frac{E_X}{K_d(A/V) + E_X} \tag{2.16}$$

where:
E_X = air exchange rate, h^{-1};
K_d = the deposition velocity of ozone, m/h;
A = total surface area, m^2;
V = the volume of the room, m^3.

Similar to the indoor NO_2 estimation method, Weschler claimed that the I/O ratio for ozone can be computed by the ratio of the air exchange rate to the sum of the air exchange rate and the surface removal rate, $K_d(A/V)$. Weschler further modified the equation in his later papers for cases in which no significant indoor ozone sources can be found (Charles J. Weschler 2006). If it is assumed that indoor ozone concentration is primarily influenced by E_X [h^{-1}] and the surface removal rate K_m [h^{-1}] stays constant, then I/O can be approximated from:

$$\frac{I}{O} = \frac{E_X}{E_X + K_m} \tag{2.17}$$

By contrast, Lai et al. (Lai, Karava, and Chen 2015) considered potential indoor sources of generating ozone but neglected the chemical possibilities between ozone and other chemicals. They developed a new I/O model expressed by the continuity equation:

$$\frac{dC_{in}}{dt} = E_X \cdot P \cdot C_{out} - (a + K)C_{in} + G \tag{2.18}$$

where:

C_{in} = the indoor ozone concentration, ppb;

C_{out} = the outdoor ozone concentration, ppb;

t = time, hours;

E_X = the air exchange rate, h^{-1};

P = the penetration factor of outdoor ozone via infiltration;

K = surface removal rate, h^{-1};

G = the generation rate of indoor ozone, ppb/h.

Building envelope is a key contributor to ozone reduction indoors and it is worth noting that human body has certain absorption capacity due to the reactions with skin. Fadeyi et al. (Fadeyi et al. 2013) estimated the values of deposition velocity v_d between 14.4 m/h and 22.3 m/h per person under the assumption of a 1.7m^2 body surface. The proportion of removed ozone by humans is computed from:

$$K_m = N \cdot v_{d\_person} \cdot \frac{A_{person}}{V} \tag{2.19}$$

where:

N = the number of people in the room;

v_{d_person} = the deposition velocity per person, m/h;

A_{person} = the body surface per person, m^2;
V = the volume of the room, m^3.

For a typical classroom scenario (N=20-30, V=240m^3, A_{person}=1.7m^2, v_{d_person}=5–22 m/h), removal rates k_m range between 0.7 h^{-1} and 4.7 h^{-1} . Under these conditions, occupants may act as sinks for absorbing over half of indoor ozone.

The above-listed models indicate that the importance of proper indoor ventilation and the ventilation system of buildings helps moderate ozone deposition velocity and reaction probability. The I/O ratio approximation methods directly present the relationship between indoor and outdoor concentrations and have a potential to rapidly calculate indoor concentrations if the outdoor concentrations are known and retrievable. On the other hand, such models cause the problem of over/underestimates if the weather stations are not close enough to the monitored buildings, since ozone is a highly reactive gas. In addition, these models hold a strong assumption regarding the absence of indoor sources and residential houses may comply with the assumption. As ozone concentrations increase dramatically and it associated health impacts become severe, WHO sets 100 μg/m^3 for an 8-hour daily average. However, the US national institutes do not specify the threshold, only recommends that ozone levels in air introduced to indoor spaces be reduced to "as low as reasonably achievable" ("American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)" 2011).

2.3.3. Summary of IAQ-Related Analytical Model Variables

Table 2. 7 summarizes variables considered in the above-mentioned analytical models. These input variables are organized in accordance with the different phases of buildings - design phase, construction phase, and occupancy phase. For example, in the architecture community, the designers investigate the environmental conditions and then make

design decisions such as room geometry, spatial configuration, and material settings. The HVAC engineering community contributes to the system design and operation. However, dealing with the uncertainties in the design stage of buildings is a complicated task to counterbalance various variables, which in turn are subject to many constraints. Data-driven modeling techniques employ a variety of relevant variables as inputs and derive them as one response to make appropriate design recommendations. Deterministic methods rely on thermodynamic or mass-transfer rules for detailed modeling and analysis, while ML algorithms do not perform such analysis, and instead learn from the historical or available data for addressing future prevalence.

Table 2. 7. Summary of input variables of IAQ-related occupants wellbeing.

Subgroups[a]	Variables of IAQ-related thermal comfort and health[b]	Topics[c]
Environmental survey	Outdoor temperature (T_{out})	TC
	Wind velocity (v_a)	TC+H
	Outdoor relative humidity (RH_{out})	H
	Outdoor contaminants concentration (C_{out})	H
Design	Room dimensions[d] (Dim)	H
	Ceiling height (H)	H
	Total surface area (A)	TC+H
	Penetration factor through envelope/door (P)	H
Material selection	Radiant temperature (T_{MR})	TC
	Temperature of surface[e] (T_i)	TC
Operation	Indoor relative humidity (RH_{in})	TC+H
	Volume flow rate (Natural, Mechanical, Infiltration) (Q)	TC+H
	Indoor temperature (T_a)	TC+H
	Air density[f] (ρ)	H
	Contaminants generation/deposition/removal concentrations/rates (G)	H
	Number of occupants (N)	H
	Exposure time (t)	TC+H
	Air exchange rate (E_X)	H

[a] Total eighteen input variables are arranged based on the different phases of buildings;

[b] The listed variables are given its abbreviation in parentheses to keep consist in Nomenclature, figures and tables;

[c] TC and H represent that this variable stem from topics of thermal comfort and health respectively; TC+H means thermal comfort and health fields both echo and cover this variable;

[d] Analytical models uses volume of a space more often, while it is determined from size of the space and ceiling height;

[e] Temperature of surface implies for surface temperatures of each material in accordance to air temperature;

[f] Air density is hardly measurable, but is correlated with air pressure, temperature, humidity and dew point.

2.4. Thermal Comfort and Health Defined Data-Driven Ventilation System

Variables concerned in thermal comfort models have been used to execute control strategies for ventilation system settings, while incorporating concerns of IAQ-related health outcomes have not been truly developed. Various data-driven modeling based on ML techniques has been employed to predict thermal comfort, the concentrations of indoor pollutants, building energy efficiency and enhance human-building interaction. Models have been used including support vector machine (S. Chen, Mihara, and Wen 2018; Shan et al. 2019; Zhao et al. 2014), neural networks (Machairas, Tsangrassoulis, and Axarli 2014; Ayata, Arcaklıoğlu, and Yıldız 2007), logistic regression (Daum, Haldi, and Morel 2011), Gaussian process (Cheung et al. 2017), reinforcement learning (Barrett and Linder 2015; Y. Chen et al. 2018), and Bayesian inference (Tian et al. 2018). The results showed significantly improved predictive accuracy (17-40%) compared to deterministic methods computation (PMV, adaptive comfort, total energy consumption), reinforcing the need for a data-mining approach to predict indoor climate.

Along with the aforementioned analytical models, this section will discuss artificial neural networks and reinforcement learning applications and what variables are missing in these two ML algorithms for delivering a healthy and comfortable indoor environment. These two robust algorithms help capture complex nonlinear and multivariable interactions, provide optimal policies of the output, and obtain occupant feedback about their perception as an ongoing part of building operations.

2.4.1. Overview of Artificial Neural Network (ANN)

Artificial neural networks (ANN) have been applied widely in HVAC system dynamic modeling, prediction, control and operation to tackle ill-defined non-linear problems in a supervised learning manner (Afroz et al. 2018). A typical ANN is composed of a large number of interconnected nodes (neurons) and structured with input, hidden, and output layers in a chain connection. Information is received by the neurons on input layer, trained and learned on the hidden layer by minimizing errors, and projected as an outcome variable on the output layer (e.g., the indoor air temperature) (Goodfellow, Bengio, and Courville 2016). An ANN also contains the various weights between its nodes which are adjustable towards the optimal values of the output. Information flows forward through the network is the process of feedforward propagation, while back-propagation (BP) allows information flows backwards through the network to change weights in order to compute gradient (Elbayoumi, Ramli, and Fitri Md Yusof 2015; Goodfellow, Bengio, and Courville 2016). BP is a fine-tuning learning algorithm and has the capacity of storing a plenty of mapping relations of input-output to improve the performance of ANN. Figure 2. 6 is an example referring to whether the ventilation system settings are satisfactory. A multilayer perceptron (MLP) is a class of ANN utilizing BP for training. The Levenberg–Marquardt (LM) is an efficient regularization technique and improves the convergence speed to a minimize mean square error (MSE) for non-linear problems by training this network (Mba, Meukam, and Kemajou 2016).

The use of ANN gains wide appeal on building energy conservation in the indoor environment applications. Control and prediction of thermal environment factors are first in order of magnitude, while fewer studies focus on the prevalence of air contaminates or IAQ associated health risks. Predicting indoor air temperature is the most used one in thermal and in ventilation control strategies.

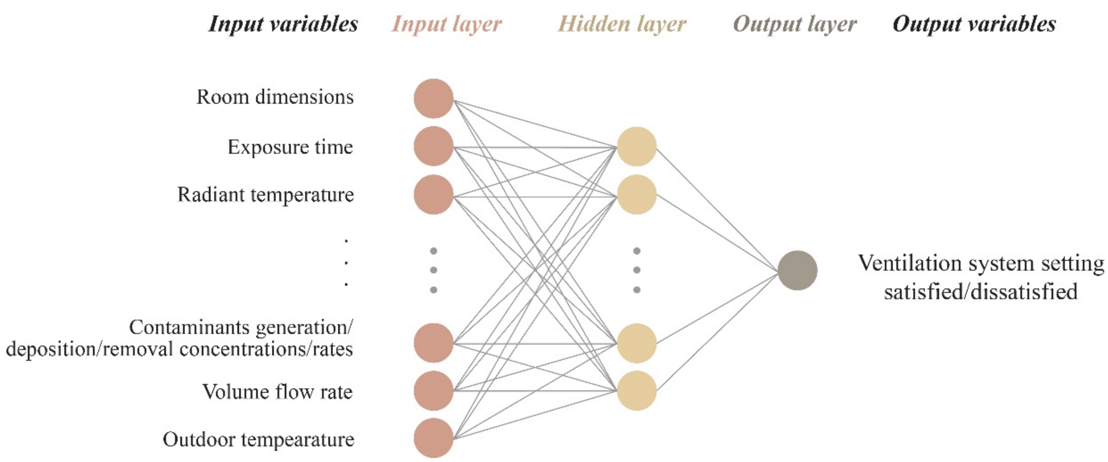

Figure 2. 6: Architecture of an ANN model for defining ventilation systems.

Moon et al. (Jin Woo Moon, Yoon, and Kim 2013) proposed an ANN-based model to forecast indoor air temperature changes. This model helps to control building's opening at different weather conditions and saves energy under unpredictable outdoor conditions. Moon et al.'s (Jin Woo Moon and Jung 2016a) another study structured an ANN model to define the right time to turn on HVAC in residential buildings by predicting indoor temperature, to avoid unnecessary energy consumption during the non-occupied period. It also helps maintain comfortable indoors in the periods of occupancy. Ashtiani et al. (Ashtiani, Mirzaei, and Haghighat 2014) dealt with the worst-case scenario during the heat waves by forecasting indoor air temperature based on urban climatic conditions and resolved predictions near to the acceptable thermal comfort in the indoor environment. By contrast, a limited number of studies, e.g. (Mba, Meukam, and Kemajou 2016; Mustafaraj, Lowry, and Chen 2011; T. Lu and Viljanen

2008; Özbalta, Sezer, and Yildiz 2012) used ANN to predict indoor temperature and relative humidity, despite many studies had revealed that relative humidity is a critical indicator of IAQ, health risks, and building energy efficiency. It lacks in the literature due to its complicated mechanism (Rupp, Vásquez, and Lamberts 2015). In line with Zhang et al. (Q. Zhang et al. 2005), humidity also affects one's perception of IAQ such that they developed an ANN-based air-handling unit to control indoor relative humidity and temperature.

Moreover, extensive studies predicted occupant thermal comfort and demonstrated corresponding control strategies following the comfort metric (i.e., temperature range (S. Kim, Lee, and Moon 2014; J. W. Moon, Chin, and Kim 2013; Jin Woo Moon and Kim 2010), 7-point ASHRAE scale (W. Liu, Lian, and Zhao 2007), PMV-PPD (Zhou and Haghighat 2009; Escandón et al. 2019; Buratti et al. 2014) and psychrometric charts (Deng and Chen 2018)). Only three studies validated and verified the proposed ANN models using a survey or actual votes: Buratti et al. (Buratti, Vergoni, and Palladino 2015) collected thermal sensation votes from occupants by giving questionnaires to valid the trained ANN model as an alternative tool for predicting thermal sensation. Sofuoglu (Sofuoglu 2008) surveyed the field to have pollutant concentrations, and occupant symptoms were collected by questionnaires to predict an index of SBS prevalence. Von Grabe (von Grabe 2016) used a dataset comprising a large number of observations of individual thermal sensation votes under varying conditions. The assembled neural network model predicted the distribution of thermal sensation votes with high accuracy. It is worth noting that Liu et al. (W. Liu, Lian, and Zhao 2007) implemented an ANN-based evaluation model to connect individual thermal comfort with the control of the air conditioner.

Control of opening strategies and the outdoor airflow rate to mitigate indoor conditions is another critical issue. Moon et al. (J. W. Moon, Chin, and Kim 2013) proposed an optimized ANN model experimenting with multiple opening strategies that evolved in double skin envelopes and effectively forecasted indoor temperatures. Li et al. (N. Li et al. 2012) proposed a dynamic ANN model for direct expansion (DX) air conditioning system, connecting the air temperature and humidity controlled by the DX air-conditioned system with various supply fan speeds.

It is evident that many studies accounted for the entire building floor as a single zone or conducted research only on a single room to develop the model. However, Huang et al. (Huang, Chen, and Hu 2015) developed a new ANN-model-based modeling approach for the airport, inputting the variables such as ventilation and mechanical cooling settings, outdoor climate conditions, and heat transfer among adjacent zones. They found that taking convective heat transfer among zones into account offers more accurate prediction results. In a similar approach, Garnier et al. (Garnier et al. 2014) established an ANN model for multiple zones based on a predictive control strategy to constrain thermal discomfort in a non-residential building. The results suggested that the consideration of heat transfer between the adjacent areas optimizes energy efficiency and satisfies thermal comfort. Spindler and Norford (Spindler and Norford 2009) predicted indoor temperature for a mixed-mode building by introducing a multi-zone ANN-based model. The research outcomes indicated that the prediction accuracy outperformed other studies' if taking the heat exchange into account.

2.4.2. ANN-Based Model for Predicting IAQ

In addition to the prediction of thermal comfort, researchers also attempted to predict indoor pollutant concentrations despite a small quantity. Elbayoumi et al. (Elbayoumi, Ramli, and Fitri Md Yusof 2015) predicted seasonal indoor levels of $PM_{2.5}$ and $PM_{2.5\text{-}10}$ in naturally ventilated schools through inputting variables of meteorological (temperature, humidity and wind speed) and measured indoor data (concentrations of $PM_{2.5}$, $PM_{2.5\text{-}10}$, CO and CO_2). The study results indicated that ANN behaves more robust when PM sources are the primary contaminant in the outdoor environment. Dai et al. (Dai et al. 2019) proposed an ANN model to examine the effect of natural ventilation on pollutant mitigation during nighttime. Challoner et al. (A. Challoner, Pilla, and Gill 2015) developed an ANN-based model to predict IAQ based on the outdoor measurements and concluded that indoor NO_2 concentrations are predictable to a high degree of accuracy. A study on particle dispersion prediction in a ventilated room was conducted in (Gheziel et al. 2016) using MLP with inputting variables such as the diameter of the aerosol particle, the velocity at the air inlet, air density, coordinates of the distance between the entrance and the exit of an area and particle duration in the room. Liu et al. (Zhijian Liu, Li, and Cao 2017) predicted the level of indoor airborne bacteria with measuring IAQ variables of indoor $PM_{2.5}$, PM_{10}, CO_2, temperature, and RH.

Studies conducted in (Ascione et al. 2017; Asadi et al. 2014) have attempted to employ ANN models to improve either energy efficiency or occupant wellbeing in retrofit scenarios. Some other studies have focused on the feasibility and effectiveness of controlling natural ventilation in residential buildings. For example, Stavrakakis et al. (Stavrakakis et al. 2010) predicted thermal comfort in naturally ventilated houses. Dai et al. (Dai et al. 2019) predicted indoor CO_2 concentrations at night based on natural ventilation rate. Ayata et al. (Ayata, Arcaklıoğlu, and Yıldız 2007) used the simulated data to design an ANN model for the prediction of indoor air velocities in naturally ventilated office spaces, and one of significant findings of this study was that a rectangular building with 1:1.7-dimensional ratio is the most desirable configuration for natural ventilation in a moderate climate region. Zhou and Haghighat (Zhou and Haghighat 2009) improved design and operation of a ventilation system by controlling the flow rate, supply air temperature and other variables. This approach resulted in enhancing thermal comfort and IAQ without sacrificing the energy costs of ventilation.

2.4.3. Summary of ANN-Defined System

In (Jin Woo Moon and Jung 2016b; Nasruddin et al. 2019; Zamora-Martínez et al. 2013; Asadi et al. 2014; Zhou and Haghighat 2009; Dai et al. 2019; Ayata, Arcaklıoğlu, and Yıldız 2007), the study results implied a clear opportunity here to enhance health and comfort while lessening energy use. These outcomes also demonstrated the significance of indoor pollutant concentrations and thermal comfort predictions in improving building energy efficiency.

The frequency of input variables used in ANN models is shown in Figure 2. 7. The studies for achieving occupant wellbeing and energy conservation are typically computed with outdoor and indoor air temperature and relative humidity measures. In contrast, design-related factors and field measures are less common. In the first place, indoor air science is applied after the design phase of buildings and mainly aims to diagnose and resolve indoor environmental problems following general guidelines for HVAC equipment and health effects. Secondly, the meteorological and field measurements of air temperature and relative humidity are relatively straightforward, making them readily available for scientific use. Most studies overlook that the effect of indoor air temperature is linked to air velocity, surface temperature, and mean radiant temperature. These related factors are rarely incorporated in ANN models, which could benefit from the use of different environmental factors, since the selection of the model is done empirically and tested against past data.

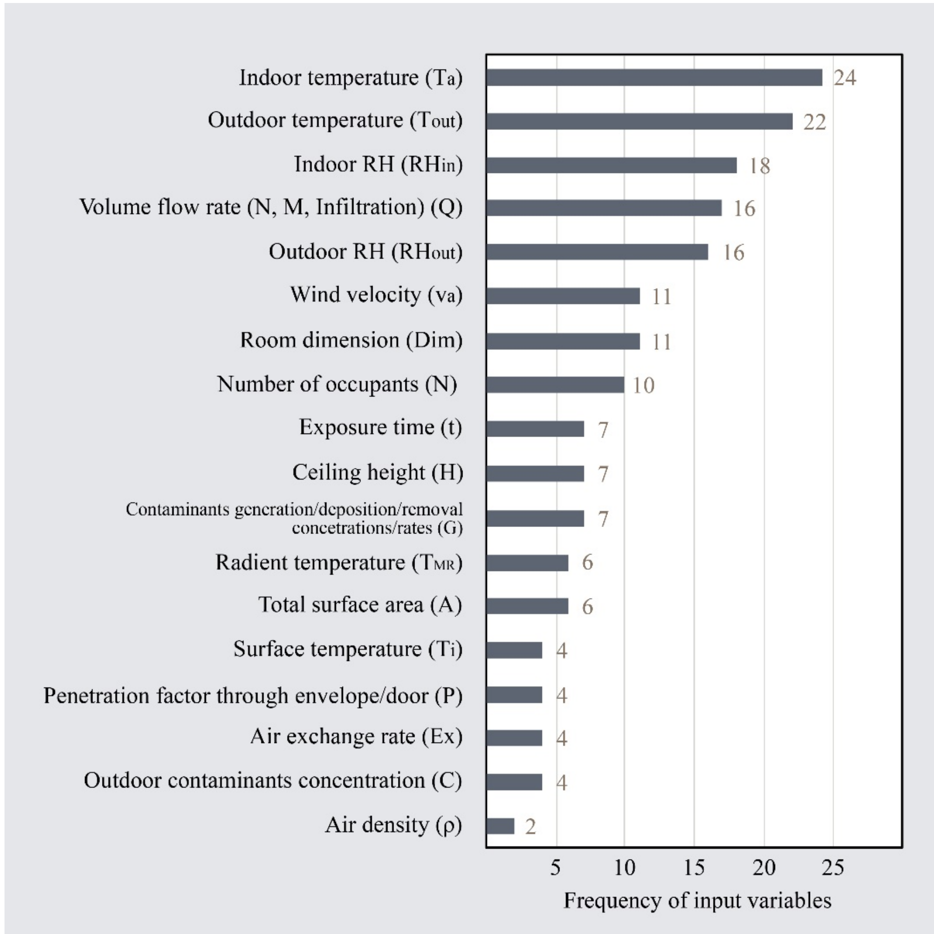

Figure 2. 7: The frequency of input variables for the study of IAQ-related health, thermal comfort and energy efficient ventilation system using ANNs.

2.4.4. Overview of Reinforcement Learning

Reinforcement learning (RL) behaves agent-environment interactions. The agents learn sequential actions and discover an optimal policy π (Figure 2. 8) (Sutton and Barto 2018). Q-learning is a model-free RL algorithm learning the policy and then inform the agent to execute an action under a specific state for any Markov decision process (MDP) problems (Watkins and Dayan 1992). RL involves an environment and an agent, and the agent takes a set of actions $a \in A$ to update the environment from one state $s \in S$ to another state s'. A state-action value function $Q(s, a)$ referred as Q-factor calculates the quality of a state-action and describes the expected discounted reward from time t on.

$$Q(s,a) = \sum_{t=T}^{\infty} \gamma^{t-T} r_t(s,a), \gamma \in [0,1] \tag{2.20}$$

Q-learning operates the reward $r_t(s,a)$ and its feedback value reflects the expected choice of control objectives. In the problem of defining ventilation systems, it determines a linear form for the received reward value under consideration of energy usage, comfort, and health in Eq. 2.25. The iterative process will leverage w_E, w_C, and w_H to propose an optimal combination scheme.

$$r_t(s,a) = w_E \cdot f(energy) + w_C \cdot g(comfort) + w_H \cdot h(health) \tag{2.21}$$

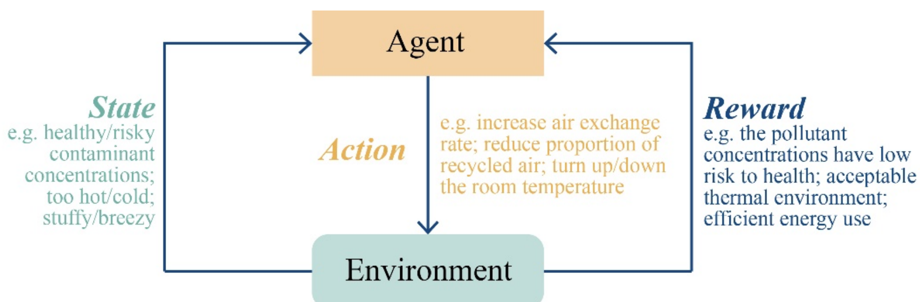

Figure 2. 8: The RL based agent interacts with the environment to optimize the environmental conditions.

2.4.5. RL-Based Model for Predicting Human Wellbeing

Many studies have paid attention to increasing energy conservation. However, occupants' health and thermal comfort, stochastic occupancy and occupant behavior are rarely concerned in formulating a model. Chen et al. (Y. Chen et al. 2018) implemented Q-learning on control of operable windows synergizing the mechanical ventilation system for energy and discomfort minimization in Miami and Los Angeles. Likewise, Yu and Dexter (Z. Yu and Dexter 2010) optimized both the energy efficiency and thermal comfort in a building complying with occupant behaviors. Dalamagkidis et al. (Dalamagkidis et al. 2007) attempted to lessen the discomfort, improve air quality in addition to energy saving by implementing RL to operate controllers. Valladares et al.

(Valladares et al. 2019) balanced the needs of thermal comfort and IAQ while using the least amount of energy from ventilation fans. Along with these RL applications, the agent has a superior PMV and temperature range control while consuming about 4–5% less energy.

In addition to this, de Gracia et al. (de Gracia et al. 2015) emphasized conserving building energy solely using RL techniques to control a ventilated façade with phase change material (PCM), and results showed the net electrical energy savings. Lu et al. (S. Lu et al. 2019) focused on maximizing comfort and implemented Q-learning into HVAC control, reaching comfortable temperature ranges for occupants after training with 100 episodes. Most importantly, the RL algorithm also helped make decisions on weaning of mechanical ventilation and dosing in Intensive Care Units (ICUs) to obtain the optimal treatment (C. Yu, Liu, and Zhao 2019).

2.4.6. Summary of RL-Defined System

Figure 2. 9 summarizes and shows the frequency of corresponding input variables. As can be seen, air temperature variables including both indoor and outdoor temperature are the most used variables. None of the studies used surface temperature or air density. Compared with ANN based prediction models, a limited number of related studies were identified. More studies using RL were from the fields of electrical energy storage, electric vehicles, and home appliances (Vázquez-Canteli and Nagy 2019). RL has advantages when applied in a complex environment because of its model-free nature. As a feature of RL, it offers the potential to learn by the trial-and-error. The iterative loop corrects and adjusts any undesired ventilation conditions incorporating the occupant preferences, feedback, and needs.

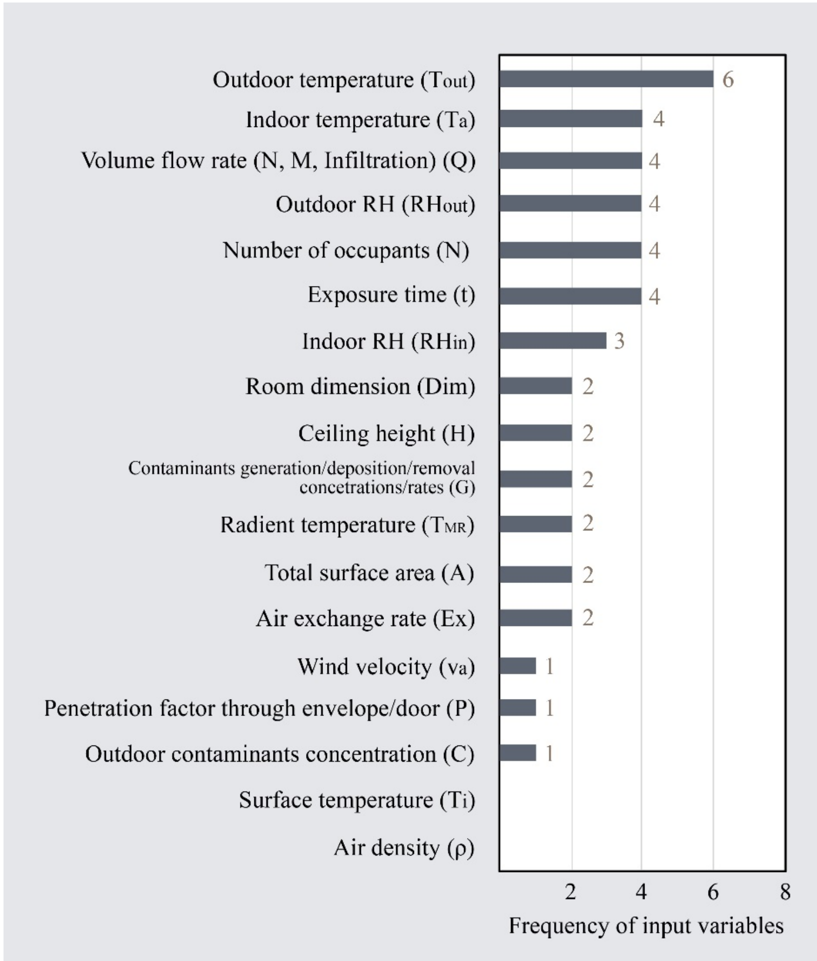

Figure 2. 9: The frequency of input variables for the study of IAQ-related health, thermal comfort and energy efficient ventilation system using RL.

2.5. Conclusion

Other than the standard temperature and humidity variables used for thermal comfort metrics and IAQ indices, which factors are also worth measuring? To respond to this question, this chapter has presented an overview of variables extracted from empirical and deterministic methods used in the fields of indoor air science, thermal comfort, and health. Next it reviewed the applicability of these input variables to predict thermal comfort and IAQ effects. Understanding the importance and effectiveness of the variables will facilitate the development of solutions to minimize negative impacts. In other words, a correct selection of variables should enhance the precision of predictions by using the results from traditional analytical models. A summary of the key findings in this review is listed below:

Eighteen critical variables are extracted from the literature including outdoor temperature, wind velocity, outdoor relative humidity, outdoor contaminants concentration, room dimensions, ceiling height, total surface area, penetration factor through envelope/door, radiant temperature, surface temperature, indoor relative humidity, volume flow rate (natural, mechanical, infiltration), indoor temperature, air density, contaminants generation/ deposition/ removal rates, number of occupants, exposure time, and air exchange rate. These variables are determined in different phases of the building life cycle - design, construction, and occupancy phase.

Among the critical factors, a limited number of studies have examined the spatial configuration of buildings, such as room dimension, ceiling height, and total surface area to adjust control system or to incorporate into modeling. Most studies consider temperature-dependent variables, particularly air temperature for the ease of measurement and the sake of comparison, evaluation, and validation. They often overlook that the effects of air temperature are linked to air velocity, surface temperature, and mean radiant temperature. Among the various models applied in HVAC, ANNs are the most commonly used, while RL is more efficient model for improving occupant-environment interaction. The variables used to construct well-performing ANN and RL models resonate with and reinforce evidence and variables from analytical models.

Most of the outcomes of ML methods emphasize indoor temperature prediction within a range of PMV-PPD, omitting relative humidity and neglecting the validation of thermal comfort predictions through occupant questionnaires. Very few studies attempted to investigate the future prevalence of indoor air pollutants. As noted by many authors, improving occupant wellbeing in addition to energy conservation should be the goal of future development.

Although 18 critical factors are identified in the analytical literature, there has been no study implementing all of them in ML models to test their effect on the accuracy of prediction due to the absence of monitoring capability. Because the field measurement of air temperature is relatively straightforward, other ambient environmental variables have been neglected. In addition to large datasets, future studies should test different variable combinations to develop truly effective models. ANN usually produces a strong correlation between decision variables and the objective function. In this regard, sample adequacy, data quality, and variability are critical. However, many studies substituted simulated data for field-collected data to test the proposed models, but those results need to be confirmed in a comprehensive study with surveys of occupant experience.

Three main topics – wellbeing, energy, and building sensing system – are critical for configuring building systems for indoor environments, but buildings can be smarter. With all the empirical and deterministic models that have been developed, there is an abundance of evidence about the critical factors to monitor. ML techniques can be used to make buildings better. There is a need for more responsive and smarter ventilation systems to maintain thermal comfort and enhance health, while reducing energy use.

Current thermal comfort and indoor health standards are too narrowly defined. ML techniques could even be used to investigate and incorporate many more of the factors in the built environment, such as warm and cool wall colors, color temperature of lighting, the presence of plants, the visual experience of a space, and how these potential variables contribute to long-term occupants' wellbeing. In so doing, building design, control and energy management can more actively incorporate the large amounts of knowledge generated by architecture, health, IAQ, and thermal comfort communities.

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CHAPTER 3: PUTTING PEOPLE IN THE LOOP

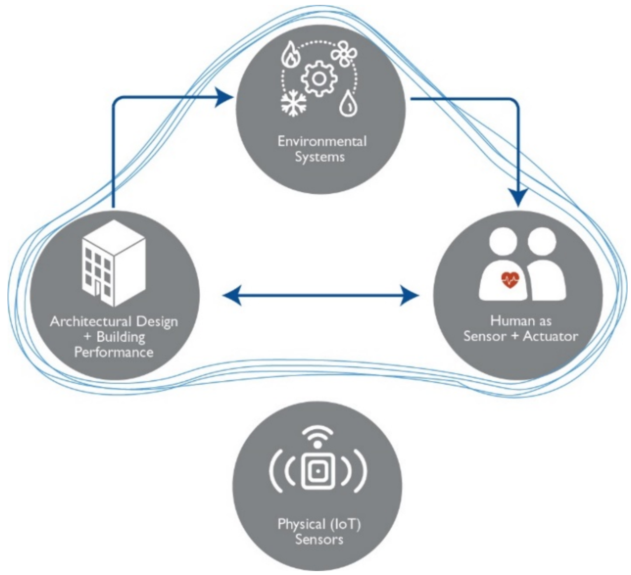

Figure 3. 1: Human as sensors and actuators.

The building performance historically overlooked human wellbeing and occupants' adaptive behavior also often overlook in the thermal comfort modeling. In addition, various observed and unquantifiable factors affect the thermal comfort of occupants in indoor environments and can lead to high uncertainty in the prediction and classification of their thermal preferences. The behavioral adaptation of occupants, by operating window systems for example, changes their thermal experience and expectations and therefore contributes to even higher prediction uncertainty. As this chapter title suggests, this chapter adapted from (Ma, Chen, et al. 2021) looks at a part of this loop and aims to examine how occupants as environmental controllers influence building performance.

Many uncertainty sources contribute to the precision of thermal comfort models. As concluded by Wang et al. (Z. Wang et al.), these sources include inter-individual and intra-individual differences, uncertainty in objective instrumental measurement, and subjective evaluation principles. The goal of this chapter is to use a Bayesian approach to incorporate these unquantifiable (unmeasurable) variables with observed (measurable) variables to improve occupant thermal preference prediction and classification. In addition, this chapter offers the following contributions to the field of thermal comfort modeling: 1) constructing a variety of structures to evaluate the model performance; 2) quantifying uncertainty in thermal preference prediction and classification probability; 3) assessing new variables (i.e., window opening/closing behavior and thermal sensation) that may improve thermal preference classification and prediction; 4) comparing Bayesian neural network with conventional thermal comfort models.

3.1. Uncertainty and Limitations in Thermal Preference Prediction

Providing a thermally comfortable indoor environment has been shown to contribute positively to occupant's productivity (Seppänen and Fisk 2006), health (Xiong et al. 2015; Ma, Aviv, et al. 2021), and wellbeing (Lamb and Kwok 2016). Thermal comfort is also of great theoretical and practical importance to architecture and environmental system design. It forms the foundation for sustainable design and if miscalculated can result in an exaggerated need for the operation of Heating, Ventilation, and Air Conditioning (HVAC) systems (Costa et al. 2013).

To improve the prediction of building thermal comfort, a number of studies have applied machine learning algorithms to correlate environmental measurements and occupant's self-reported feedback about their comfort. For example, random forest (Lu et al. 2019), support vector machine (SVM) (Chaudhuri et al. 2018), decision tree (Shetty et al. 2019), and transfer learning (Gao et al. 2020) are implemented to mine data and improve predictive performance. All of these studies showed a promising direction, though the input variables and comfort measures might be chosen differently. However, the uncertainty and stochasticity of occupant behavior can be troublesome and limit predictive performance in practice. Previous studies also found that the dynamic responses of occupants to indoor climates change their thermal sensation. Adaptive behavior impacts thermal experience, reducing the discomfort tolerance of occupants (Deng and Chen 2018; Shahzad et al. 2018; Sun et al. 2018; Liu et al. 2017). Previous research has demonstrated that integrating occupant adaptive behavior such as thermostat adjustments (Ghahramani, Jazizadeh, and Becerik-Gerber 2014), personal comfort system control (Kim et al. 2018), and interaction with window system (Tan and Deng 2020) provides more data points, captures an individual's distinctive thermal characteristics, and therefore enhances the reliability and reproducibility of models.

Research shows a number of variables that influence thermal preference prediction are inherently uncertain yet critical, such as clothing insulation level (Havenith, Holmér, and Parsons 2002), age difference (Z. Wang, Zhang, et al. 2020; Jiang et al. 2020), the stochasticity of occupant heating/cooling behavior (Kim et al. 2018), human adaptations to the environment (Indraganti 2010), thermal sensation (Shahzad et al. 2018), and non-uniformity of the thermal environment (Ma, Aviv, et al. 2021). Considering these cases, thermal environment variables-based models might not be comprehensive enough to predict occupant thermal preference accurately. Even further, a recent review study (Schweiker et al. 2020) found that unmeasurable or indirect influencing factors are driving occupants' thermal preference. For example, occupants' social and cultural experiences, physical properties of the building design, and open plan office space configuration may not be universally quantifiable. Moreover, the data collection process is costly and labor-intensive given the number of sensors needed, the appropriate sample size of monitoring duration, and occupant participation required. All of these circumstances increase the prediction uncertainty of deterministic data-driven models.

Optimization techniques are used to minimize the error between observed and predicted values, where the approach does not incorporate the presence of prior knowledge when modeling. It is known that occupants who experience “cool (-2)” thermal sensation are very likely to vote “prefer warmer (+1)” for their thermal preference. Another example of prior knowledge is that the Gaussian distribution can be used to specify the probability distribution for all uncertain variables in the field of thermal comfort (Auffenberg, Stein, and Rogers 2015; Lee et al. 2017; Laftchiev and Nikovski 2016). In contrast, previous studies imposed categorical distributions (also called generalized Bernoulli distributions) to condition the multiclass response variable with an observed noise (Lork et al. 2020; Cho et al. 2020; Francis et al. 2019).

Given the nature of inter-individual differences (“variance of comfort responses between people”) and intra-individual variability (“how an individual feels in the same environment on different occasions”) (Z. Wang et al. 2018), it is important to acknowledge that different individuals perceive the thermal stress differently and prefer different thermal conditions. This is a fully Bayesian mechanism. The conventional methods where deterministic approaches are adopted do not have the capacity of aiding thermal environment design by covering more possibilities and counting possible variances.

Much research in recent years has implemented Bayesian inference by incorporating prior knowledge and considering the uncertainty to develop probability distributions of occupants’ thermal demands. Wong et al. (Wong, Mui, and Cheung 2014) employed Bayesian estimation to approach occupant thermal responses and compare it with Fanger’s model prediction. Lee et al. (Lee et al. 2017) clustered occupants into different groups considering individuals’ thermal characteristics and then proposed a new Bayesian algorithm to infer thermal preference profiles of occupants. Langevin et al.

(Langevin, Wen, and Gurian 2013) implemented Bayesian linear regression models with different sampling methods to predict seven-point thermal sensation, acceptability, and preference distributions for office building occupants. Wang and Hong (Z. Wang and Hong 2020) also used a Bayesian linear regression method focusing on office buildings to approximate the comfortable temperature ranges and investigate the proper thermostat set points.

3.2. ASHRAE Global Thermal Comfort Database II

To clarify our overall research approach, Figure 3. 2 is a flowchart demonstrating data preprocessing, sampling methods, model structure, and model performance evaluation. More detailed explanations of each step are presented in the following sections.

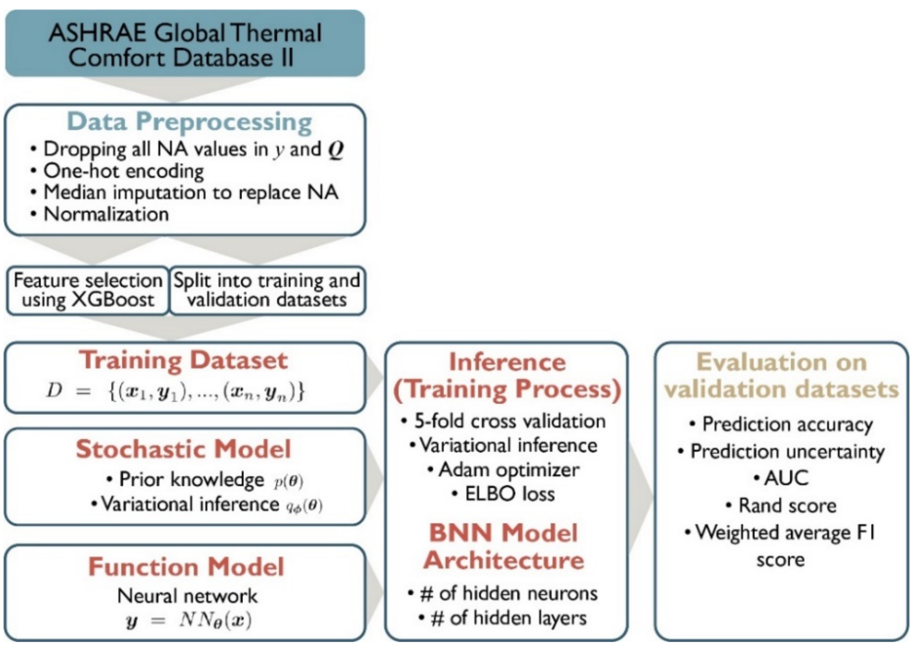

Figure 3. 2: The workflow of overall research design.

3.2.1. Dataset Description

The dataset used in this chapter is the ASHRAE Global Thermal Comfort Database II (Ličina et al. 2018), which consists of objective environmental monitoring and "right-now-right-here" subjective measures from 107,463 occupants. Each occupant has 45 variables containing information about the ambient environment, the subject's subjective evaluation, personal parameters, and building characteristics. We excluded samples collected in nursing homes for two reasons. First, opening or closing windows is usually unlikely for the seniors living in nursing homes for safety purposes (Chau et al. 2018). Second, older people are less responsive to thermal environment changes than younger people due to the loss of cognitive functions (van Hoof et al. 2017; Ma et al. 2017; Chau et al. 2018; Noguchi et al. 2018). Our focus is on offices (n=55,238), classrooms (n=12,755), and multifamily housing (n=10,120), which leaves 78,113 data points from the original database and formed our sub-dataset.

Figure 3. 3 visualizes how environmental, personal, and behavior-related factors drive the diversity and variability in thermal preference votes. We represented the distribution of outdoor monthly air temperature (T_{out}), air temperature (T_{ind}), relative humidity (RH), air velocity (v), age, window, operative temperature (T_{op}), subject's weight (SW), and thermal sensation (TS) relating to 3-point thermal preference votes in the sub-dataset. The overlapping area of three distributions indicates a variability between individual thermal preference. Taking the example of the air temperature distribution plot: occupants vote different scale values for their thermal preference although they are exposed to an indoor environment with the same temperature of 25 degrees. A substantial number of occupants appear to prefer a "no change" condition, while a considerable number of persons either prefer cooler or warmer. As shown in the distribution plot of age, the occupants vote for different thermal preferences though they are at the same age and in the same air temperature (T_{ind} = 25.5°C) and air velocity (v = 0.1m/s). Similar to the rest of the plots in Figure 3, the distribution of cooler and warmer preference votes always overlaps with no change votes. These observation are consistent

with other study results (Khalid et al. 2018, 2019) and emphasize that the variation cannot be overlooked when predicting occupant thermal preference and implies that there could be unobserved variables **z** related back to the individual thermal expectations.

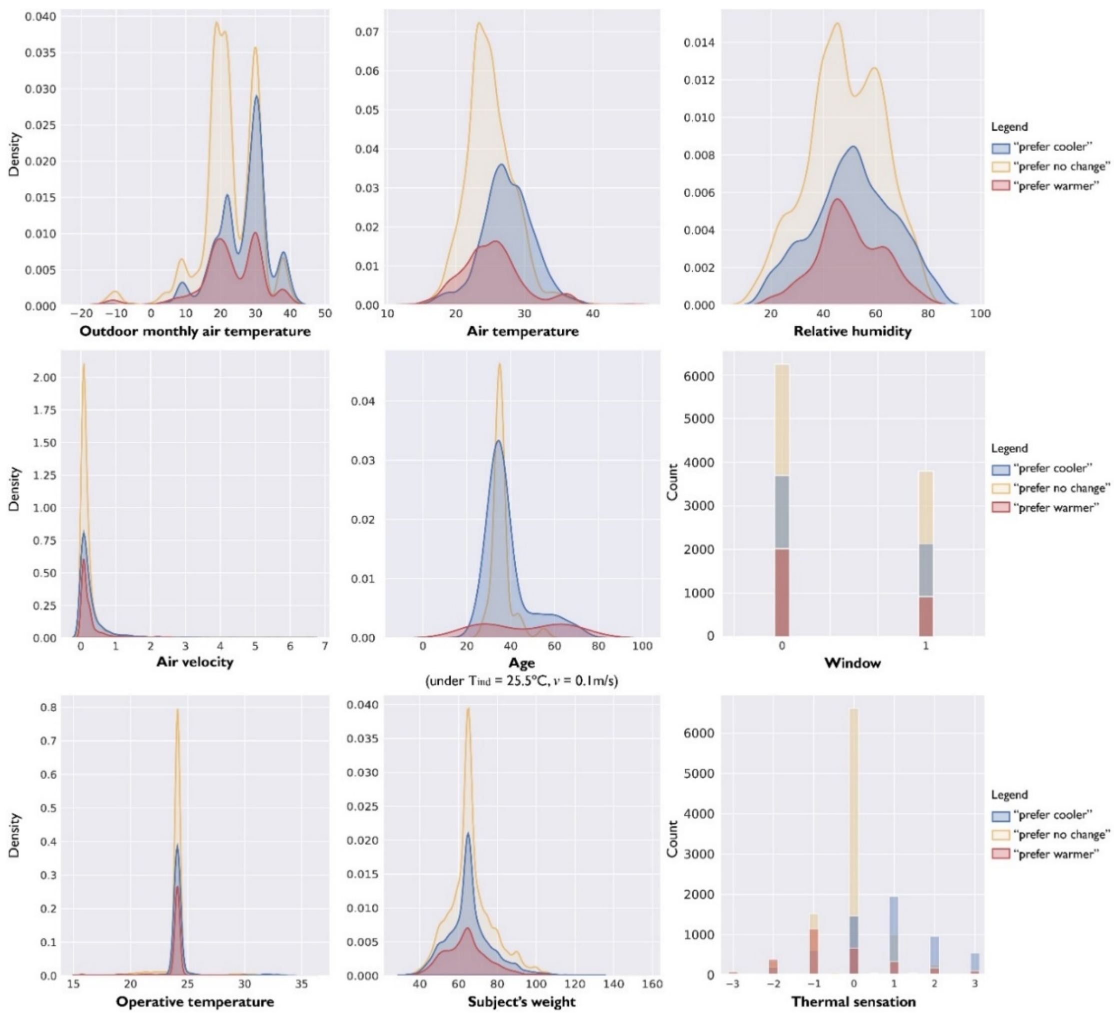

Figure 3. 3: Distribution of three thermal preference classes over the selected variables.

3.2.2. Data Preprocessing

The entire sub-dataset was preprocessed to meet the criteria of data mining before implementing BNN algorithms. The following preprocessing steps were carried out: 1) dropping all the not applicable (NA) data in the outcome variable of thermal preference and window states; 2) one-hot encoding – conversion of categorical variables; 3) missing data imputation; 4) normalization.

We dropped samples with the missing target variable for the sake of reducing the error from the imputation method and maintaining the underlying pattern of the true label. We also removed all missing inputs of window states on account of the significant uncertainty and unpredictable nature of an individual occupant behavior (Yan et al. 2015). Since the entry of the BNN algorithm needs numerical inputs, we encoded categorical variables such as sex, season, building type, and thermal preference to the numerical representation. Note that the current dataset is imbalanced with the "prefer cooler" labeled class (n = 5,825), "prefer no change" class (n = 10,046), and "prefer warmer" class (n = 2,938). To avoid this imbalance, we randomly resampled the "prefer no change" class to 5,000 samples (i.e., down-sampling).

The ASHRAE Global Thermal Comfort Database II is made up of a spectrum of measurements in various studies conducted by different research groups, therefore it is not uncommon to have a substantial number of missing values in the dataset. We used median imputation to handle the missing values since it is fair to assume that the missing values are close to the median value of the distribution if data is missing at random. Before the dataset was split up into training and validation datasets, the instances in the dataset were normalized to regularize the measurements in different scales and improve the numerical stability. The ith occupant with jth features formed x_{ij} in the training dataset were normalized using Eq. 3.1 where μ_j denotes the mean of jth feature over all observations of the training data, and σ_j represents the corresponding standard deviation.

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{3.1}$$

Since the feature space is high-dimensional, extreme gradient boosting (XGBoost) as one of the state-of-the-art ensemble approaches is used to evaluate the importance of each variable. XGBoost is a scalable, parallelizable, and effective algorithm to rank features and typically outperforms other methods (Chen and Guestrin 2016).

3.3. Bayesian Neural Network Modeling Methodology

3.3.1. A Brief Theory of Bayesian Inference and Bayesian Neural Network

To overcome challenges discussed above, we present a Bayesian approach to classify and predict thermal preference labels. Bayesian models aim to extract and deduce properties about a probability distribution from data using Bayes' theorem Eq.3.2.

$$p(\boldsymbol{\theta}|\mathcal{D}) = \frac{p(\mathcal{D}|\boldsymbol{\theta}) \times p(\boldsymbol{\theta})}{p(\mathcal{D})} \tag{3.2}$$

where $\boldsymbol{\theta}$ represents a set of free model parameters that need to be calibrated using a dataset $\mathcal{D}$. A prior distribution over $\boldsymbol{\theta}$ is denoted $p(\boldsymbol{\theta})$ and this distribution represents our knowledge on how the data are generated before observing them. $p(\boldsymbol{\theta}|\mathcal{D})$ known as posterior distribution summarizes uncertainty quantities of parameter values that best explain the observed data. The likelihood function $p(\mathcal{D}|\boldsymbol{\theta})$ expresses how likely the observed dataset $\mathcal{D}$ is given by different setting of $\boldsymbol{\theta}$. and $p(\mathcal{D})$ normalizes the posterior distribution with a valid probability density.

Bayesian inference is selected as a tool in this study to infer occupants' thermal preference for two reasons. First, Bayesian inference provides a natural approach to quantify uncertainty or stochasticity in estimating model parameters when occupant behavioral adaptation and inter- and intra-variabilities are accounted to design thermal environment. Second, the Bayesian approach can help us account for the effect of unobserved variables including the universally unquantifiable factors which also influence occupants' thermal preference (e.g., occupants' social and cultural experiences).

Bayesian inference for neural networks has gained significant attention. In this study, we aim to extend the application of Bayesian neural networks (BNN) in predicting the thermal preference of a large group of individuals. Here we refer BNN to a neural network that is trained to fit observed data using Bayesian inference by considering that the network's parameters (i.e., its weights and biases) are random according to a prior probability distribution (Neal 2012). Different types of neural networks have varying methods to learn from data and update network's weights in training procedure (H. Wang and Yeung 2016). A typical neural network's weights are considered to be deterministic and a single point estimate for them is obtained once the model has been trained. In contrast, the weights of a BNN are represented by probability distributions over possible values, rather than assuming a single point estimate after training. The network distribution of weights informs model performance uncertainty by evaluating its variance. Figure 3. 4 illustrates the difference between a deterministic neural network and a BNN. The left one is a typical neural network showing that each weight has a fixed value. The right one is a BNN where each weight is assigned a probability distribution with mean and variance.

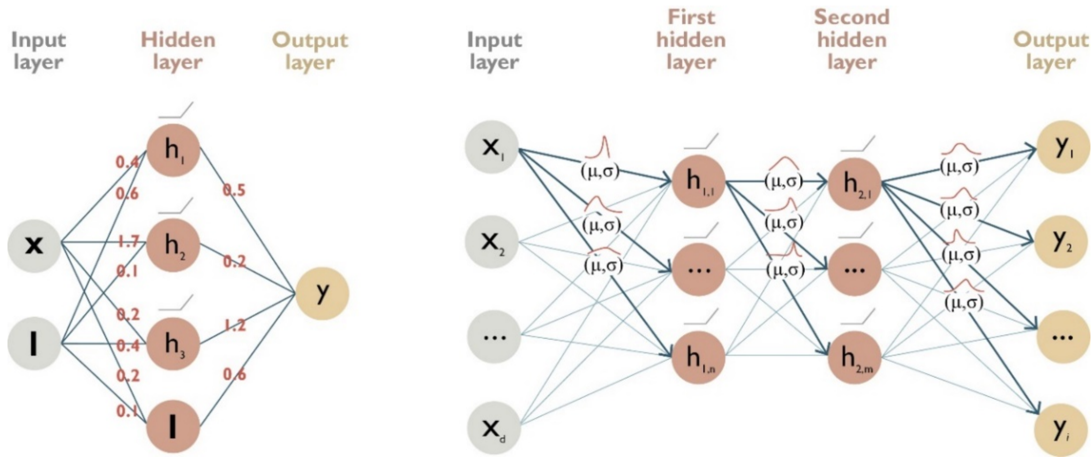

Figure 3. 4: (Left) A typical neural network; (Right) A Bayesian neural network.

3.3.2. BNN Algorithm for Inference and Sampling

To be able to compute the various probability distributions, we assume that ith sample has the following properties in Bayesian inference process: 1) each p_i can be sampled; 2) the pointwise probability density function (PDF) of each p_i is computable; 3) each p_i is differentiable with respect to the model parameters $\boldsymbol{\theta}$.

We now view a neural network as a probabilistic model. Our dataset $\mathcal{D}$ is comprised of $\{(\mathbf{x}_n, \mathrm{y}_n)\}$ where each datapoint has features $\mathbf{x} \in R^d$ and $\mathrm{y}_n \in R$. The likelihood for each datapoint is written as:

$$p(\mathrm{y}_n \mid \mathbf{z}, \mathbf{x}_n, \sigma^2) = \text{Normal}\,(\mathrm{y}_n \mid \mathbf{NN}(\mathbf{x}_n; \mathbf{z}), \sigma^2) \tag{3.4}$$

$$p(\mathbf{z}) = \text{Normal}\,(\mathbf{z} \mid \mathbf{0}, \mathbf{I}) \tag{3.5}$$

where NN represents a neural network whose weights and biases form the latent variables $\mathbf{z}$. We set the prior on the weights and biases $\mathbf{z}$ followed a standard normal distribution. For our multiclassification task, we aim to classify the occupants into three classes: “prefer warmer”, “prefer no change”, and “prefer cooler”. Note that $p(\mathrm{y}_n|\mathbf{x}_n, \boldsymbol{\theta})$ is a discrete distribution which requires to convert output values y_n into probabilities using a softmax function (Eq.3.6). Softmax rescales the probability of each class to fall in the range between 0 and 1 and add up to 1. The highest probability computed by softmax among the three thermal preference classes will be the predictive class output.

$$\mathrm{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} \tag{3.6}$$

Performing Bayesian inference on a neural network requires the posterior distribution of the network weights and biases given the training data $p(\boldsymbol{\theta} \mid \mathcal{D})$. However, direct computation of the exact posterior distribution is intractable even if we use a graphical model to simplify the distribution (Blundell et al. 2015). Mathematically, the predictive distribution of an unknown label $\hat{\mathbf{y}}$ on a validation data item $\hat{\mathbf{x}}$ is given as:

$$p(\hat{\mathbf{y}} \mid \hat{\mathbf{x}}) = \mathbb{E}_{p(\boldsymbol{\theta} \mid \mathcal{D})} \left[p(\hat{\mathbf{y}} \mid \hat{\mathbf{x}}, \boldsymbol{\theta}) \right] \tag{3.7}$$

As Eq.3.7 indicates, the distribution answers predictive queries about unobserved data where the expectation is taken across the data generating distribution. Instead, we need to use variational inference for parameterizing Bayesian posterior distributions. Our goal is to find the optimal parameter $\boldsymbol{\theta}$ where it means we need to infer the posterior over the latent variable $\mathbf{z}$. Variational inference offers a way to find $\boldsymbol{\theta}_{max}$ and then to approximate $p_{\theta_{\max}}(\mathbf{z}|\mathbf{x})$ by introducing a parameterized distribution $q_{\phi}(\mathbf{z})$ (Graves 2011) where ϕ is known as the variational parameters. Suppose that the variational posterior is a Gaussian distribution with a diagonal covariance matrix over the latent space, we used the Evidence Lower Bound (ELBO) to move the variational distribution as close as possible to the exact posterior where each training iteration can take a correct step in $\theta - \phi$ space (Dean et al. 2012):

$$\mathrm{ELBO}(\phi) = \mathbb{E}_{q_{\phi}(\mathbf{z})}\left[\log p_{\theta}\,(\mathbf{x}, \mathbf{z}) - \log q_{\phi}\,(\mathbf{z})\right] \tag{3.8}$$

Note that the variational distribution is parametrically distributed, therefore we can compute Monte Carlo estimates of this quantity. The dissimilarity between approximating distribution $q_\phi(\mathbf{z})$ and the true posterior $p_\theta(\mathbf{z}|\mathbf{x})$ is given by Kullback-Leibler (KL) divergence. Minimizing the dissimilarity KL $[q||p]$ can be turned into an optimization problem if we seek to push the log evidence higher (in expectation) by taking stochastic gradient steps to minimize the ELBO objective. Calibrating the variational parameters ϕ is done using the Adaptive Moment Estimation (Adam) optimizer that can adaptively adjust ϕ:

$$\log p_\theta(\mathbf{x}) - \mathrm{ELBO}(\phi) = \mathrm{KL}\left(q_\phi(\mathbf{z})||p_\theta(\mathbf{z}|\mathbf{x})\right) \tag{3.9}$$

$$\phi^* = \arg\max_\phi \mathrm{ELBO}(\phi) \tag{3.10}$$

All the models described in this chapter used Python (version 3.6) in a Jupyter Notebook environment on Google Colab with GPU acceleration. The models were implemented using PyTorch (version 1.6.0) (Paszke et al. 2017) and Pyro (version 1.5.1) (Bingham et al. 2019) to execute probabilistic programming.

3.3.3. BNN Model Performance Evaluation

To mitigate biases and overfitting during model training, the K-fold cross-validation technique was applied to randomly split an entire dataset into 5 exclusive subsets with a roughly equal number of data points. The following criteria are used to evaluate the performance of the BNN models on classifying and predicting thermal preference:

- Prediction accuracy: In our multi-class case, prediction accuracy is given by the total number of correct predictions across all classes out of the total number of predictions. Prediction accuracy is one of the most important evaluation metrics to show how accurate our classification model is.

- Weighted average F1-score: In the multi-class prediction, we used weighted average F1-score to calculate metrics for each class and get their average weighted by finding the number of truly predicted instances.

- AUC: The Area Under the Receiver Operating Characteristic (ROC) Curve was used to evaluate a scoring classifier at multiple cutoffs. The average AUC of all possible pairwise combinations of classes was computed (Hand and Till 2001).

- Adjusted rand index (ARI): It measures similarity between two classes by considering all sample pairs and counting pairs allocated in the same or different classes in the truly predicted classes (Hubert and Arabie 1985). A higher score means the identified classes are more identical.

3.4. Results and Discussion

3.4.1. Important Features Selection

The state-of-the-art XGBoost algorithm was implemented to filter unnecessary variables for developing a Bayesian-inferred thermal preference model. The XGBoost technique has been proven its superior on different kinds of non-linear classification problems, but very limited application in thermal comfort studies (Chen and Guestrin 2016; Z. Wang, Wang, et al. 2020). The importance score used in the XGBoost algorithm is known as F-score, where a variable represented more information for classification will be weighted with a higher F-score. The F-score computation is based on the number of times a variable is used for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all possibilities (Chen and Guestrin 2016). The F-score computed by the XGBoost algorithm can treat continuous and discrete variables as inputs equally to rank the variables. This property powers discrete subjective measures collected from the occupants which can weight as important as continuous environmental monitoring data when ranking the variable importance. Not all the variables that the ASHRAE Global Thermal Comfort Database II has were ranked due to a very high proportion of missing data such as globe temperature (97.5%) and radiant temperature (97.5%), even though researchers have shown their importance. We did not impute estimated values to replace these variables with a high missing rate. If substantial information is incomplete, the generalizability of a model will be weakened as the impustation is based on available data points to generate.

As a result, the XGBoost algorithm was implemented over 31 variables and Figure 3. 5 displays the feature ranking results ordered by its importance. The top 15 significant variables include T_{out}, TS, T_{ind_h}, T_{ind}, clo, T_{gl_h}, RH, T_{op}, AMP, v, SW, TSA, Age, TC, and HS. It is worth noting that the feature of window operation was not selected by XGBoost within the top 15. Despite this, the feature of window states was manually inputted into the BNN model since plenty of studies have highlighted its important role in learning individual's thermal preference based on their interaction with controllable comfort systems (Kim et al. 2018), improving building energy performance to sustain desired indoor environmental quality (L. Wang and Greenberg 2015), and identifying occupant adaptation to thermal conditions (Trebilcock, Soto-Muñoz, and Piggot-Navarrete 2020).

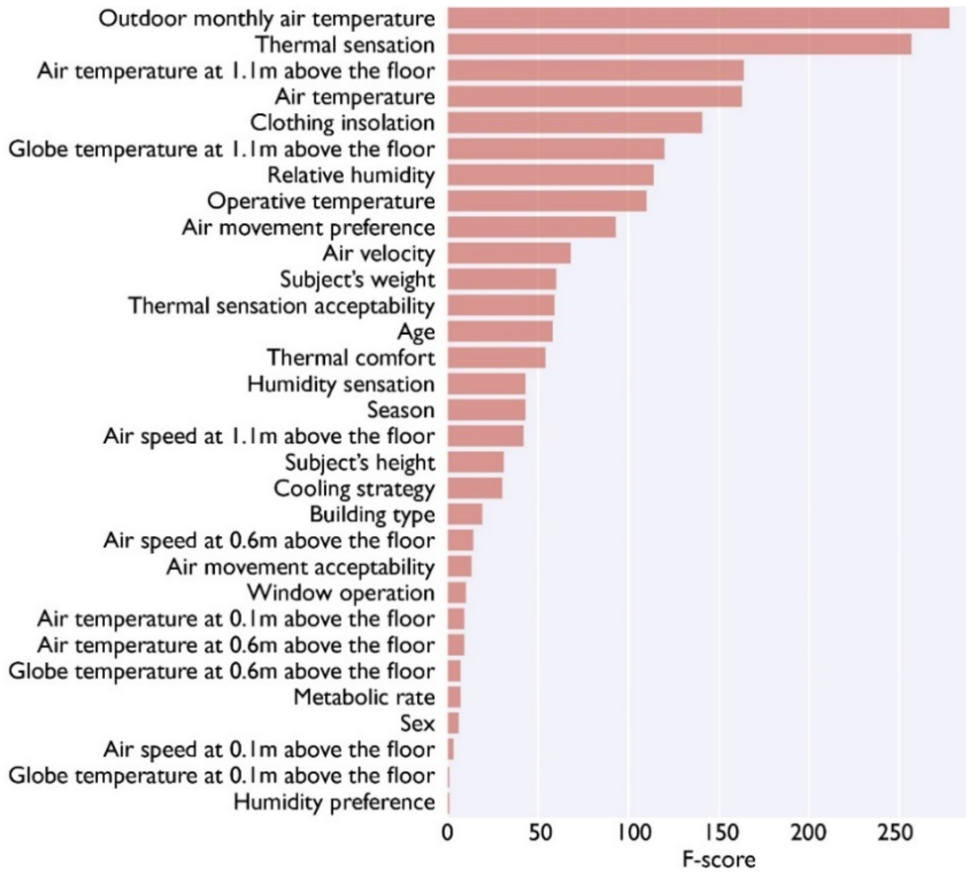

Figure 3. 5: Feature importance analysis by implementing the XGBoost algorithm. The larger F-score, the more important the feature is.

Table 3. 1 shows the descriptive statistics of the 16 features that were identified for training the BNN model. In general, large variances are found in all of the environmental, personal and behavior variables. The dispersion of each variable presents a source of uncertainty or variability and leads to classification errors. This fact means that deterministic models cannot estimate the natural variability of environmental variables and capture inter and intra-variabilities in thermal preference.

Table 3. 1. Statistical summary of the 16 input features.

Category	XGBoost Selected variables	Unit	Minimum	Maximum	Mean	Standard deviation
Outdoor Environment	Outdoor monthly air temperature (T_{out})	°C	-16.80	43.60	23.95	8.50

Indoor Environment	Air temperature at 1.1m above the floor (T_{ind_h})	°C	14.60	39.80	25.43	2.21
	Air temperature (T_{ind})	°C	13.90	45.30	25.74	3.86
	Globe temperature at 1.1m above the floor (T_{gl_h})	°C	13.30	39.80	26.88	2.70
	Relative humidity (RH)	%	13.70	88.80	52.59	14.56
	Operative temperature (T_{op})	°C	15.60	35.50	24.18	1.45
	Air velocity (v)	m/s	0.00	6.54	0.22	0.37
Behavioral adaptation	Window operation (WO)	open/close	0.00	1.00	0.36	0.48
Personal thermal characteristics	Clothing insolation (clo)	clo	0.00	2.24	0.67	0.25
	Subject's weight (SW)	kg	35.00	150.00	65.86	11.70
	Age	-	6.00	75.00	36.26	10.06
Subjective measures	Thermal comfort (TC)	From 1 (very uncomfortable) to 6 (very comfortable)	1.00	6.00	4.92	0.73
	Thermal sensation acceptability	0 (unacceptable), 1 (acceptable)	0.00	1.00	0.85	0.35
	Thermal sensation (TS)	From -3 (cold) to +3 (hot)	-3.00	3.00	0.15	1.13
	Humidity sensation (HS)	From -3 (very humid) to +3 (very dry)	-3.00	3.00	0.005	0.36
	Air movement preference (AMP)	less, no change, more	0.00	2.00	0.41	0.57

3.4.2. BNN Model Configuration and Performance Evaluation

Designing an appropriate neural network architecture is problem and dataset dependent. To get started, the Rectified Linear Unit (ReLU) was added between the successive hidden layers as the activation function to introduce non-linearity into the neuron's output. A batch size of 64 was used as the number of samples from the training dataset to estimate the error gradient. Different learning rates for Adam optimizer setup were tested (e.g., 0.001, 0.01, 0.1) and monitored ELBO loss on both training and validation datasets to diagnose the error gradient of the model optimization in the learning process.

Figure 3. 6 illustrates how learning rates affect model convergence based on a BNN model structure configured with one hidden layer (hidden units = 16) in the thermal preference prediction scenario. The left plot in Figure 6 shows a good fit as the training and validation loss gradually increases to a point of stability and has a minimum difference between the two final loss values. The middle and right plots demonstrate noisy movements around the training and validation loss where each iteration takes a too large step size moving forward due to a large learning rate. The learning rate of Adam optimizer was setup as 0.001 to tune the BNN model to find an optimal number of hidden neurons and hidden layers.

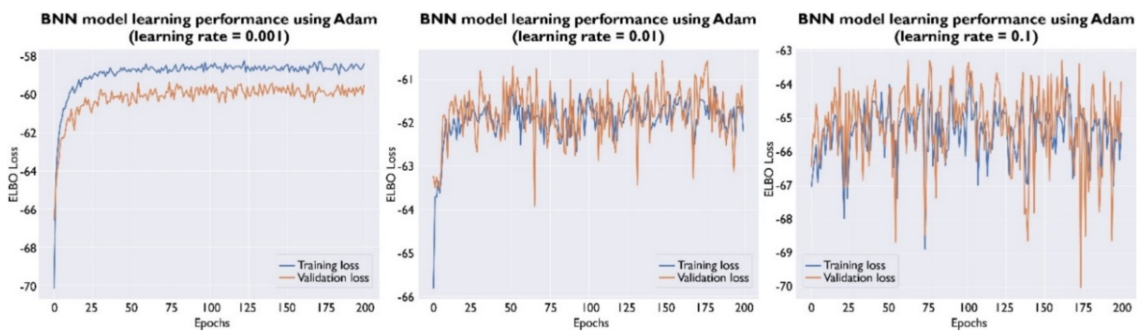

Figure 3. 6: Comparison of the BNN model convergence with learning rate of 0.001, 0.01, and 0.1.

The BNN was trained with different structures for 200 epochs. Table 3. 2 summarizes the prediction accuracy and uncertainty of BNN as well as the results of model performance evaluation for developing Bayesian-inferred thermal preference model. We report and compare the predictive performance with the average predicted cross-validated results and how uncertainty that different model structures can overcome. The last three columns show the model performance under different evaluation metrics.

Table 3. 2. Predictive performance with different BNN architectures.

Network structure	Hidden layers	Average training accuracy	Average validation accuracy	Prediction uncertainty	AUC	ARI	Weighted average F1-score

(number of hidden neurons)							
(16)	1	0.702	0.687	0.009	0.834	0.312	0.693
(32)	1	0.703	0.676	0.008	0.813	0.282	0.671
(64)	1	0.709	0.661	0.007	0.801	0.259	0.654
(128)	1	0.716	0.633	0.006	0.775	0.216	0.621
(16, 8)	2	0.691	0.682	0.010	0.816	0.285	0.677
(16, 16)	2	0.693	0.686	0.011	0.805	0.281	0.674
(32, 8)	2	0.668	0.655	0.011	0.807	0.272	0.668
(32, 16)	2	0.677	0.666	0.007	0.804	0.261	0.659
(32, 32)	2	0.672	0.662	0.002	0.799	0.259	0.657
(8, 8, 8)	**3**	**0.703**	**0.693**	**0.008**	**0.838**	**0.311**	**0.698**
(16, 8, 8)	3	0.688	0.681	0.008	0.817	0.292	0.673
(16, 16, 8)	3	0.679	0.673	0.012	0.803	0.275	0.668
(32, 8, 8)	3	0.671	0.662	0.003	0.779	0.250	0.649
(32, 16, 8)	3	0.673	0.660	0.010	0.793	0.255	0.653
(32, 32, 16)	3	0.677	0.654	0.003	0.792	0.257	0.653
(64, 32, 16)	3	0.662	0.626	0.012	0.777	0.230	0.631

In terms of predictive accuracy on validation datasets, the BNN made up of 3 hidden neuron layers with 8 hidden nodes in each layer (i.e., (8, 8, 8)) displays the highest performance (cross-validated mean accuracy = 0.693), followed by a BNN architecture with a hidden layer comprising 16 units (i.e., (16)). The middle tier is the networks with large neuron size in one hidden layer or relatively large neuron size in multiple hidden layers. The worst two predictive network structures are (128) and (64, 32, 16). It is not surprising that a single-layer network or multi-layer neural network configured with a relatively large neuron size in the hidden layer leading to an overfitting problem. Regarding the BNN model performance uncertainty as shown in Table 2, the (8, 8, 8) configured BNN presents a considerably narrower range of prediction uncertainty (SD = 0.008), while the wider ranges of standard deviation (SD = 0.012) are observed in BNN net made up of (16, 16, 8) and (64, 32, 16). With regards to the model classification performance, it is evident from the ARI results that a single-layered BNN with 16 hidden neurons is the highest-ranking network (ARI = 0.312) but is just slightly better than a BNN net structured with (8, 8, 8) (ARI = 0.311). Likewise, these two model configurations perform similarly in terms of AUC with a very small difference. The (8, 8, 8) BNN net has the highest weighted average F1-score, which indicates that the model gains success of classifying thermal preference classes.

As observed in the training and validation accuracy difference, the networks with high training accuracy are not necessarily consistent with its cross-validated accuracy, AUC, ARI, and F1-score. A better predictive accuracy does not always improve the model classification performance. It is important to test the learning rates and compare different BNN architectures in line with a variety of performance evaluation metrics. Depending on the application and problem that the model targets, other perspectives affect the design decision on BNN model structure, such as the computational cost, computational speed, and scalability. For our study's objectives, the correctness of classifying occupant thermal preference and how certain/uncertain the BNN model can reach determine our model refinement. Overall, the BNN architecture with 3 hidden layers and 8 hidden neurons in each layer (i.e., 8, 8, 8) performs reasonably well in all cases. In the following sections, we focus on this BNN model to explore how classification uncertainties of the model impact thermal preference prediction.

3.4.3. Uncertainty Quantification in Prediction and Classification Probability

In order to digest the BNN model's classification errors, a Sankey plot was created to visualize the nexus of true labels and predicted labels (see Figure 3. 7). The Sankey plot's left color nodes represent the actual classes and the right color nodes show the predicted classes. The color nodes and flows have a width proportional to the quantity of data points. As illustrated by Figure 8, the cooler preferences are mostly forecasted to “prefer no change,” with fewer incorrectly predicted as “prefer no change” class and even fewer predicted as “prefer warmer.” However, over half (51.3%) of the warmer preferences are predicted to prefer “no change” and “cooler.” Most of the “no change” votes are predicted correctly. About 25% and 10% of “no change” votes are predicted as “prefer cooler” and “prefer warmer” classes, respectively. The comparison of the prediction performance over each class implies that our BNN model classification on “prefer cooler” class is superior to “no change” and “warmer” preference with 83.7% correct prediction rate, followed by no change preference with 63.9 percentage correct and then warmer preference with 48.7% correct predictions.

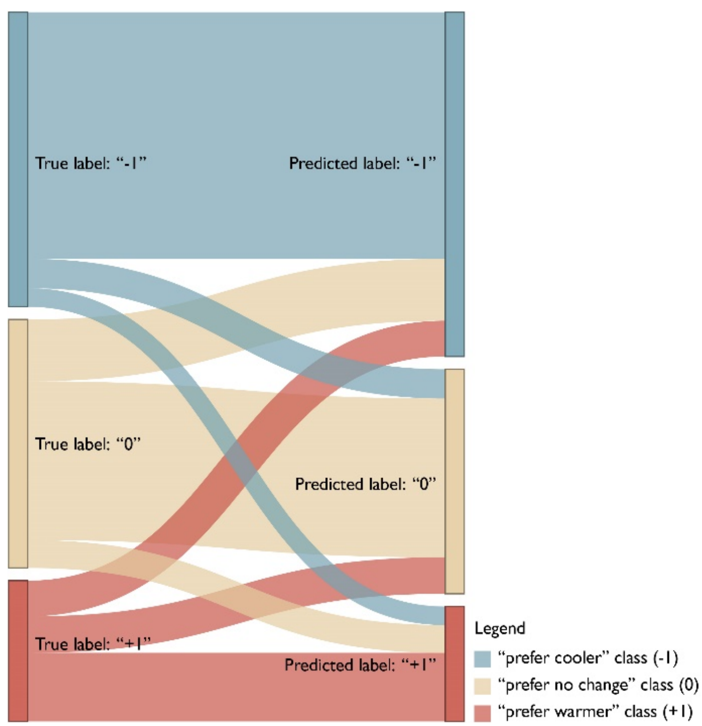

Figure 3. 7: The number of correct and incorrect predictions classified by the BNN model.

Beyond this, the Bayesian method offers two outstanding properties: providing predictive class probabilities instead of the deterministic class label predictions and offering the standard deviation of the posterior predictive to reflect the degrees of the uncertainty. We present the results as a raincloud plot which combines an illustration of data distribution and box plots overlapped with jittered raw data. As displayed in Figure 3. 8, the plot shows the variability of the predictive probabilities for three thermal preference classes along with the predictive uncertainty. The “prefer cooler” class is the only one containing an outlier, which indicates these posterior predictive probabilities differ significantly from the rest. The probability values are primarily concentrated in the high possibility areas which are in the range of 0.9-1.0, as shown in the thick parts. The predictive uncertainty of “prefer cooler” class is densely clustered between 0.0-0.05 and this interprets a low degree of uncertainty. The BNN model has fairly high confidence to classify cooler preference class in most cases given observed and unobserved variables. Thinking of its practical application in winter months in the built environment, the model classifies the occupants in the cooler comfort zone where less energy would be required to keep a slightly cooler condition.

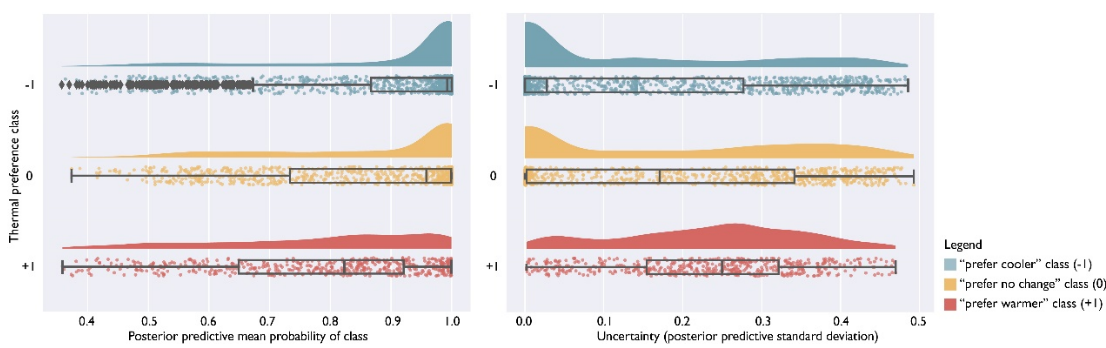

Figure 3. 8: Variation of posterior predictive mean probability and uncertainty of each class label.

In terms of no change and warmer preference class, we can observe a visible spread of these two classes’ posterior predictive probability. The box plot of class “prefer no change” is more skewed to the right, indicating that the values concentrate at the high probability end of the scale. By contrast, class “prefer warmer” has a squeezed and quite flat distribution of peak probability values between 0.8-1.0. The distribution shape implies that occupants experience different thermal stress and take corresponding behavior actions occurring an equiprobability to be classified as “prefer warmer” class. As evident from the right plot in Figure 3. 9, “prefer warmer” class has a minimum variation in predictive uncertainty, while it has the highest level of uncertainty and over half of the predictive uncertainty ranges between 0.2-0.4. We visualize how the BNN model performs across all occupants in relation to predictive probability and uncertainty in a scatterplot. As can be seen from the fitted regression lines in Figure 10, the predictive class probability and the deviation of prediction are not following a nonlinear relationship. These three regression lines created the boundary region show that the majority (75.8%) of predicted thermal preference classes has predictive probabilities greater than 0.7 and uncertainties lower than 0.35. The BNN that classified occupants as “prefer warmer” has a lower predictive class probability and higher uncertainty, whereas the “prefer cooler” class has a higher predictive mean probability and lower classification uncertainty. The BNN model’s uncertainty can be concisely quantified with a high posterior predictive mean probability. In general, the BNN model for classifying cooler preference outperforms no change and warmer preference.

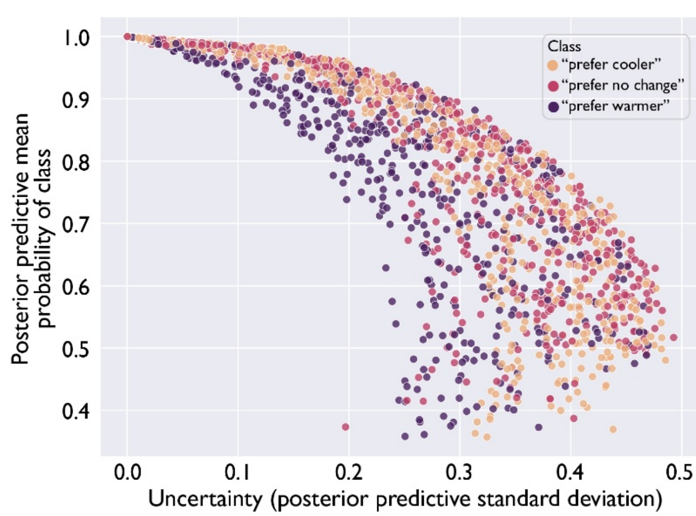

Figure 3. 9: Posterior predictive mean probability and predictive uncertainty across all occupants.

3.4.4. Understanding Variable Importance

Understanding the effect of variables on a model's predictive power helps reduce the cost of collecting data related to occupants' thermal comfort when conducting a field study. However, testing the importance of all selected features and their possible combinations is time-consuming and computationally expensive. We then grouped 16 XGBoost-selected variables based on the category that they belong to. We used a stepwise approach to run the BNN model by updating or adding a new variable group until all variable combinations were tested. We monitored the model performance at the same time to understand the minimum number of measurements that one needs to collect but also have robust predictive performance. The results of model runs are given in Table 3. 3 and visualized in Figure 3. 10. The order of testing different variable combinations follows the data collection efforts during the field study. In this case, the easily obtainable variables were input to the model first. The outdoor and indoor environment data were investigated first, because they are fundamental measures and are automatically streamed by sensors. Occupant interaction with the window system requires additional sensor installation, therefore it was tested in the second place. Both personal thermal characteristics and subjective measures involve the most efforts as they require an Institutional Review Board (IRB) approval and occupants' survey participation.

Table 3. 3. The BNN model performance is tested with different variable combinations.

Combination groups	Variable Combinations*	Training accuracy	Validation accuracy	AUC	ARI	Weighted average F1-score
COMB 1	O+I	0.552	0.540	0.703	0.127	0.526
COMB 2	O+I+B	0.572	0.568	0.712	0.138	0.549
COMB 3	O+I+P	0.557	0.549	0.702	0.120	0.533
COMB 4	O+I+SM	0.688	0.684	0.818	0.288	0.679
COMB 5	O+I+B+P	0.561	0.551	0.708	0.122	0.531

COMB 6	O+I+P+SM	0.696	0.687	0.822	0.310	0.693
COMB 7	O+I+B+SM	0.692	0.686	0.824	0.321	0.700
COMB 8	O+I+B+P+SM	0.703	0.689	0.831	0.311	0.698

*Note: The category that a variable belongs to is clarified in Table 1. 'O' and 'I' in this table refer to outdoor and indoor environment measurements, respectively. 'B' stands for behavioral adaptation. 'P' points to personal thermal characteristics, and 'SM' refers to subjective measures.

It is evident from the results that there is a marked performance improvement when occupant window opening/closing behavior is added (COMB 2) upon outdoor and indoor environment measures (COMB 1). This finding is in line with previous studies in the field (Park et al. 2020; Damiati et al. 2016; Mustapa et al. 2016; Zaki et al. 2017) where they also reported the importance of inputting occupant adaptive behavior to predict thermal comfort. A small improvement is noted here (COMB 3) when individual thermal characteristics are included. A substantial increase occurred in COMB 4 for validation accuracy, AUC, ARI, and weighted average F1-score highlights that subjective measures are very important features. Not surprisingly, having subjective measures together with behavioral adaptation (COMB 7) provides even better model performance. These findings extend those of Deng and Chen's (Deng and Chen 2018), confirming that adaptive behavior changes occupant perception of thermal surroundings and is beneficial for thermal preference prediction and classification.

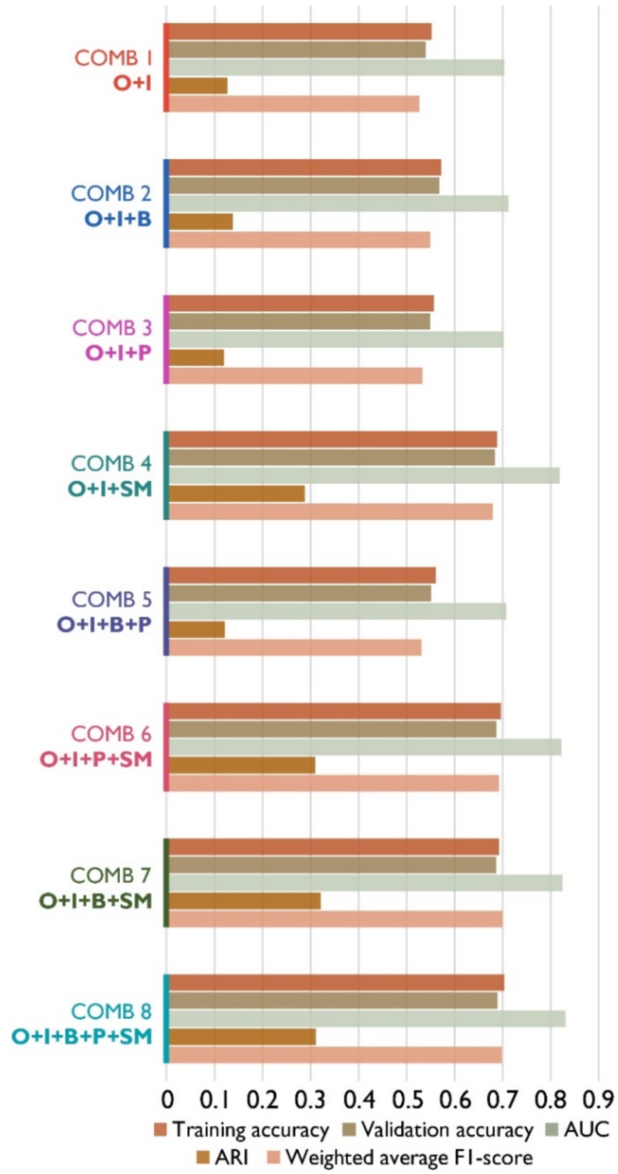

Figure 3. 10: The BNN model performance with different variable combinations.

The similar model results of COMB 6 and COMB 7 could be explained by the variations of proximity to a window and radiant temperature asymmetry, which are not recorded in the ASHRAE Global Thermal Comfort Database II, yet implicitly are embodied in the 'right-now-right-here' subjective measures. Lyons et al.'s (Lyons, Arasteh, and Huizenga 2000) study outcomes also support the idea that occupants' location towards and/or away from a window can adversely affect thermal sensation regardless of the window open or close state. Occupants may prefer and experience different thermal conditions even if the room is maintained at a comfortable temperature. However, the surveyed subjective measures can offset the weakness of personal thermal characteristics or window opening behavior by not considering the asymmetry of radiant temperature. This analysis on variable importance indicates that the BNN model improvement of thermal preference prediction gained from surveying "the condition of mind that expresses satisfaction with the thermal environment" (ASHRAE 2013) and linking it to occupant behavioral adaptation. Most notably, this is the first study to our knowledge implementing Bayesian inference on neural network to explore thermal preference prediction performance.

3.4.5. Comparing BNN to PMV and Adaptive Model

We employed the pythermalcomfort (version 1.3.3) (Tartarini and Schiavon 2020) to compute the PMV and adaptive model aligned with calculation methods proposed in ASHRAE 55 (ASHRAE 2013). As the PMV model is a steady-state model that is developed through climate chamber experiments, we used static values and field measurements of air temperature (T_{ind}), relative humidity (RH), and operative temperature (T_{op}). The static values include thermal insulation of clothing (clo = 0.6), sedentary metabolic rate (met = 1.0), stand still air velocity (v = 0.1m/s). Radiant temperature (T_{MR}) is a critical factor of the PMV model, for which the ASHRAE database has a high missing rate. Therefore, we implemented the following equation derived by Butera to compute T_{MR}:

$$T_{op} = (T_{ind} + T_{MR})/2 \tag{3.22}$$

Note that T_{MR} and T_{ind} defined in the ASHRAE standard are only applicable to those greater than 10°C and less than 40°C, respectively. Measurements that are not within the ranges were removed. In order to compare the results of PMV with respect to thermal preference votes on the same scale, we adopted Ghahramani et al.'s (Ghahramani, Tang, and Becerik-Gerber 2015) developed rules to transform PMV's value into thermal preference classes: PMV between -0.5 and 0.5 is "prefer no change"; $PMV < -0.5$ is "prefer warmer"; $PMV > 0.5$ is "prefer cooler". In compliance with ASHRAE 55, the adaptive model applies to outdoor air temperatures greater than 10°C and less than 33.5°C and air speeds slower than 2m/s. As a consequence, we excluded the meteorological and air velocity data that are outside the thresholds. To convert adaptive thermal comfort into a thermal preference scale, we assumed that T_{op} fell in the range of 80% acceptability limits is regarded as "prefer no change". If T_{op} is greater than the acceptable comfort temperature for 80% occupants, we converted it to "prefer cooler". Likewise, we converted the condition into "prefer warmer" if T_{op} is less than the lower acceptability limit.

Table 3. 4. Comparing the BNN model to conventional thermal comfort models.

	Prediction accuracy	ARI	Weighted average F1-score
PMV model	0.334	0.013	0.395
Adaptive model	0.383	0	0.523
BNN model	0.693	0.311	0.698

Table 3. 4. Comparing the BNN model to conventional thermal comfort models. summarizes the PMV and adaptive model's performance on prediction accuracy, ARI, and weighted average F1-score. AUC score is not computable in this case since the probability of the class with the greater label is unknown. The PMV and adaptive model predict thermal preference slightly better than taking a random guess (0.333). The PMV model's ARI score is very low and adaptive model's is equal to 0. This phenomenon could be explained by an extremely imbalanced class prediction. However, the weighted average F1-score accounts for the label imbalance, potentially leading to a better score

for adaptive model evaluation. It appears from these reported results that our Bayesian inferred thermal preference model provides compelling evidence for the prediction and classification. This model appears to be effective and accurate if subjective measures and behavioral adaptation variables are incorporated.

3.5. Conclusion

In this chapter, BNN models were developed using the ASHRAE Global Thermal Comfort Database II in order to provide reliable thermal preference predictions based on environmental measurements, personal thermal characteristics, subjective measures, and behavioral adaptation. The BNN models were configured with different architectures to test their performance and investigated their associated model predictive uncertainty for each thermal preference class. From our results, the BNN model structured 3 hidden neuron layers with 8 hidden nodes in each layer (i.e., 8, 8, 8) produced the average accuracy of 0.693 as the best performing configuration. The developed BNN model in this chapter demonstrated a promising capacity of forecasting "prefer cooler" class. Its corresponding posterior predictive probabilities are in the high possibility regions and the predictive uncertainty is densely clustered in the range of 0-0.05, indicating a high level of predictive certainty.

Although the Bayesian inferred thermal preference model is able to represent occupants' future thermal expectations accurately, we have to acknowledge that there is no "one size fits all". It is even harder to design environmental systems to meet 100% thermal satisfaction for all occupants in high-performance buildings. In this sense, this chapter demonstrates that the importance of accounting for the actions that people take to make themselves comfortable (e.g., opening and closing windows). This finding emphasizes that high-performance buildings need more information about people. "Putting people in the loop" helps get better thermal preference predictions with more data related to people.

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CHAPTER 4: MAKING VISIBLE THE INVISIBLE

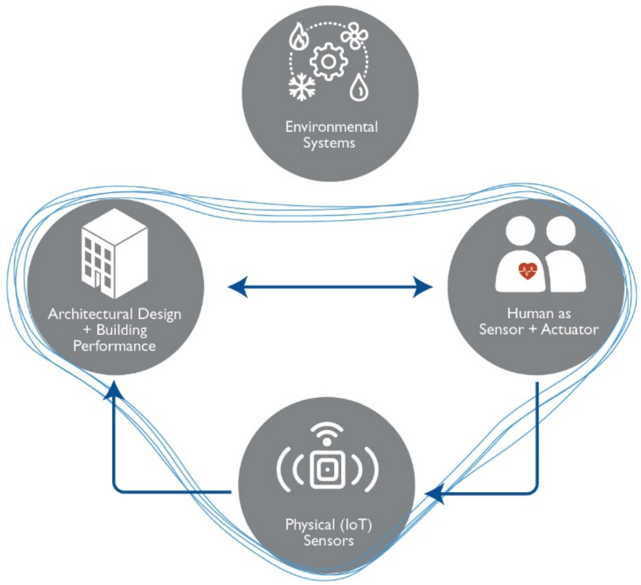

Figure 4. 1: The physical IoT sensors stand in for people.

The building envelope provides a physical barrier and separates the indoor and outdoor environments which consists of fenestration (doors and windows), roofs, walls, and insulations. Since a building envelope separates the unconditioned exterior environment from the conditioned interior space, it is one of the key factors that impact building energy performance. Architects intentionally select the proper materials and design the envelopes to alter local climate and enhance the indoor environment by adjusting the walls and windows. Meanwhile, the unintentional airflows of building envelope offer pathways for outdoor contaminants penetrating into the indoor environment. Adapted from (Ma et al. 2022), this chapter aims to unpack how the physical IoT sensors could stand in for people to evaluate the indoor health risks if building occupants cannot sense these colorless and odorless air pollutants, such as ozone. Given this background, this study focuses on the envelope design of typical residential houses in the urban area of Philadelphia and performs a preliminary evaluation of the health risks of indoor ozone exposure. To that end, this chapter investigates the extent to which that ozone penetrates and cumulates in occupied houses by taking the following steps: (1) analyze the temporal variability of indoor and outdoor ozone concentrations during occupied periods; (2) assess the relationship between indoor ozone concentration and associated factors (i.e. building characteristics, design and environmental features) in the urban environment; and (3) test models to infer indoor ozone concentration using different variable combinations.

4.1. Building Envelope Responses to Urban Ozone Pollution

Ozone is widely recognized to be one of the important air pollutants that yields risk factor for global health. It is one of two primary pollutants (along with fine particulate matter) that is consistently evaluated in the Global Burden of Diseases Study (Cohen et al. 2017) as well as being one of six criteria pollutants regulated by the United States Environmental Protection Agency (EPA) National Ambient Air Quality Standards (NAAQS). Long-term exposure to ozone has been linked to decreased pulmonary function (Levy et al. 2001; Mudway and Kelly 2000), increased asthma incidence (Fann et al. 2012), cardiovascular disease (Anenberg et al. 2010), and other respiratory diseases (Dockery and Pope 1994). Considering all these health risks, the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) recommends that ozone concentrations in air introduced to indoor spaces be reduced to “as low as reasonably achievable” (ASHRAE 2016).

In the urban environments, ozone is generated by the photochemical reaction products of nitrogen oxides (NO_x) and volatile organic compounds (VOCs) under exposure to sunlight. NO_x is a direct byproduct of fossil fuel combustion, particularly from vehicles, while VOCs come from transportation and other natural emissions from vegetation. Outdoor ozone concentrations are significantly elevated during the summer and climate change will further exacerbate this problem because higher temperatures accelerate ozone formation (Chang, Hao, and Sarnat 2014; Zhong, Lee, and Haghighat 2017). The phenomenon of an urban heat island (UHI) attributes to higher air temperatures in urban core areas than in rural areas and therefore, intensifies the urban ozone pollution (Liang et al. 2022).

Ozone primarily originates in outdoor air while exposures occur mainly indoors given that people spend most of their time in the built environment. Building envelopes are partially but incompletely protective against the indoor exposure to ozone. Outdoor air with higher ozone concentration flowing through the building envelope’s cracks and gaps - in unintended air infiltration - is the primary source of indoor ozone (Weschler 2000). Building factors can influence indoor ozone concentrations and therefore ozone exposures. The amount of ozone inhalation is cumulatively determined not only by urban ozone pollution levels but also by how much ozone enters and persists in occupied buildings. While the interiors of commercial and civic buildings tend to be mechanically ventilated, residential houses are more often naturally ventilated. Buildings without mechanical ventilation systems appear to be affected by outdoor concentrations of ozone through infiltration (Lai, Karava, and Chen 2015). The infiltration of outdoor ozone into indoor environments through the building envelope depends on several factors, including the building fabric, the permeability of building envelopes, building geometry, weather, and urban environment conditions. In addition, the age of buildings and various housing characteristics, such as the size of window openings and crack geometry, are also associated with indoor ozone concentrations (Salonen, Salthammer, and Morawska 2018).

However, a limited number of recent studies were found in the archival literature investigating indoor exposures to ozone in normally occupied residential houses in the

U.S. urban environments (Ma, Aviv, et al. 2021; Nazaroff and Weschler 2021). To our knowledge, very rare studies explored the implication of building envelope design variables on outdoor ozone penetration. The field investigations in the previous studies have not been conducted in the most ozone polluted cities as identified by the American Lung Association's 2020 State of the Air (American Lung Association 2020). The urban ozone pollution in the Philadelphia-Reading-Camden (PA-NJ-DE-MD metro area, called the greater Philadelphia area) are consistently unhealthy, and the city of Philadelphia is among the nation's 25 worst ozone-polluted cities. Given this background, this study focuses on the envelope design of typical residential houses in the urban area of Philadelphia and performs a preliminary evaluation of the health risks of indoor ozone exposure.

4.2. Material and Methods

4.2.1. Houses Description and On-Site Measurements

The hourly outdoor ozone data in the unit of parts per million (ppm) were retrieved from the United States EPA's AirNow station web (https://www.airnow.gov). This is the only monitoring site within a reasonable distance of the study area. In addition, a HOBO weather station (Onset Computer Corporation, Bourne, MA, USA) was set up on a building roof within the study area reporting outdoor air temperature, relative humidity, wind speed, and solar radiation. The monitored houses and meteorological stations are provided in Figure 4. 2.

Figure 4. 2: Locations of study houses and meteorological stations in Philadelphia.

Four exterior walls (ENV A, ENV B, ENV C, and ENV D) located in the urban area of Philadelphia were selected for the field studies. The selected envelopes were built between the 1860s and 1930s without major renovations or refurbishment. During the monitoring period of time, we did not ask the building occupants to limit their behaviors such as window opening habits since it is known that human-building interactions tend to cause uncertainties in the IAQ performance and modeling (Cho et al. 2020; Ma, Chen, et al. 2021). We took a thorough home investigation for each site and did not find any photocopiers or printers in the study houses. It is important acknowledge because it indicates no significant indoor ozone emission source. We used a UV-absorbance ozone monitor with 1 min sampling time intervals (Model 202, 2B Technologies Inc.; Accuracy: 1.5 ppb). The ozone analyzer measures concentrations between 0 and 250 ppm by the principle of UV absorption at 254 nm. In addition to ozone measurements, we also recorded a set of IAQ variables such as CO_2 concentrations by using an infrared absorption CO_2 monitor (Telaire 7001, Amphenol Inc; Range: 0 - 2500 ppm, accuracy: ± 50 ppm), PM2.5 with AirVisual Pro (IQAir; Range: 400 - 10,000 ppm), and Volume flow rates were measured by a hot-wire anemometer (9545, TSI Incorporated, Shoreview, MN, USA; Range: 0 – 30m/s, accuracy: ± 0.01 m/s). All devices were manufacturer-calibrated before every field monitoring. Table 4. 1 summarizes the study envelopes characteristics and sampling period, including general building information and envelope design variables. All envelopes are rectangular and straight from floor to ceiling, except ENV4 which was designed in a hexagonal-shaped wall for sweeping views. The geometric configurations of the envelope design are shown in Figure 4. 3.

Table 4. 1. Building characteristics of inspected and measured envelopes.

Wall ID[1]	House ID	Year of construction	Exterior wall finishes	Thickness of the wall (mm)	Wall surface area (m^2)	Window perimeter (m)	Length-to-width ratio	Window-to-wall ratio
ENV1	House A	1863	Stucco	280	13.26	10.08	1.555	0.213
ENV2	House B	1935	Brick	420	12.47	10.18	1.624	0.222
ENV3	House C	1915	Brick	320	16.36	18.72	2.085	0.298
ENV4	House A	1863	Painted fiber cement siding	250	7.31	9.48	1.008	0.951

[1] Window was replaced in 2015 for the ENV3 and the ENV4 had a glass patio door replacement in 2018.

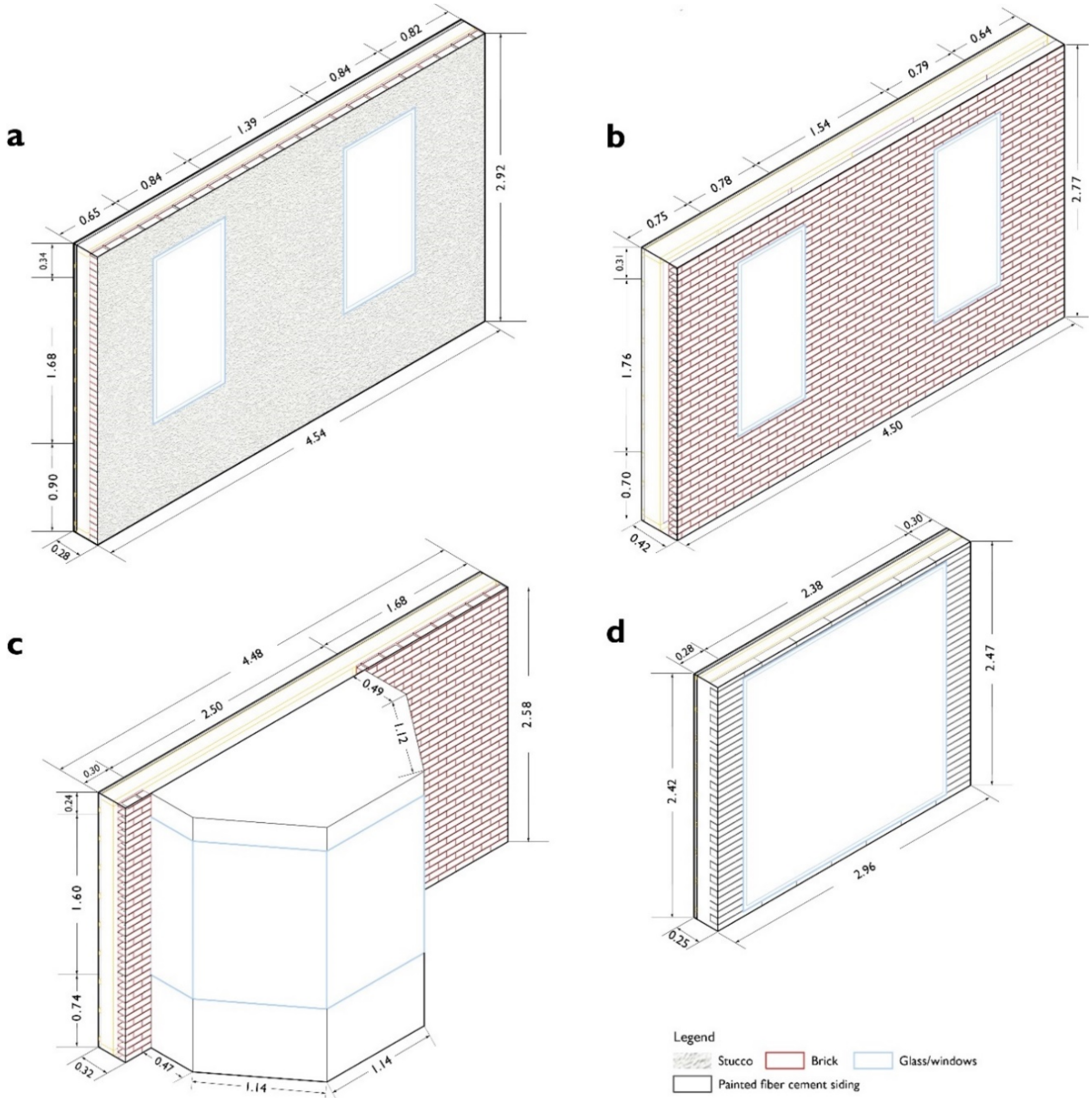

Figure 4. 3: The geometric configuration of (a) ENV1, (b) ENV2, (c) ENV3, and (d) ENV 4. The dimensions are in the meters.

4.2.2. Infiltration Rate Determination and Tracer Gas Experiment

CO_2 tracer gas analysis was conducted to determine the bulk air infiltration/exfiltration rate for the building envelopes. This is a well-established technique that has been applied many times in the literature (Cui et al. 2015). The tracer gas experiments for this study were conducted in test houses when they were unoccupied, mitigating concerns of indoor

CO_2 generation. The windows and doors were also closed to better evaluate the impact of unintended air infiltration. To facilitate the tracer gas analysis, a series of controlled CO_2 releases were performed in each of the buildings. CO_2 was released from a regulator connected to a compressed CO_2 cylinder (~25 kg full) until the indoor CO_2 concentration was measured to be 2,500 ppm, at which point the valve to the cylinder was closed. Next, a fan was turned on for 5 minutes to mix the air in the space, ensuring a consistent CO_2 concentration through the indoor air. The indoor CO_2 concentration was continuously recorded every minute using a Telaire 7001 CO_2 monitor connected to an Onset HOBO U12 data-logger. The experiment was concluded when the CO_2 concentration stepped down at about the same background level (less than 700 ppm). The tracer gas analysis relies on describing the overall shape of the decay curve; therefore, the high CO_2 concentration data was more than enough to characterize the air infiltration rate.

4.2.3. Data Analysis

All of the statistical tests and models were described in this chapter using R Studio (version 3.5.2). The initial analysis compared the exposure to indoor ozone with building characteristics, design variables, and environmental features using Pearson correlation analyses (also known as Pearson's r) (Eq. 4.1).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4.1}$$

$\bar{x}$ and $\bar{y}$ are the means of the data. The Pearson's r ranges between -1 and 1. If the absolute value of r is close to 1, this implies that x and y are nearly linearlly correlated. If r is a negative number, it indicates that a negative linear correlation is observsed between x and y. If r is close to 0, then it presents that x and y do not have a linear correlation.

Additionally, quantitative estimates of indoor ozone exposures and the impact of the design and environmental variables on indoor ozone exposure were derived. The mixed effect model's marginal R-squared value was computed to assess the goodness of fit. The higher R-squared value means the model has a better fit for data. A supervised forward stepwise procedure was adopted to adjust the multivariate model. Only the outcome variable that remained statistically significant was included in the final model. All tests were two-sided and statistical significance was acknowledged for p-values below 0.05. A p-value less than 0.01 was selected to identify statistically significant relationships and minimize false positives. Further, a p-value less than 0.001 was used to determine the strongest relationship.

4.3. Results and Discussion

4.3.1. Tracer Gas Test Results

In line with the trace grace decay results in the study houses, the CO2 concentration was measured as it decayed back down to the benchmark levels over a few hours. The ASTM E741 standard suggests that to transform the CO2 readings into the natural logarithm expression (ASTM 2017) and the exponential decay curve would turn into a linear form. The best linear fit can be derived and the regression slope describes the air infiltration rate of the envelope. Table 4. 2 reports the linear model fits and computed infiltration rate. In summary, the goodness-of-the-fit is quite good with R-squared values between 0.894 and 0.992. It indicates that the CO2 concentration decay can describe the trace gas experiment results. ASHRAE 90.1 recommends an infiltration rate of at least 0.03 m^3/h for residential buildings, and the results of the tracer gas study show that these houses are above that threshold (ASHRAE 2004). This would suggest that average houses would expect to experience even higher levels of indoor ozone concentration than were observed in the test houses.

Table 4. 2: Tracer gas test results of all envelopes.

Wall ID	Test duration (h)	Infiltration rate *N* (h^{-1})	R-squared	MSE	Std. Error
ENV1	2.93	0.4360	0.9661	0.0048	1.028E-04
ENV2	2.37	0.4390	0.8942	0.0108	1.127E-04
ENV3	3.60	0.3523	0.9920	0.0011	3.587E-05
ENV4	4.02	0.2124	0.9334	0.0097	9.088E-05

4.3.2. Variations in Indoor and Outdoor Ozone Concentrations

The temporal profile of indoor and outdoor ozone concentrations for each of the monitored envelopes are graphed in Figure 4. 4. The graphs show that the indoor ozone concentrations typically follow the same pattern as the outdoor ozone concentration. In addition, indoor ozone concentrations were almost always significantly lower than outdoor ozone, suggesting that building envelopes filter the outdoor air yielding lower indoor ozone concentrations. This finding agrees with data reported in the literature (Gao and Zhang 2012; Walker and Sherman 2013). Additionally, Figure 5 shows that ozone concentration follows a distinct diurnal pattern. The ozone concentration fluctuates most dramatically during the daytime and early night (7:00–21:00), and changes in ozone concentration from 00:00–06:00 are relatively low. The relatively low ozone concentrations before 7:00 local solar time (LST) are produced by weak photochemical reactions. The phenomenon was observed in previous studies (Xu et al. 2021; Masiol et al. 2017). The dramatic changes in indoor ozone concentration can be explained by variations in the strength of sunlight and photochemical processes of local traffic emissions, as well as the building's location and orientation. Different peak ozone concentrations in indoor spaces can be caused by slow airflow under durative stagnant weather conditions.

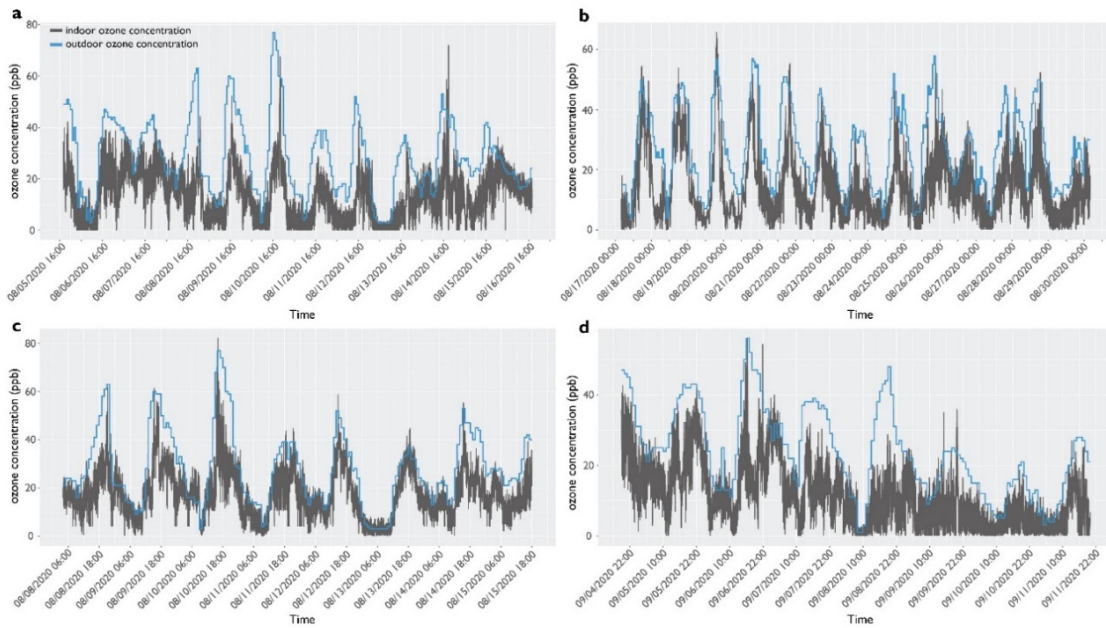

Figure 4. 4: Indoor and outdoor ozone concentrations of (a) ENV1, (b) ENV2, (c) ENV3, and (d) ENV4.

Average indoor and outdoor ozone concentrations were 14.23 and 27.19 ppb, respectively. The mean (± SD) of the ratio of indoor to outdoor ozone concentration was 0.53 ± 0.22. ENV3 has the highest median indoor concentrations and I/O ratio. Compared to the other study envelopes, ENV3 has the largest window and wall surface area implying a greater potential for cracks which allow more high ozone concentration outdoor air to infiltrate into the space. In addition, ENV3 is located in the heavy traffic zone of the downtown area and its UHI severity is evaluated as 5 (The Trust for Public Land 2021). Severity is measured on a scale of 1 to 5, with 1 being a relatively mild heat area and 5 being a severe heat area. It is believed that the chemical transformations and transport of ozone are effectively exerted by thermal circulations induced by UHI (Li et al. 2016).

By excluding the daily window closed periods, the I/O ozone ratios were found to be 0.652, 0.740, 0.694 for ENV1, ENV3, and ENV4, respectively, when windows were open. Open windows lead to higher air exchange rates and can remarkably elevate indoor ozone levels, particularly when urban ozone pollution is poor. In previous residential field studies, a noteworthy study by Zhang and Lioy reported I/O was 0.625 with windows open in six New Jersey residences (Zhang and Lioy 1994). Lee et al.'s study reported the I/O ratio was 0.68 with windows open in houses in California (Lee et al. 1999). Our findings are in line with the considerable variances of I/O ratios as a result of window opening behavior and air-conditioning system operation presented in Avol et al. and Lee et al.'s investigation (Avol, Navidi, and Colome 1998; Lee et al. 2002). Additionally, the wide range of I/O ratios measured in our study homes can be ascribed to a combination of differences in infiltration rate, furnishings, exterior envelope finishes, and window opening size (Zhong, Lee, and Haghighat 2017; Fadeyi 2015).

It is worth noting that ENV2 has not undergone any renovation since 1935 when it was built, and the windows were kept closed during the monitoring period. However, the median I/O ratio was still higher than ENV1. This could be ascribed to the size of the leakage area and the infiltration rate which is the second highest among all the study envelopes. A few published studies have found that the average pollutant concentration in exfiltrating air, air leaving the building, is proportional to the concentration in infiltrating air, air entering a building (Liu and Nazaroff 2001; Salonen, Salthammer, and Morawska 2018; Fadeyi 2015). A greater number of cracks might cause greater air infiltration and therefore contribute to an elevated indoor ozone concentration.

4.3.3. Exploration of Variables Affecting Ozone Penetration

To evaluate the hypothesis that the building characteristics and environmental features influence the indoor ozone exposure risk, a number of potential explanatory variables — the year of construction, infiltration rate (N), indoor air temperature (T_{ind}), relative humidity (RH_{ind}), CO_2 (C_{CO2}), $PM_{2.5}$ (C_{PM}), volume flow rate (Q), solar radiation (G), outdoor air temperature (T_{out}), outdoor relative humidity (RH_{out}), outdoor ozone concentration(C_{O3_out}) and wind speed (v) — were statistically evaluated against the indoor ozone concentration. Envelope design variables that may play a critical role in reducing outdoor ozone penetration were examined as well, including the thickness of the wall (t), exterior envelope finishes (EEF), wall surface area (A_{wall}), window perimeter (L_{win}), wall length-to-width ratio (LWR) and window-to-wall ratio (WWR).

Pearson correlations were performed between indoor ozone concentration (C_{O3_ind}) and 18 of the above-mentioned factors across the four envelopes. Some of the correlation coefficients were excluded from Figure 4. 5 due to the small effect size. For example, infiltration rate and exterior envelope finishes are highly correlated while only four samples in total were observed. The small sample size tends to reduce the power of correlation tests and increase the margin of error. As can be observed from , indoor ozone concentrations are significantly and positively associated with outdoor ozone levels ($r = 0.774$, $p < 0.001$), solar radiation ($r = 0.507$, $p < 0.001$), outdoor temperature ($r = 0.492$, $p < 0.001$) and wind speed ($r = 0.413$, $p < 0.001$). By contrast, RH_{out} and C_{O3_ind} have significant and negative correlation ($r = -0.534$, $p < 0.001$). The relationship between RH_{out} and C_{O3_out} also follows the correlative tendency of RH_{out} and C_{O3_ind} which are significantly and negatively correlated ($r = -0.681$, $p < 0.001$). Additionally, indoor ozone concentration is weakly but significantly correlated with LWR, A_{wall}, L_{win} and C_{CO2}.

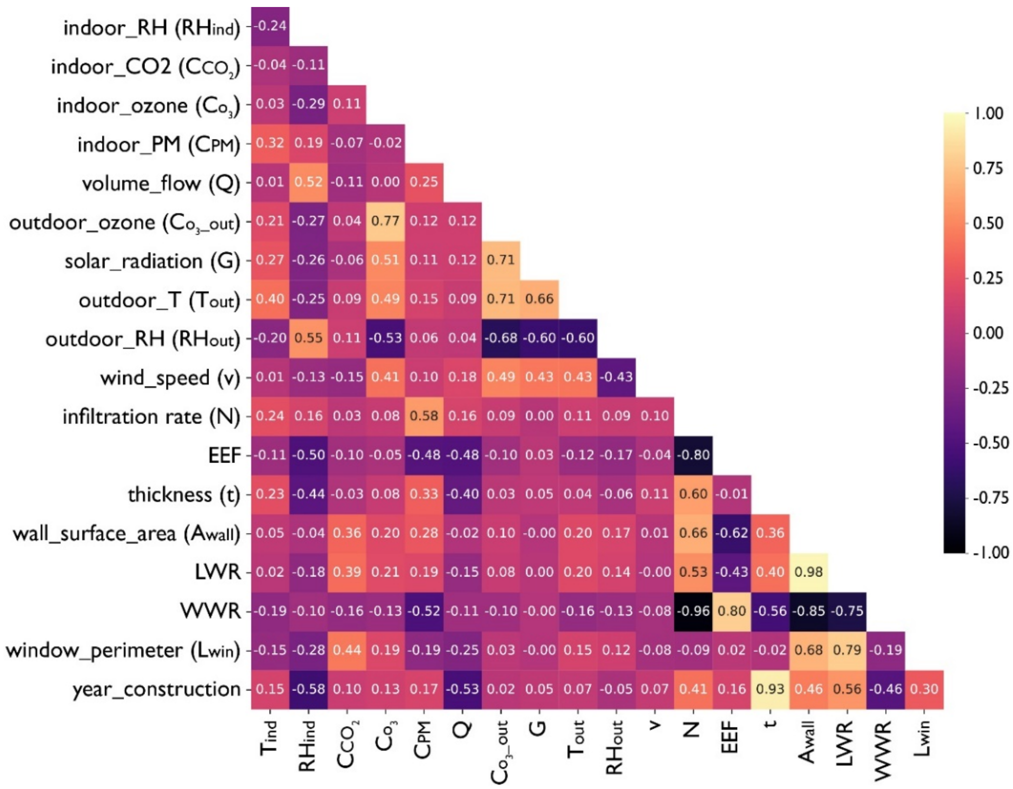

Figure 4. 5: Heat map representation of the correlation matrix for the observed dataset.

4.4. Discussion and Limitation of This Study

This study examines how building characteristics, design variables, window conditions and environmental features determine the accumulation of indoor ozone from outdoor sources in four envelopes during occupied periods of time. The results were used to estimate the lifetime health risks for exposure to measured ozone concentrations with an emphasis on public health implications.

The envelope design variables EEF and WWR play equally important roles of inferring indoor ozone concentration. EEF was selected as one of the important independent variables because exterior envelope materials can chemically react to outdoor ozone decreasing the concentration in air near the building. As Lamble et al. (Lamble, Corsi, and Morrison 2011) reported in their study, intentionally selecting indoor and outdoor surface materials like brick can passively control ozone concentration without the need for an energy intensively active system. Other green building materials such as bamboo and ceramic tile, which were not covered in this study also hold promise as a means of reducing indoor exposure to ozone through chemical reactions with ozone (Hoang, Kinney, and Corsi 2009). No previous discussion was found and revealed the design variable of WWR has mixed effects with other independent variables on indoor ozone concentrations. However, much study has shown that greater WWR increases energy usage intensity due to higher unwanted infiltration (Troup et al. 2019; Mathur and Damle 2021). The intentional and unintentional infiltration tends to pull outdoor ozone through the envelope into indoors. In addition, the surface area of the envelope A_{wall} is also considered as an important factor in this model configuration which is determined by the building envelope geometries. The wall surface area is linked to infiltration rate which can be computed as a function of the surface area of the building envelope using the ASHRAE standard default values (Lambie and Saelens 2020). However, A_{wall} is usually determined at building design phase prior to the infiltration rate that can be measured.

4.5. Conclusion

This study is a snapshot reflecting the ability of ambient ozone to penetrate and persist in residential houses in one of the most ozone polluted cities. The findings of our four-envelope study, together with those of previous investigations, showed that indoor ozone concentrations are consistently lower than those outdoors. The mean (±SD) indoor to outdoor ozone concentration ratio was derived which is between 0.48 ± 0.20 to 0.68 ±

0.19 in all building conditions, with an average value of 0.53 ± 0.22; while the mean ratios are 0.700 ± 0.13 with window open. These results highlight that building envelope plays a critical role in removing urban ozone pollution and reducing the associated health risks of exposure to elevated indoor ozone concentration.

The outcome of this study suggests ozone concentration follows a distinct diurnal pattern. The ozone concentration fluctuates most dramatically during the daytime and early night (7:00–21:00), and changes in ozone concentration from 00:00–06:00 are relatively low. This finding indicates that opening windows during nighttime (e.g., 12AM – 6AM) can help dilute indoor ozone levels. Overall, this chapter investigates the importance of sensors to measure factor that people cannot sense and the importance of the envelope design and operation in ozone reduction indicating the complementary responses of human and instrumental detection (e.g., physical IoT sensors). The sensors can monitor the factors that people cannot sense and let them be aware of IAQ issues so that they can take actions to modify IAQ accordingly (e.g., open windows and turn on air purifier). Night ventilation, or night flushing, is more demand compared to daytime ventilation concerning ozone pollution in residential houses.

4.6. References

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CHAPTER 5: SENSING THE ENVIRONMENT: ENVIRONMENTAL DETERMINATORS OF SLEEP HEALTH

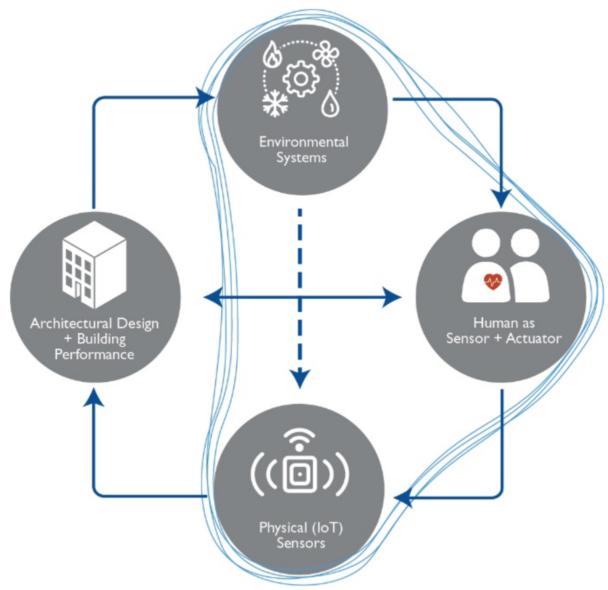

Figure 5. 1: Human acts as passive receptors while sleeping

In Chapter 1, I discussed that two kinds of occupant involvement with indoor environments. This chapter looks into how the building performance influences sleep quality when humans become the passive receptors of environmental factors. Sleep is essential for the body to recover from both physical and psychological fatigue suffered throughout the day and to restore bodily functions. Recent consensus reports that the ideal amount of sleep required each night for children and adults are 8-12 hours and 7-9 hours, respectively. Up to 50% of children experience a sleep problem and approximately 30% of adults complain of sleep disruption. Environmental sleep disrupters such as temperature, humidity, light, ambient noise, and air quality are recognized as contributors to sleep disorders. However, there are some unsolved questions in the building standards and design guidelines regarding the design and operation of an environment conducive to sleep. In addition, there are few resources available to architects and engineers providing explicit guidance on the necessary characteristics for the design of an optimal sleep environment, especially for children. Specifically, it has not been well-defined how the environmental parameters potentially affect children sleep quality and how to utilize available demographic, environmental, physiological, and polysomnographic parameters to optimize current sleep environment design. Therefore, this chapter aims to examine the effects of thermal, ambient, luminous, and acoustic environments on children's sleep quality in mechanically ventilated study rooms.

5.1. Environmental Parameters and Sleep Quality

Thermal parameters and sleep disturbance: The thermal environment is one of the primary causes of sleep disturbance (Okamoto-Mizuno and Mizuno 2012). However, thermal comfort theories and standards in sleep health are limited. Few guidelines or standards specify the design criteria of air temperature for sleep environment. For example, the World Health Organization (WHO) recommends a minimum air temperature of 18oC for sleep environment (Ranson and Organization 1988), while other guidelines such as those by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) exclude sleep temperature recommendations. Are people thermally satisfied when they sleep? Humans usually set their sleep environment based on their thermal preference at the pre-sleep waking state; and most importantly, parents usually set it up for their children possibly based on their own comfort. This assumes that there is no difference between adults and children with respect to thermal preference. Some research studies have demonstrated that thermal comfort differs between wakefulness and sleep (Wang et al. 2015; L. Lan et al. 2017). High air temperature or cold exposures have been shown to reduce total sleep time, duration of rapid eye movement (REM) and slow-wave sleep (SWS), and increased sleep onset latency and wakefulness (Li Lan et al. 2014; Haskell et al. 1981). The negative effects of heat exposure are aggravated when the humidity is high, but the appropriate range of humidity in children's sleep environment remains unknown. The ambient temperature and humidity are associated with body sweat loss as sweating significantly increases with increasing heat and humidity. Another important consideration is that children and adults usually sleep with bed coverings, especially during cold months. However, many studies investigating the effects of thermal parameters on sleep quality were carried out with naked subjects. The total insulation of the bedding environment varies greatly and depends on the mattress, covering, sleepwear and percentage of covering. All of these factors can affect the bed thermal micro-environment of the human body.

Indoor air quality and sleep health: Airflow is an effective way to increase heat loss. A faster air velocity increases the convective heat loss and decreases skin temperature and wakefulness (Tsuzuki et al. 2008). It is worth noting that lower ventilation rates usually characterize sleep environments, promoting pollutants’ accumulation. Insufficient airflow velocity and air exchange rate lead to elevated CO_2 concentrations and decreased sleep quality. Contaminants, such as Formaldehyde embedded in mattresses and pillows, contribute to a significant impact on children and adults’ respiratory health, including diseases like asthma and chronic obstructive pulmonary disease (Kim, Jahan, and Lee 2011). More research is also needed on how airflow directs the close proximity of the pollutant source to the breathing zone as we identified very few studies examining these factors. Other air pollutants such as PM2.5 and PM10, their elevated concentration is significantly associated with respiratory disturbance index and increased severity of obstructive sleep apnea (OSA) (Lappharat et al. 2018). Reducing exposure to air pollutants in the sleep environment may promote sleep quality and health.

Light, sound, and sleep quality: Lighting and acoustic conditions also play an important role in designing an optimal sleep environment. The potency of the light stimulus on the human circadian physiology depends on the light's wavelength and intensity. More research is needed to understand how the wavelength, intensity, and timing of light before and after sleep should be optimized to improve sleep outcomes in children. In terms of ambient noises, intermittent noise is generally perceived to be more disruptive to sleep than continuous noise. There are numerous sources of intermittent noise that can infiltrate the sleep environment (Basner, Müller, and Elmenhorst 2011), such as door slamming, trains, aircraft flyovers, and traffic noise. The state-of-the-art environmental noise guidelines by WHO suggested controlling the noise exposure below 40 dB (Pirrera, De Valck, and Cluydts 2014), regardless of age. Few studies have focused on children's noise sensitivity, and very few studies have investigated the importance of window orientation, and window opening/closing behavior. The soundproof performance of the window system is usually worse than those of walls and windows.

5.2. Study Procedures and Subject Recruitment

This study was conducted in full accordance all applicable Children's Hospital of Philadelphia (CHOP) Research Policies and Procedures and all applicable Federal and state laws and regulations including 45 CFR 46. All episodes of noncompliance were documented. The protocol and all accompanying materials provided to participants were reviewed and approved by the institutional review boards (IRB) at CHOP (IRB#: 20-018313). Collection, recording, and reporting of data were accurate and ensured the privacy, health, and welfare of research subjects during and after the study.

As illustrated in Figure 5. 2, this was a prospective cohort pilot study of environmental determinants on children and adults' sleep quality. Children scheduled to have a polysomnography (PSG) as part of clinical care and their parent/legal guardians were recruited to wear an actigraphy device on their wrist. Participants who met the inclusion criteria completed self-rated questionnaires and wore skin temperature, skin heat flux, and skin conductance sensors. The sleep environment was monitored during the sleep study night using environmental sensors which include ambient temperature, black globe temperature, supply air temperature, relative humidity, air velocity, volume flow rate, surface temperature, CO2, luminous, and sound levels. The environmental sensors were placed next to the bed, and they normally are quiet when operating.

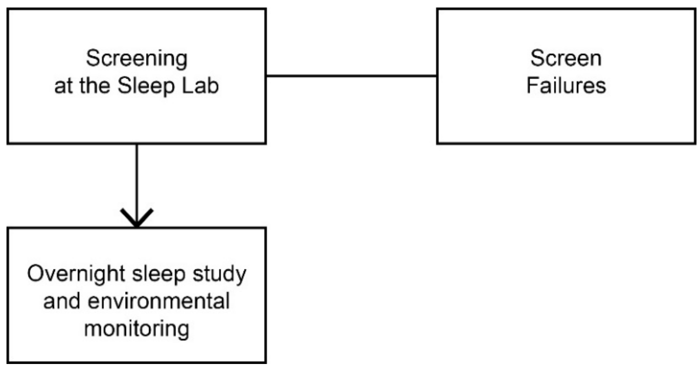

Figure 5. 2: Schedule of study procedures.

5.2.1. Study Population

This study involved the participation of children and their parents/ legal guardians, who may or may not experience sleep disorder but are physically and psychologically healthy. The following inclusion criteria was used for recruiting children: 1) Parental/guardian permission (informed consent) and child assent for child subject; 2) Children are English-speaking; 3) Children referred to a clinical PSG; 4) Children aged between 8 -17 years old. The inclusion criteria were adopted for recruiting parents/legal guardians include parental/guardian permission (informed consent) and parents/legal guardians are English-speaking. However, the children were excluded at the screening phase if they have claustrophobia, autism, sensory processing disorder, distortion of the perception of smell, and mental disorders such as depression and anxiety. Children were also excluded if they were unable to feel the environmental conditions and/or complete the questionnaires due to brain injuries or other neurological disorders that affect brain function and structure. A few exclusion criteria were applied for the parents/legal guardians such as: 1) Non-English proficient as questionnaires will be conducted in English; 2) Parent/legal guardians experience sensory processing disorder, distortion of the perception of smell so that they are unable to complete the questionnaires; 3) Parent/legal guardians have a prolonged exposure in highly polluted environments due to occupation. Subjects that did not meet all the enrollment criteria were not enrolled. The procedures performed for the overnight sleep study are clarified in the following sections.

5.2.2. Sleep Quality and Efficiency Measures

Polysomnography (PSG) studies were performed overnight. A Rembrandt polysomnography system (Embla, Broomfield, CO) recorded the following parameters: electroencephalogram (C3/A2, C4/A1, F3A2, F4A1, O1/A2, O2/A1), left and right electroculograms, submental electromyogram (EMG), chest and abdominal wall motion using respiratory inductance plethysmography, heart rate by electrocardiogram, arterial oxygen saturation (SpO2) by pulse oximetry (Masimo, Irvine, CA); end-tidal PCO2 (PETCO2), measured at the nose by infrared capnometry (Novametrix Medical System, Inc., Wallingford, CT), airflow using a 3-pronged thermistor (Pro- Tech Services, Inc., Mukilteo, WA), nasal pressure by a pressure transducer (Pro-Tech Services, Inc., Walnut Cove, NC), and bilateral tibialis anterior EMG. Study participants were continuously observed by a polysomnography technician and were recorded on video with an infrared video camera. Studies were scored using standard pediatric sleep scoring criteria.

5.2.3. Sleep Environment Monitoring

Environmental quality by sensing: Environmental measurements and sampling were carried out at mechanically ventilated rooms at the Sleep Center. The thermal variables such as temperature and relative humidity were continuously measured by placing a sensor (HOBO 1104, temperature accuracy: ±0.20 °C, humidity accuracy: ±2.5%) on the ground next to the bed. The supply air temperature was measured, and the sensor was installed next to the vent on the ceiling (Onset UX100-011, accuracy: ±0.21°C). Globe temperature was measured by a temperature sensor (Onset S-TMB-M002, , accuracy: ±0.21°C) placed on the center of a 10 mm-diameter matt-black ball. The bedding micro-climate temperature was recorded with iButton sensor (DS1922L, iButtonLink, accuracy: 0.0625°C) at 1-min time interval which was placed under the subject's bedding coverage. The air velocity and volume flow rate will be collected at the same position with an air flow sensor (Model 9545, TSI Inc., Shoreview, MN, USA, range: 0.00 –30.00 m/s, accuracy: ±3% of reading). CO_2 was continuously measured at 1-min sampling intervals by Telaire 7001 (Amphenol, St. Marys, PA, USA, range: 0-5,000ppm, accuracy: ±3% of reading) to give an impression of the CO_2 levels at one point in the sleep environment. The level of environmental brightness was monitored using a HOBO 1104 (accuracy: ±10% of the readings). A low/high range noise level meter (EXTECH SDL600, accuracy: ±1.4dB) will be used to measure environmental noises.

5.2.4. Questionnaires Completion Before and After Sleep

Self-evaluated questionnaires on sleep quality and perceived environmental effects on sleep will be performed before and after sleep during the monitoring period.

I am aware of no published article examining the full range of environmental conditions in children. Therefore, we will assess the children's perception of sleep quality and environment, with items adapted from valid questionnaires (Bruni et al. 1996; Mezick et al. 2008; LeBourgeois et al. 2005; Schmit et al. 2021) and empirical research related to the subjective pediatric sleep measures (Storfer-Isser et al. 2013; Bagley et al. 2015). To explore the mediating role of environmental conditions in relations to sleep quality, I include pre-sleep and sleeping environment evaluations as well as the overall satisfaction of sleep on a Likert-type rating scale. In terms of overall sleep quality rating and it will be assessed by children: (1) I awakened last night due to the coldness or hotness; (2) I feel tired in the morning; (3) I prefer to be cooler or warmer when stay in this room; (4) I am uncomfortable with the bed.

5.3. Thermal Environment, IAQ, and Sleep Disturbance

The results and discussions shown in this chapter were based on four female and four male children subjects (mean ± SD age: 11.6 ± 1.9 years, height: 148.3 ± 11.4 cm, weight: 64.5 ± 33.1 kg) that were recruited for the experiment. The subjects received financial compensation for participating in the experiments.

Mean radiant temperature (MRT) is first calculated based on air temperature, relative humidity, wind velocity and black globe temperature, according to the Eq. 5.1 given in the Eq. 5.1 given in (ISO 1998).

$$MRT = \left[\left(T_g + 273\right)^4 + \frac{1.1 \times 10^8 \times v_a^{0.6}}{\varepsilon \times D^{0.4}}\left(T_g - T_a\right)\right]^{1/4} - 273 \qquad (5.1)$$

where:

MRT = mean radiant temperature (°C);

T_g = black globe temperature (°C);

v_a = air velocity at the level of the globe (m/s);

ε = emissivity of the globe (black globe's emissivity is 0.95);

D = the diameter of the globe (m); The diameter of the globe used in the experiment is 0.1m.

T_a = air temperature (^{o}C);

Figure 5. 3 compares different measurements related to the thermal environment for all subjects. It is apparent that air temperature and MRT are very close to each other with mean ± SD 22.71 ± 3.13 and 22.4 ± 3.08, respectively. The mean value of supply air temperature and bedding microclimate temperature is the lowest and highest one, which is 18.39 (SD = 2.26) and 31.42 (SD = 3.17), respectively. The descriptive statistics may suggest that when the supply air temperature and the bedding insulation value changes, as long as the bed temperature is appropriate, the conditions can meet the demand of thermal comfort for sleep. The results also could have practical implications in achieving energy saving in residential buildings, where the indoor temperatures are usually kept being unnecessarily high with air conditioner in winter.

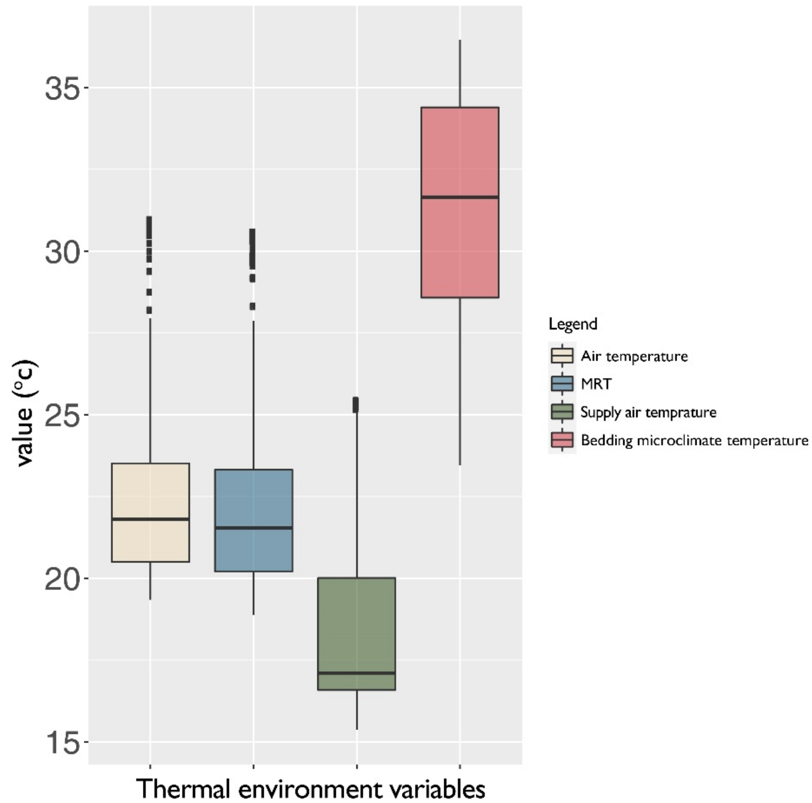

Figure 5. 3: Comparisons of different thermal environment measurements for all subjects.

To further reveal the thermal environment that each subject experienced, Figure 5. 4 reports the variance of air temperature, MRT, bed temperature, and supply air temperature. The widest range of air temperature was found in subject ID 3 and 4's overnight study, and accordingly MRT had largest range as well. Noticeably, the supply air temperature for the subject ID 3 and 4's overnight study ranged narrowly, and no large temperature difference was observed. It could be ascribed to substantial heat generated in the room which contributed to the room temperature increases. In addition, analyzing to what extent the room temperature changes influence local skin temperature changes is worth investigating.

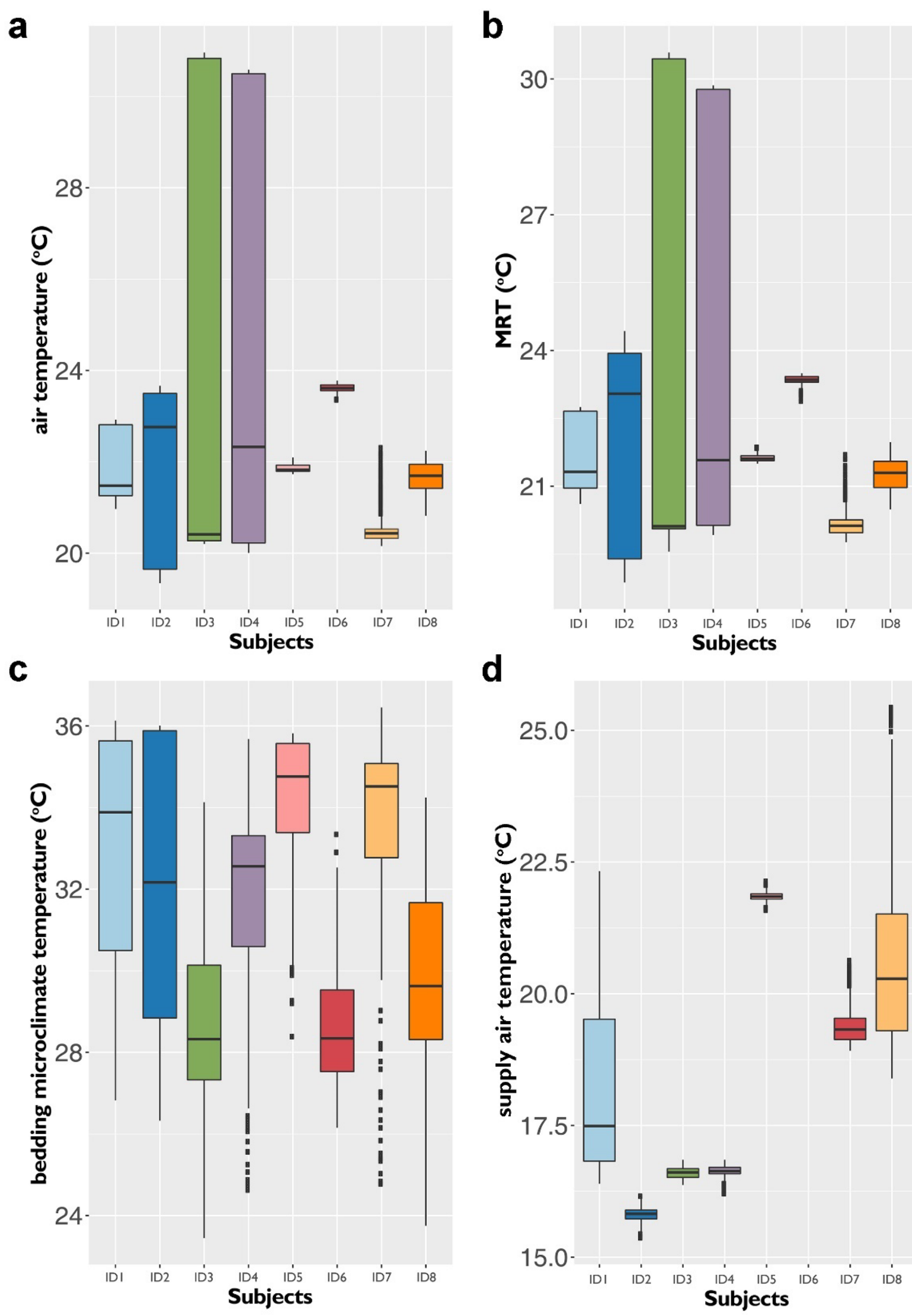

Figure 5. 4: Comparisons of different thermal environment measurements for each subject.

Among many sleep scorings that the PSG examines, arousals are important indicator to quantify sleep disruptions. Frequent arousals cause sleep fragmentation leading to impaired cognitive function and decreased sleep quality (Azarbarzin et al. 2015). Arousals are scored according to the American Academy of Sleep Medicine (AASM) criteria (Berry et al. 2020), which require an abrupt shift in electroencephalography (EEG) including alpha, theta, and/or frequencies greater than 16 Hz for at least 3 sec preceded by at least 10 sec of stable sleep. In addition, self-reported evaluation on sleep quality and thermal environment was retrieved in questionnaires, including feeling rested or tired, sleep quality, thermal sensation, and thermal comfort. Their descriptive statistics are reported in Table 5. 1.

Table 5. 1. Statistical summary of arousals and self-reported measures.

Variables	Unit	Minimum	Mean ± SD	Maximum
Total count of arousals	-	31	83 ± 54.54	191
Feeling rested or tired	From 1 (very rested) to 5 (very tired)	1	3 ± 1.60	5
Self-reported sleep quality	From -3 (very bad) to +3 (very good)	-1	0.57 ± 1.27	3
Thermal sensation	From -3 (very cold) to +3 (very warm)	-3	0.125 ± 1.89	3
Thermal comfort	From -3 (very uncomfortable) to +3 (very comfortable)	-2	-0.375 ± 1.18	2

The two-sample *t* test (also known as the independent samples t-test) is a method of inferential statistics which was applied to judge that whether the average of the two groups is significantly different. Therefore, it can be used to analyze change of self-reported sleep quality, thermal sensation, and thermal comfort under different thermal conditions. The main output parameters include calculated test statistic observed value, corresponding possibility P and mean difference. Wherein, test statistics is t statistics, its mathematical definition is:

$$t = \frac{\overline{X_1} - \overline{X_2}}{S_{\overline{X_1} \cdot \overline{X_2}}} \tag{5.2}$$

where:

$\overline{X_1}$ = mean of the first group of samples;

$\overline{X_2}$ = mean of the second group of samples;

$S_{\overline{X_1}\cdot\overline{X_2}}$ = standard error of the difference between the mean of the first group of samples and the second group of samples.

The null hypothesis is that there is no difference between these two groups that are classified based on the self-reported sleep quality and total number of arousals. The significant level was selected as 0.05 and the p-values were calculated consequently, with a statistically significant difference when the p-values are less than 0.05. In addition, when p value is smaller than 0.05, the null hypothesis that there are no significant differences between the two populations shall be rejected, and it shall be thought that there are significant differences between the two populations; vice versa.

The t-test results of sleep quality evaluations against different thermal environment variables are shown in Figure 5. 5. The p-values of each level of sleep quality evaluation are less than 0.05, which indicates that all of these thermal environment variables (i.e., Figure 5(a) air temperature, Figure 5(b) bed temperature, Figure 5(c) MRT, and Figure 5(d) supply air temperature) can have great impacts on children's sleep quality. In addition, it is worth noting that the subjects who voted "good" sleep had the highest mean bed temperature and lowest supply air temperature. It suggests a practical implication, which is that the supply air temperature can be increased to conserve building energy, while the bed temperature can still maintain comfort without sacrificing children's sleep quality. When considering the PSG-measured total number of arousals against different thermal environment variables, the results are illustrated in Figure 5. 6. The t-statistics' p-values are always less than 0.5 for bed temperatures and supply air temperature implying that there are statistically significant differences across different level of sleep interruptions. However, the pairwise comparison on children's arousals showed the statistically significant differences in terms of air temperature and MRT in the most cases, except for the group of 55 and 67 as well as group of 112 and 120. It indicates that there was no difference with the statistical significance was found.

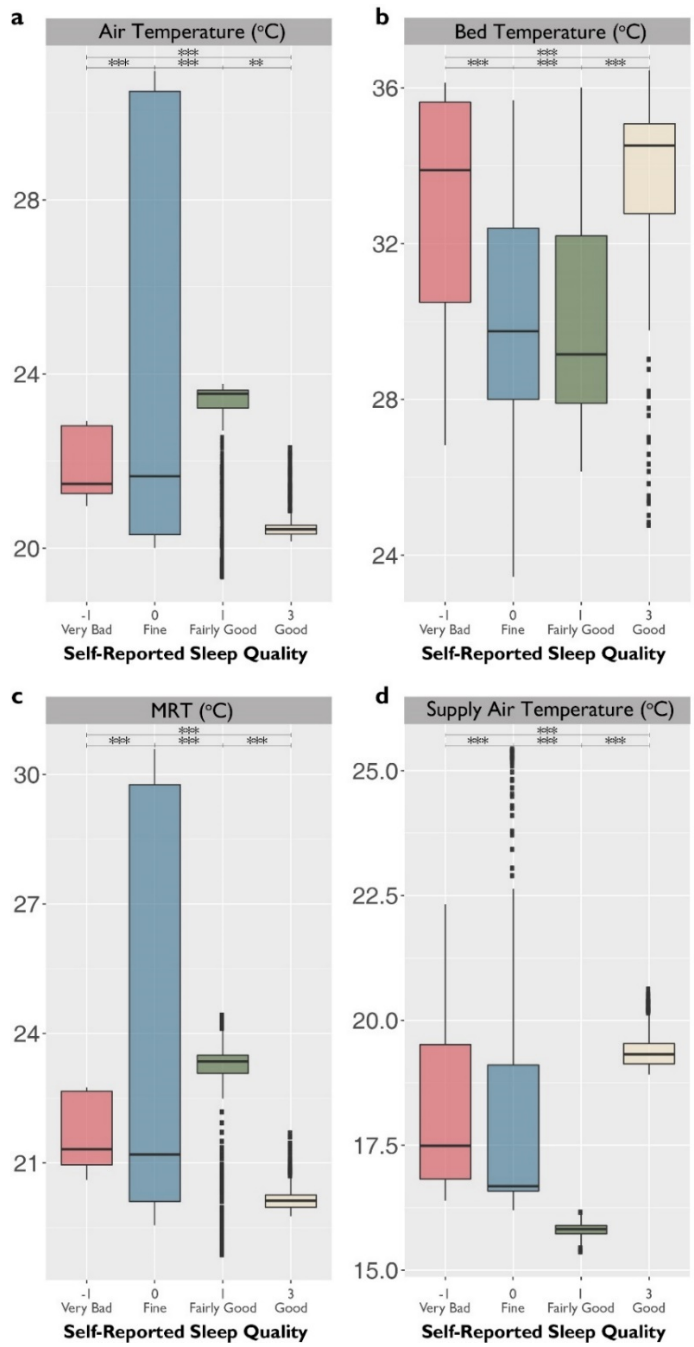

Figure 5. 5: Thermal environment and self-reported sleep quality.

***: p-value <0.01, **:p-value <0.5

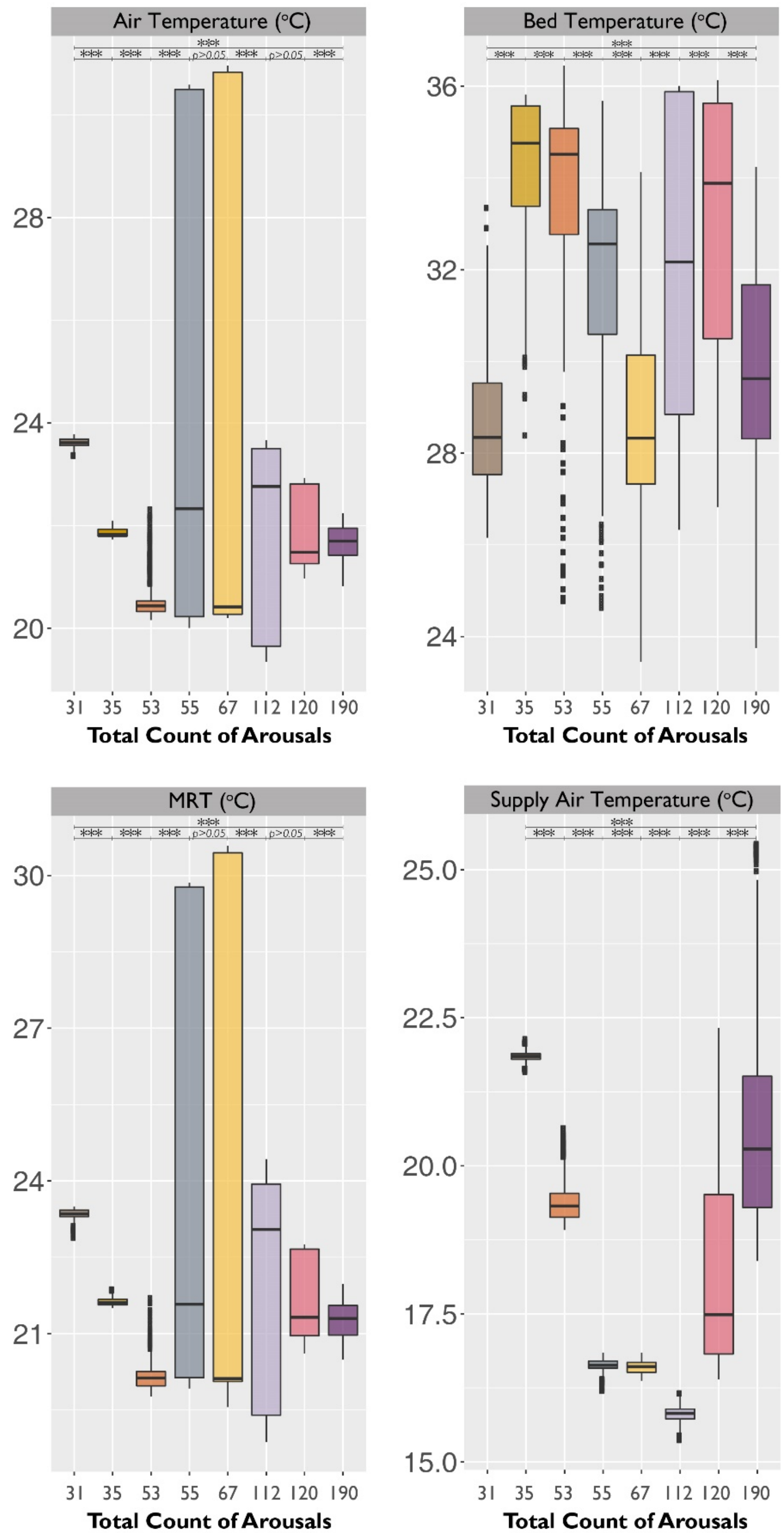

Figure 5. 6: Thermal environment and total count of arousals measured by PSG.

Carbon Dioxide (CO2) level is often used as the proxy for ventilation rates and IAQ evaluation. Figure 5. 7 illustrates CO2 concentrations across different voting levels of self-evaluated sleep quality and total count of arousals. According to the independent t-test, significant differences were found among the IAQ conditions. Noticeably, the “very bad” sleep quality had the highest average CO2 concentration compared to other voting results. Children who had less number of arousals (e.g., 31, 35, 53, and 55) were exposed to very low CO2 concentrations.

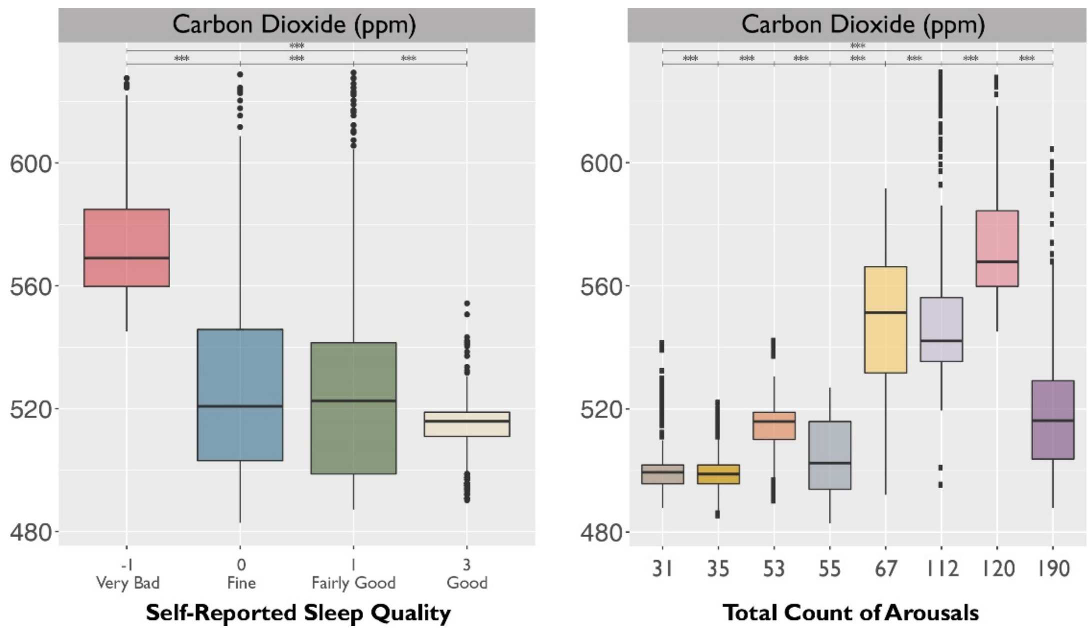

Figure 5. 7: IAQ against (left) perceived sleep quality and (right) arousals.

5.4. Luminous and Acoustic Environment Analysis

The noise levels were recorded at 5-second intervals for all nights. The noise levels were generally stable throughout the night with mean value 42.12 lux. During some part of the nights, the recruited children and/or their parents snored, and this is represented in the outliers shown in Figure 5. 8 and Figure 5. 9. The subjects went out to the bathroom during night as well which contribute to the noise box plots’ outliers, and this affected the average measured noise levels.

Table 5. 2. All night averaged noise and brightness levels.

Environmental Parameters	Minimum	Median	Mean ± SD	Maximum
Noise levels (db)	35.90	40.90	42.12 ± 3.74	71.3
Brightness levels (lux)	3.9	11.8	11.8 ± 13.09	130.1

A pairwise T-test was performed for further comparison, as illustrated in Figure 5. 8 and Figure 5. 9. For the self-reported sleep quality, the statistically significant differences were found for all groups indicating that the difference of noise and brightness levels are greatly important for the children. It is worth noting that the subject(s) voted "very bad" sleep quality actually had the darkest night compared to the rest of night. The "very bad" sleep quality might be ascribed to the uncomfortable noise levels.

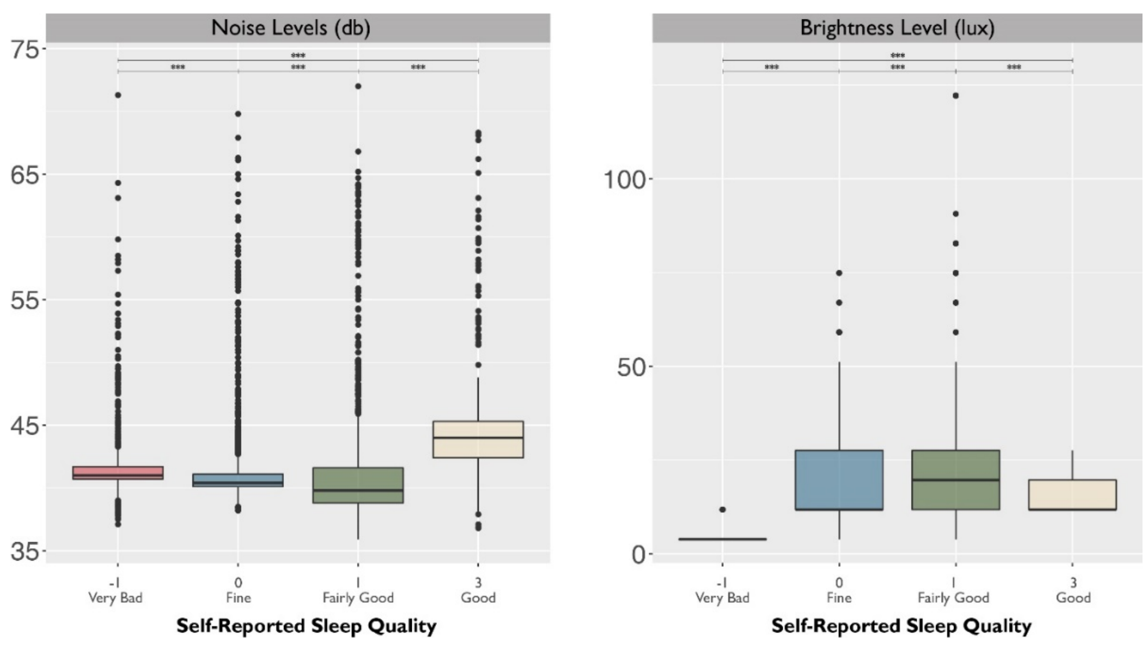

Figure 5. 8: Noise level (left) and brightness level (right) against perceived sleep quality.

The statistically significant differences were found in seven groups out of eight groups and only one group's p-value is larger than 0.05, as Figure 5. 9 demonstrates. The results are sufficient to conclude that the noise and brightness levels of the sleep environment offer important arousal reductions.

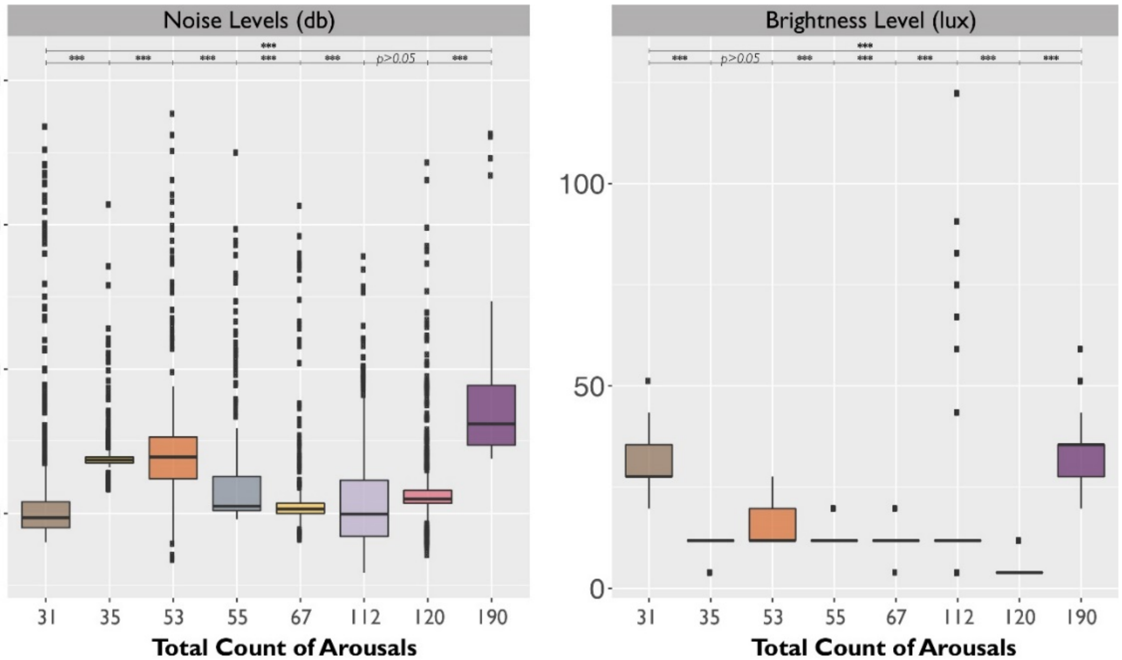

Figure 5. 9: Noise level (left) and brightness level (right) against arousals.

In general, the findings support the importance of reducing noise and light pollution on sleep. In buildings where sleep and common spaces must be co-located, such as in hospitals and hotels, measures to reduce noise emanating from other rooms (such as sound attenuating doors) should confer a positive impact on sleep quality for children. More research is needed to understand how the wavelength, intensity, and timing of light before and after sleep should be optimized to improve sleep outcomes.

5.5. Discussion and Conclusion

This preliminary analysis presented in this chapter was based on the sleep environment measured in the study rooms at CHOP and investigated the total number of arousals, self-reported sleep quality and thermal comfort of 8 children subjects (four girls and four boys) using subjective questionnaires, objective environment and PSG measures. An important result observed in this study was that both self-reported sleep quality and total count of arousals were statistically significantly affected by environmental factors (e.g., thermal, luminous, and acoustic measures), as shown from the two-sample t-test results in Figure 5. 5 - Figure 5. 9. The results of this study also highlighted that the bedding microclimate temperatures against either self-reported sleep quality or total number of arousals were consistently critical compared to the other measured environmental factors. This finding is very important for understanding energy-saving potentials in the sleep environment as heating energy with reduced setpoints and/or cooling energy with increased setpoints tend to be possible without sacrificing sleep quality. However, the analysis that was performed and conducted in this chapter was only based on eight subjects. The sample size is generally small and may not be representative of the general children population. Future work should be carried out to confirm the observed relationships in larger sample size. Since skin temperature and conductance are usually considered as human peripheral signals. Additional studies are required to investigate how human physiological responses are regulated with sleep architecture and the duration of light sleep and deep sleep for children.

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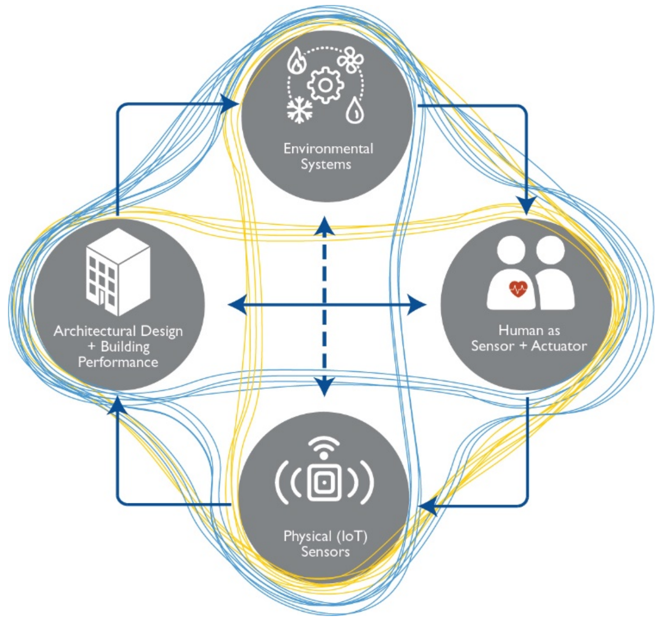
CHAPTER 6: REFLECTION AND OUTLOOK



People are the reason buildings exist. Buildings are designed to facilitate many aspects of human activities. Modern research to quantify human thermal comfort arose to support HVAC equipment's massive deployment and create a super-controlled environment for people. To achieve carbon-neutral or net-zero buildings, it is imperative to enhance building performance by implementing better controls of the building system. Yet by and large, contemporary architecture overlooks the fact that it is people we are attempting to make comfortable, rather than buildings. The reasons for this failure should be examined from different perspectives. First, architects have to make compromises between contradictory performance requirements. First, architects have to make compromises between contradictory performance requirements. For example, a problem in thermal performance may render more difficult an optimal solution for the illumination system. Second, almost all buildings are expected to satisfy the often divergent environmental requirements of the people and the processes inhabited under one shelter. However, we have to admit that there is no "one size fits all".

Such conflicts must be studied, understood, and resolved, though they involve factors that are subjective and objective, dynamic and static, theoretical and practical. The main aim of this dissertation is to provide more information which allows the human-system-building nexus to work together better and to investigate when and where sensors could enhance our understanding of the environment and when humans themselves are the best sensors. Coordination between the four parts - building, technical solutions, people, and sensors - is currently undervalued in architectural discourse and this dissertation is aimed at bringing this topic to the forefront of discussion. The problems outlined here evolve around what lessons we can learn from the occupied buildings and their inhabitants to improve future building design and how much uncertainty sources can be quantified given human-building dynamic interaction.

To clarify what solutions architects can have, this dissertation firstly investigates which factors are worth measuring in addition to the standard temperature and humidity variables used for thermal comfort metrics and IAQ indices, as portrayed in Chapter 2. Eighteen critical variables were extracted based on the systematic literature review including outdoor temperature, wind velocity, outdoor relative humidity, outdoor contaminants concentration, room dimensions, ceiling height, total surface area, penetration factor through envelope/door, radiant temperature, surface temperature, indoor relative humidity, volume flow rate (natural, mechanical, infiltration), indoor temperature, air density, contaminants generation/ deposition/ removal rates, number of occupants, exposure time, and air exchange rate. It is evident that these variables resulted from decisions made in different phases of the building life cycle - design, construction, and occupancy phase. However, a limited number of studies have examined the building geometry, such as room dimension, ceiling height, and total surface area to incorporate into building modeling and environmental system control in the real buildings.

Chapter 3 examined how building occupants as environmental controllers influence building performance and how to integrate our prior knowledge to quantify the uncertainty associated with the model predictions in building thermal environmental studies. The proposed Bayesian inferred thermal preference model is able to represent occupant thermal preference accurately (0.693), but we have to acknowledge that there is no “one size fits all”. It is even harder to design environmental systems to meet 100% thermal satisfaction for all occupants in high-performance buildings. The proposed BNN model demonstrates that the importance of accounting for the actions that people take to make themselves comfortable (e.g., opening and closing windows). “Putting people in the loop” helps get better thermal preference predictions with more data related to people.

Compared to thermal comfort, many colorless and odorless pollutants are not sensible to humans. Therefore, Chapter 4 focused on ozone and showed how physical IoT sensors could stand in for people as indicators of environmental health. The field investigation was carried out on four envelopes and results showed that design variables such as the exterior envelope finishes, wall surface area, window-to-wall ratio are reasonable predictors if outdoor ozone concentration measurements are not available in the study region while urban ozone pollution can reach unhealthy levels. The outcome of this study also suggested ozone concentration follows a distinct diurnal pattern indicating that opening windows during nighttime (e.g., 12AM – 6AM) can help dilute indoor ozone levels. Night ventilation, or design intervention such as night flushing, would be beneficial for ozone removal compared to daytime ventilation in residential buildings.

Two kinds of occupant involvement (i.e., active and passive role) in indoor environments were discussed in Chapter 5. The study conducted in Chapter 5 looked into how the building performance influences sleep quality when humans become the passive receptors of environmental factors. The preliminary analysis based on eight subjects suggested that bedding microclimate temperatures, noise, and light intensity were consistently important. The findings on bedding microclimate temperature implied potential energy savings as heating energy with reduced setpoints and/or cooling energy with increased setpoints tend to be possible without sacrificing sleep quality.

As I continue to tread across the human dimensions of building performance, I intend to continue to pursue opportunities in the area of IEQ modeling and occupant behavior to search for answers - how building sensors and human senses can synthesize and inform the organization and optimization of various performance targets such as sustainability, resiliency, and public health. The research plans that I will take immediately include 1) further exploration of thermal comfort in the sleeping environment and its association with sleep quality, 2) Energy saving potentials due to the temperature differences between bedding microenvironment and ambient environment, and 3) Effects of environmental noises on children sleep based on PSG EEG results.