Enabling Thermally Adaptive and Sustainable Built Environments through Sensing and Modeling of Human-Building Interactions

by

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Abstract

Fundamental interactions between buildings and their occupants have a multitude of significant impacts. First, built environments critically affect occupants' health and wellness, especially given that people spend more than 90% of time indoors. Among several environmental factors, the lack of thermal comfort is a common problem despite nearly half of the building energy being consumed by heating, ventilation, and air conditioning (HVAC) systems. Humans, in turn, closely influence the sustainable operation of buildings through various occupant energy-use behaviors. Recent studies indicate that actions performed or abstained by occupants have a major influence on building energy performance and can negate the benefits of investing in energy-efficient building systems. This dissertation focused on these two primary interplays of human-building interactions.

First, uncertainties in occupants' thermal comfort due to the varying human physiological, psychological, and behavioral factors lead to significant thermal dissatisfaction and often result in sick building syndrome. A potential solution is the human-in-the-loop approach to sense thermal comfort and provide more personalized environments. However, existing comfort assessing approaches have several key limitations including the need for continuous human input to adjust setpoints, lack of actionable human data in comfort prediction, intrusiveness and privacy concerns, and difficulty in integrating within HVAC operations.

To address these issues, this research first investigated the integration of environmental data with human bio-signals collected from wristbands and smartphones for thermal comfort

prediction and achieved 85% classification accuracy. This approach however required humans to provide their information from wearable devices and respond to a polling app. To address these limitations, the research further explored low-cost infrared thermal camera networks to non-intrusively collect facial skin temperature for real-time comfort assessment in both single and multi-occupancy spaces. Similar prediction accuracy is achieved without using any personal devices. Building on these comfort sensing approaches, this dissertation demonstrates how to bridge personal comfort models and physiological predictive models to determine optimum setpoints for improved overall satisfaction or reduced energy use while maintaining comfort. The proposed sensing and optimization methods can serve as a basis for automated environment control to improve human experience and well-being.

The second part of this research addressed why behavior interventions result in different energy reduction rates and identified two important gaps: lack of fundamental understanding of behavioral determinants of occupants, and lack of methods to quantitatively describe the varying occupant characteristics which affect the effectiveness of interventions. To address these gaps, the research developed a conceptual framework which explains occupant behaviors with three determining factors - motivation, opportunity, and ability (MOA) incorporating insights from building science and social psychology. Based on MOA levels, clustering analysis and agent-based modeling were applied to classify occupancy characteristics and evaluate the effectiveness of a chosen intervention. The framework was improved by integrating MOA factors with two classical behavioral theories to address the challenges in defining and measuring MOA factors. The results showed an improved explanatory power over a single theory and suggested that favorable behaviors can be promoted by motivating occupants, removing environmental constraints, and improving occupants' abilities. This framework enables decision-makers to develop effective and economical interventions to solicit behavioral change and achieve building efficiency.

Building upon these two perspectives of human-building interactions, future studies can investigate how personalized thermal environments will improve occupant behaviors in interacting with HVAC systems and the corresponding impacts on building energy consumption.

CHAPTER 1

Introduction

This research aims at two important areas that arise from the interconnections between buildings and human occupants. First, buildings critically affect human experience via their functions of providing healthy, comfortable, and productive built environments, including thermal comfort, indoor air quality, lighting, acoustics, among others. On the other hand, human occupants in turn closely influence the sustainable design and operation of buildings through various human activities and behaviors in relation to energy consumption. As a result, the scientific questions this research addressed are how to achieve a robust and continuous interpretation of the indoor environmental quality, based on a range of new capabilities that have emerged in recent years, including novel data sensing, modeling, communication, and actuation techniques, as well as a fundamental understanding of the determinant factors of occupant energy-related behaviors to design effective interventions for long-term sustainability.

1.1 Importance of the Research Activity

Buildings, as shelters to support various human activities, play an important role in their day-to-day interactions with human occupants and also significantly affect the global ecological environment. Buildings consume approximately 40% of the energy produced each year and account for 28% energy-related carbon dioxide emissions[1], and most importantly, 82% of this

[1] This percentage only represents the CO_2 emissions caused by existing buildings. New building constructions account for another 11% of CO_2 emissions in each year.

energy consumption is supplied by fossil fuels (coal, natural gas, and oil) (EU Commission 2018, EIA 2018, UN 2017). In the next few decades, the projected energy use for buildings in developing and developed countries will increase by 2.2% and 0.2% per year (Berardi 2015, UN 2017). As a result, significant social, environmental, and economic impacts of buildings can be anticipated in the near future.

Among the energy consumption within buildings, the heating, ventilation, and air conditioning (HVAC) systems represent the biggest energy end-use, accounting for approximately 50% of the total energy required to operate residential and commercial buildings (DOE 2017, European Commission 2016). However, despite the significant amount of energy consumption dedicated to space conditioning, of particular interest to the research community is the commonly observed lack of thermal comfort among occupants in the built environments. For example, studies revealed that up to 43% of occupants are dissatisfied with the thermal environment in their workplace (Karmann et al. 2018). Similar thermally dissatisfied environments have also been reported in residential settings (Peeters et al. 2009, Yoshino et al. 2006).

It is not surprising that thermal comfort is an influential factor on occupants' satisfaction, health, and wellbeing, especially given that people spend more than 90% of their time indoors (Klepeis et al. 2001). Several studies have shown that satisfying thermal environments can lead to a reduced number of complaints, absenteeism, and improved work productivity (Roulet et al. 2006). Other studies reported the sick building syndrome symptoms, such as headaches, eye and throat irritation, can be alleviated at low room temperature and humidity (20 °C and 40%) compared to higher levels (26 °C and 60%) (Fang et al. 2004). Besides, it is also suggested that warm environments (28.6 °C) can result in a relatively higher mental workload, which can cause fatigue and even health problems if it occurs over time (Wang et al. 2019a and 2019b).

On the other hand, human occupants interact with building environments and systems in their daily routines through various occupant behaviors, resulting in significant impacts on the energy consumption as more than 80% of building energy is consumed during the occupancy phase (UNEP 2010). The importance of occupant behavior has been reflected by many existing studies, such as Azar and Menassa (2012, 2014a, 2015), Gandhi and Brager (2016), Hong and Lin (2013), Masoso and Grobler (2010). For example, Azar and Menassa (2012) analyzed the impact of nine occupant behaviors (e.g., after-hours equipment and light use) on energy use in thirty commercial buildings using eQuest and concluded that the combined effect of "actual after-hours equipment use" and "occupied heating setpoint" can increase the building energy use by 23.6% compared to the default settings defined in standards. Hong and Lin (2013) simulated the energy consumption of typical occupant behaviors in private offices (e.g., heating or cooling setpoint) and suggested that occupants who are proactive in saving energy can reduce energy use by up to 50% during working hours. Klein et al. (2012) highlighted that occupant engagement in building energy reduction strategies is critical and can be achieved through interventions of informed feedback and suggestions. This study found that adjusting building systems according to occupancy status and preference can achieve a 12% reduction in energy consumption and also a 5% improvement in occupants' comfort in a testbed building. In an energy-auditing study, Masoso and Grobler (2010) found that more energy (56%) was consumed during non-working hours mainly due to occupant behaviors of leaving lights and other equipment on after work. Other studies such as Chen et al. (2012), Moezzi et al. (2009), Sanchez et al. (2007), Webber et al. (2006) support these findings and emphasize that significant energy reduction can be achieved if building occupants are engaged in the process.

Considering the importance of these two interrelated areas resulting from the interactions between buildings and occupants, this dissertation focuses on two main research themes as summarized in Figure 1-1.

Research theme 1 aims at assessing the impacts of building systems and environments on human well-being, with a specific emphasis on thermal comfort, which is one of the most important factors of indoor environmental quality. However, existing thermal comfort assessing approaches have several key limitations including the need for continuous human input to adjust setpoints, lack of actionable human data in comfort prediction, intrusiveness and privacy concerns, and difficulty in integrating within HVAC operations. To address these issues, this research first investigated the integration of environmental data with human bio-signals collected from wristbands and smartphones for thermal comfort prediction and achieved 85% classification accuracy. This approach however required humans to provide their information from wearable devices and respond to a polling app. To address these limitations, this research further explored low-cost infrared thermal camera networks to non-intrusively collect facial skin temperature for real-time comfort assessment in both single and multi-occupancy spaces. Similar prediction accuracy is achieved without using any personal devices. Building on these comfort sensing approaches, this research demonstrates how to bridge personal comfort models and physiological predictive models to determine optimum setpoints for improved overall satisfaction or reduced energy use while maintaining comfort. The proposed sensing and optimization methods can serve as a basis for automated environment control to improve human experience and well-being.

Research theme 2, on the other hand, addressed why behavior interventions result in different energy reduction rates and identified two important gaps: lack of fundamental understanding of behavioral determinants of occupants, and lack of methods to quantitatively describe the varying occupant characteristics which affect the effectiveness of interventions. To address these gaps, the research developed a conceptual framework which explains occupant behaviors with three determining factors - motivation, opportunity, and ability (MOA) incorporating insights from building science and social psychology. Based on MOA levels, clustering analysis and agent-based modeling were applied to classify occupancy characteristics and evaluate the effectiveness of a chosen intervention. The framework was improved by integrating MOA factors with two classical behavioral theories to address the challenges in defining and measuring MOA factors. The results showed an improved explanatory power over a single theory and suggested that favorable behaviors can be promoted by motivating occupants, removing environmental constraints, and improving occupants' abilities. This framework enables decision-makers to develop effective and economical interventions to solicit behavioral change and achieve building efficiency.

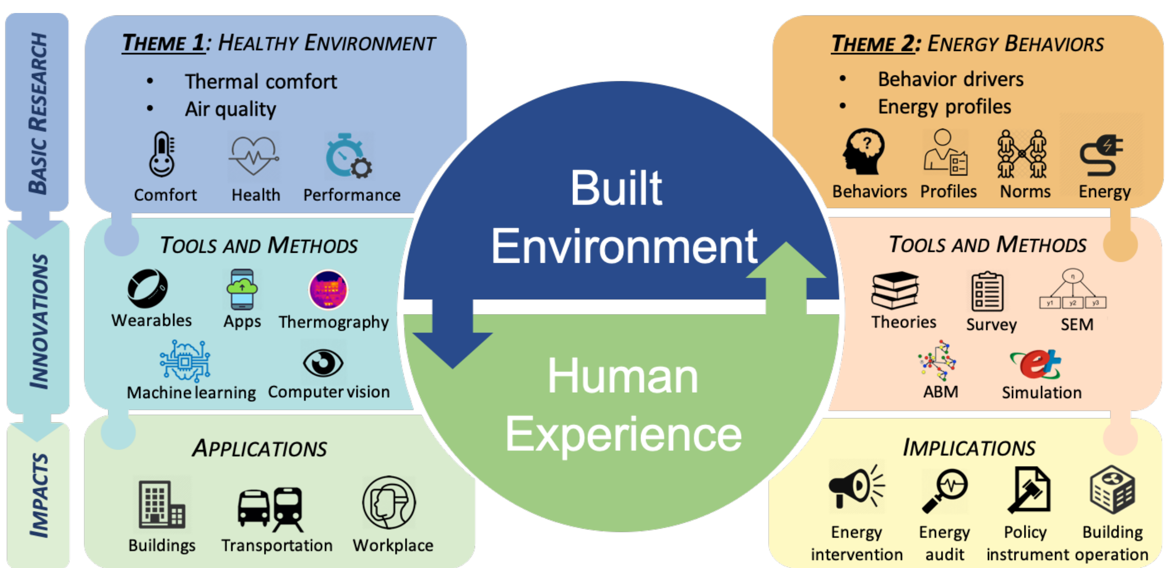

Figure 1-1 Overview of the Research

1.2 Background of the Research

This section provides an overview of existing studies on the two research themes. Limitations of these approaches are discussed at the end of each subsection.

1.2.1 Theme 1 - Occupants' Thermal Comfort Modeling and HVAC Control

Thermal comfort is defined as "*the condition of mind which expresses satisfaction with the thermal environment and is assessed by subjective evaluation*" (ASHRAE 55 2010). The thermal comfort is affected by several human factors including physiological (e.g., gender, age), psychological (e.g., expectation, stress), and behavioral (e.g., activity level) attributes (Brager and De Dear 2000, Karjalainen 2007, Li et al. 2017a, Parsons 2014). As a result, thermal sensation and satisfaction have been observed to change over time in a single individual, and also vary from one person to another. Even exposed to the same indoor environment, occupants can still have diverse thermal sensations and preferences due to variations in their personal factors. To assess occupants' thermal comfort, existing studies have explored the Predicted Mean Vote Model and participatory sensing introduced as follows.

1.2.1.1 The Predicted Mean Vote Model

The most widely used approach to evaluate occupant's thermal comfort is the Predicted Mean Vote (PMV) model which was proposed in the 1970s (Fanger 1970) and was later adopted by the national standards (e.g., ASHRAE-55 2010, ISO-7730 2005). The PMV model was developed based on the thermal transfer of the human body and environments. Six parameters are considered in the PMV model including four environmental factors - air temperature, relative humidity, air velocity, and mean radiant temperature, and two human factors - metabolic rate, and clothing level. The output of the PMV model is an index ranged from -3 to 3, which represents occupants' mean thermal sensation from cold to hot. A thermally acceptable indoor environment is defined to maintain the PMV index between −0.5 and 0.5. The Predicted Percent Dissatisfied (PPD) model is associated with the PMV model and predicts the percentage of thermally dissatisfied occupants in a particular thermal environment. ASHRAE Standards 55 recommends maintaining the PPD index at less than 10%.

Despite the PMV and PPD models have been intensively used in the field of thermal comfort assessment, this method suffers from several limitations. First, the PMV model is developed based on the mean feedback of a large group of people in laboratory settings. This generalization can have a bias towards certain occupants in a given environment. For example, an occupant who prefers cold or hot environments may not be well represented by this model. Second, the PMV model is originally developed for steady-state conditions in mechanically ventilated buildings. The predictions may not hold under transient-state conditions or in naturally ventilated environments (de Dear and Brager 2002, Yao et al. 2009). Also, the PMV model assumes the human body as a passive recipient of thermal stimuli (Yao et al. 2009). However, occupants can perform various adaptive behaviors, e.g., opening windows or putting on an extra layer of cloth, to maintain or restore the thermally comfortable state. These adaptive behaviors can result in a wider comfort range than predictions of the PMV model (de Dear 2011, de Dear and Brager 2002). Third, expensive devices are required to measure parameters such as the mean radiant temperature and metabolic rate, which makes the PMV model not suitable in real operational settings.

1.2.1.2 Participation Oriented Thermal Comfort Assessment

With the rapid development of wireless sensor network, mobile devices, and ubiquitous computing, researchers have explored various approaches to assess and control the indoor climate using environmental conditions and the corresponding human feedback (Bermejo et al. 2012, Daum et al. 2011, Erickson and Cerpa 2012, Feldmeier and Paradiso 2010, Gao and Keshav 2013, Hang-yat and Wang 2013, Jazizadeh et al. 2013, Lee et al. 2019a and 2019b). This is also known as the "human-in-the-loop" approach which brings occupants' actual thermal sensations into the HVAC control loop. As illustrated in Figure 1-2, this approach is typically initiated by the feedback received from building occupants using a phone or web application. In each cycle, decision algorithms calculate the comfortable setpoint based on environmental conditions and the actual thermal votes collected during this period. Finally, the updated setpoint is implemented to adjust the thermal environment.

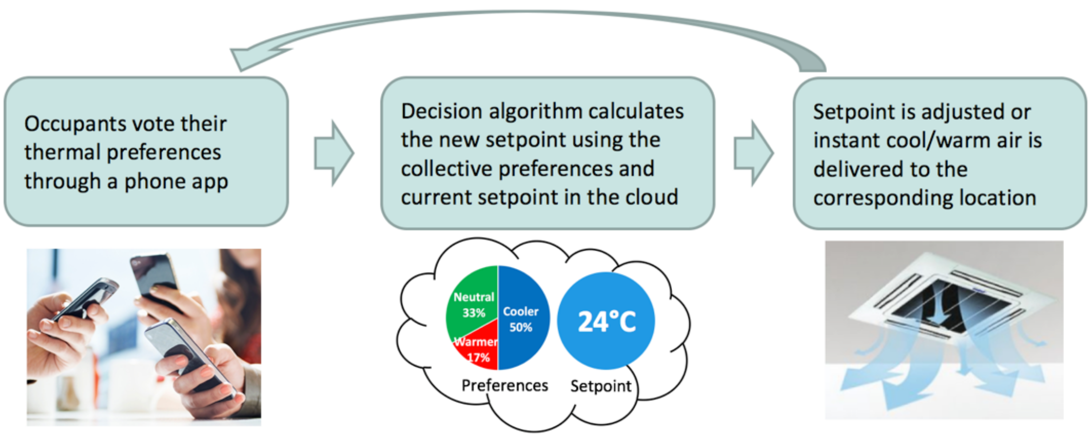

Figure 1-2 Typical Steps of Current "Human-in-the-loop" Approach for HVAC Control

For example, Feldmeier and Paradiso (2010) collected occupants' thermal votes (hot, cold and neutral) together with the ambient temperature and humidity from a wrist-worn sensor to model one's thermal comfort state under various environmental conditions. The authors trained a Fisher Discriminant classifier using two features (room temperature and humidity) to find the boundary of hot and cold sensations. Jazizadeh et al. (2013) used a phone application to collect thermal preferences and developed fuzzy predictive models which predict the comfort probability under different room temperatures. Other studies such as Erickson and Cerpa (2012) and Purdon et al. (2013) adopted a similar approach which used occupants' actual thermal votes from phone applications and environmental data from commodity sensors to either directly adjust the HVAC settings or model the comfort state using different statistical methods. In a recent study, Kim et al. (2018a) developed machine learning models using occupants' heating or cooling requests collected by a personal comfort chair. This study achieved a 73% accuracy in predicting three-point thermal preferences (i.e., warmer, no change, cooler), which significantly outperformed the PMV and adaptive models. In the market, commercial products such as Comfy, CrowdComfort, Keen and Wally also adopted the idea of continuously collecting occupants' thermal votes and indoor conditions to improve thermal comfort in the workplace through the optimization of temperature setpoint and air flow.

Although this direct occupant participation-oriented approach provides a feasible way to understand occupants' thermal comfort in the HVAC control loop, three major limitations should be acknowledged.

First, these aforementioned studies modeled occupants' thermal comfort based on environmental conditions and subjective feedback but failed to consider the influential human physiological or behavioral factors which can affect thermal comfort. For example, the same individual with different workload can have direct opposite thermal sensations and preferences in the same environment. In this case, a direct mapping from the measured environmental conditions to a certain thermal comfort level is incapable of producing a robust prediction, not to mention that human factors are changing over time.

Second, in these studies, the human body is assumed as a passive recipient of thermal stimuli. Several field studies suggested that occupants' adaptive behaviors (e.g., wearing a jacket when feeling cold) can play an important role in determining thermal comfort. However, this behavioral adaptation is not considered in the current voting methods. Developing the capability to capture this behavioral adaptation can result in a more flexible comfortable temperature (de Dear and Brager 2002).

Third and most importantly, this action-required approach heavily relies on continuous human feedback to understand occupants' comfort state over time. This is based on the assumption that the human body is the best "comfort sensor" of the thermal environment which can periodically, if not always, indicate the need to adjust temperature setpoint through feedback (i.e., requests to make the room warmer or cooler). In this case, human feedback is either used as the ground truth to rectify the comfort prediction or to directly determine the new temperature setpoint. In real-life circumstances, however, this assumption is far from expected as (1) the frequency of feedback tends to decrease with time as the novelty and excitement of the system fades away (which was observed in the Li et al. 2017a); and (2) the requirement of human effort in the feedback can be distracting during regular work time (especially over heavy workload periods or in any frustrating situations) and sometimes occupants are unable to vote due to a variety of reasons (e.g., the phone is not at hand).

1.2.2 Theme 2 - Interventions on Occupants' Energy Use Behaviors

To reduce building energy consumption, two major categories of approaches have been extensively studied. The first category focuses on the application of technical solutions in improving the energy performance of buildings, such as upgrading building management systems to optimize the mechanical and electrical systems, implementing hybrid ventilation to reduce energy demand on space heating or cooling (Dubois and Blomsterberg 2011, Menassa et al. 2013a). However, technical solutions are often challenged by high uncertainties in the energy-saving outcome (Azar and Menassa 2011a), lack of building information (Martinaitis et al. 2007), high initial or retrofit investment (Yudelson 2010), and reluctant stakeholder commitment due to long economic payback period (Menassa 2011).

Compared to technical solutions, in general, intervention strategies aiming to invoke behavioral change that reduces waste of energy have several merits, including low economic costs (e.g., campaigns that offer low or non-monetary incentives), high energy-saving potential (e.g., McCalley and Midden (2002) reported 21% savings in electricity due to goal setting and feedback), and flexible applications in different types of buildings, to name a few (Abrahamse et al. 2005, Azar and Menassa 2012, Li et al. 2017b, Staddon et al. 2016). To leverage these benefits, intervention strategies can be designed to invoke either voluntary or involuntary behavior changes in occupants' energy consumption (see Figure 1-3). Voluntary behavior changes can include education to teach and create awareness about benefits of a particular behavior (Abrahamse et al. 2005), and persuasion that offers reinforcing incentives or consequences to invite voluntary behavior changes at low economic costs. Prior studies have explored different approaches to enable voluntary behavior changes, such as information distribution outlets (e.g., posters, videos, brochures) (Agha-Hossein et al. 2015, Marans and Edelstein 2010), feedback (e.g., comparing current energy use with historical use that provides consumers with personalized evaluation and a means to monitor progress) (Timm and Deal 2016, Van Houwelingen and Van Raaij 1989), peer-comparison (e.g., allowing occupants to acknowledge their energy consumption compared to their peers) (Peschiera et al. 2010), incentives (e.g., monetary incentives) (Handgraaf et al. 2013), and pledging campaigns to encourage energy conservation behaviors (Whitsett et al. 2013).

On the other hand, involuntary behavior changes can include penalties that consist of negative consequences, which discourage an unfavorable behavior, and technological tools and systems (e.g., installing energy-efficient insulation materials) that solve problems without any human involvement (e.g., occupancy and light sensors). In general, interventions at education and persuasion level usually deal with posters, emails, or small amount cash incentives which can be implemented at low costs. Penalties can incur extra administrative costs of regulations and sanctions while technology intervention may require retrofit of existing buildings or installing new equipment. The economic and environmental costs associated with these intervention methods increase across the spectrum from voluntary to involuntary methods (Li et al. 2017b).

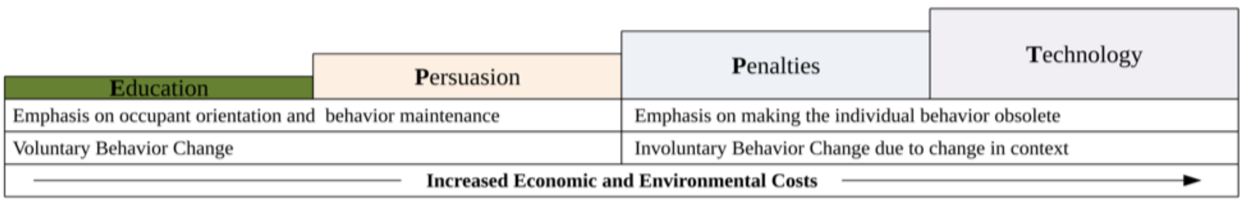

Figure 1-3 Multi-Level Building Energy Use Intervention Strategies

To invoke voluntary behavioral changes, existing studies have implemented various intervention strategies. Abrahamse et al. (2005) reviewed thirty-eight studies and categorized intervention strategies in residential settings as commitment (e.g., written pledge to conserve energy), goal setting and feedback (e.g., setting a target of reduction and providing feedback for occupants to monitor the progress), information distribution outlets (e.g., workshops), modeling (e.g., providing recommended behaviors), and rewards (e.g., monetary rewards). Many of these strategies can also be applied in office environments but necessary modifications are required due to the differences between these two settings (Staddon et al. 2016). In a review study, Staddon et al. (2016) summarized nine common intervention strategies adopted in the workplace, such as persuasion, training, and coercion.

Although existing studies on behavioral intervention observed different success rates in promoting energy conservation. However, little attention has been drawn to identify the determinants of occupants' energy-saving behaviors (Abrahamse et al. 2005). This is an important research gap as it is unclear why certain intervention will succeed or fail for a particular situation. Besides, several studies have suggested the existence of "rebound effect" in behavioral interventions that occupants' energy consumption tends to increase after the intervention is removed (Peschiera et al. 2010). Therefore, an understanding of the determinants of energy-saving behaviors is much needed as it not only contributes to explaining the effectiveness of certain interventions but also helps decision-makers customize intervention strategies that target on the constraining factors and enhance them to achieve effective and long-term energy conservation.

Second, the existing studies assume that occupants react in the same way to interventions without the varying characteristics of occupants, which has been suggested to significantly influence energy consumption. In this context, the various energy use characteristics of occupants represent the heterogeneity in energy use intensity and their likelihood of behavioral change (In Azar and Menassa 2013, the characteristics are defined as *intensity* and *variability*). For example, occupants with extreme energy use behaviors will react differently to interventions as compared to others with moderate energy use patterns. Education might be sufficient to reduce the energy use of the latter but might need to be supplemented with interventions from higher levels as shown in Figure 1-3 to affect the extreme users (Azar and Menassa 2015). As a result, the impact of a single intervention strategy can be limited when occupants with different characteristics co-exist in the same environment. This emphasizes the need for multi-level intervention strategies targeted towards the diverse occupant characteristics to produce and maintain energy savings over time (Karatas et al. 2015, Li et al. 2017b). In addition, the social network around occupants also plays a key mediation role to induce changes in occupant characteristics and behaviors. For example, Azar and Menassa (2015) investigated the existence of extreme energy consumers and their impacts on the building overall energy consumption. In this study, the extreme consumers are characterized by a very narrow energy variability, which represents the occupants with strong energy use habits who are unlikely to change behaviors than flexible peers. The results showed that extreme consumers have an important negative impact on flexible peers (i.e., increased the energy use intensity of moderate users), which can contribute to revoke the benefits of energy interventions. As a result, decision-makers are challenged with designing and delivering energy interventions effectively and efficiently due to high uncertainties in understanding occupants' energy use characteristics, their corresponding behaviors, and the resulting energy savings.

1.3 Research Objectives

1.3.1 Theme 1 – Developing a Robust and Non-Intrusive Approach for Thermal Comfort Prediction

The overall objective of this research theme is to investigate methods to replace the current "user-initiated" passive and cumbersome thermal comfort feedback and control mechanism with a new "non-intrusive and synchronous" approach that can result in a comfortable, data-driven thermal environment without encumbering any proactive occupant feedback and empirical inputs from facility managers. In particular, this research aims to explore the premise that thermal comfort can be measured non-intrusively and reliably in real, operational, multi-occupancy-built environments. This will lead to a better understanding of the intricate characteristics of optimum setpoints given the inferenced individual comfort levels to improve the overall satisfaction of occupant groups. The followings are identified as the specific objectives of this chapter:

- Evaluate the feasibility of using actionable human and environmental data to predict thermal comfort in naturalistic settings.
- Design a personalized HVAC control framework using heterogeneous human and environmental data.

- Develop non-intrusive and scalable approaches which can predict human thermal comfort in various settings in real-time.
- Validate the effectiveness of the new methods to improve overall thermal comfort in single and multi-occupancy spaces.

1.3.2 Theme 2 – Developing an Integrated Framework to Identify the Determinants of Occupants' Energy-Saving Behaviors

The overall objective of this research theme is to identify the determinants of occupants' energy-saving behaviors and occupant characteristics. In particular, a conceptual framework incorporating insights from interdisciplinary perspectives including social-psychology and building science is proposed. This research will provide insights into understanding the characteristics and constraining factors of targeted occupants and help decision-makers design and implement effective occupancy-focused energy interventions to reduce energy use. The followings are identified as the specific objectives of this chapter:

- Identify major determinants of behavioral change in social-psychology theories.
- Adapt the identified determinants into the context of energy use behaviors in buildings.
- Develop an integrated framework to establish the relationship between the determinants of energy use behaviors.
- Develop an approach to quantitively measure and describe occupant characteristics based on the behavioral determinants.
- Evaluate the proposed framework using survey data.
- Demonstrate the capabilities of the proposed framework to determine energy reduction through a case study.

1.4 Dissertation Outline

This dissertation is a compilation of peer-reviewed scientific manuscripts which includes a total of seven chapters including the current chapter. Chapter 1 introduces the research questions that arise from the interactions between buildings and their occupants, and subsequently discusses the importance of this research effort to the environment, as well as people's comfort, health, and wellness. The rest of chapters in this dissertation are organized into two parts presented as follows.

Part I – Personalized Thermal Comfort Interpretation with "Human-in-the-loop"

Part I, including chapters 2, 3, 4, and 5 describes the human-centered and personalized HVAC control frameworks using actionable human data (e.g., skin temperature) to dynamically interpret occupants' thermal comfort, as well as their applications in the built environment. Title and brief contents of each chapter are summarized as follows.

Chapter 2 – Thermal Comfort Interpretation through Wearables and Participatory Sensing

This chapter presents a personalized HVAC control framework which is capable of dynamically determining the optimum room conditioning mode (mechanical conditioning or natural ventilation) and temperature setpoint in single and multi-occupancy spaces. This control strategy is implemented based on the environmental data, as well as the human physiological and behavioral data obtained from wearables and smartphone polling apps. The main questions that the research addresses are: (1) how to integrate environmental and human data collected from various sources to predict occupants' thermal comfort? (2) how to optimize the HVAC operation based on the individual thermal comfort level to achieve a thermally comfortable environment.

First, a smartphone application is prototyped to integrate human and environmental data collected from wristbands, commodity sensors, thermostat, and weather station. Second, personalized comfort models are developed using different machine learning algorithms. Third, a

HVAC control algorithm is proposed and evaluated in the multi-occupancy space based on the predictions of comfort models.

This chapter is a compilation of a research paper that has been published in the peer-reviewed journal: "Li, D., Menassa, C. C., & Kamat, V. R. (2017c). Personalized human comfort in indoor building environments under diverse conditioning modes. *Building and Environment*, *126*, 304-317."

Chapter 3 – Non-Intrusive Thermal Comfort Interpretation through Infrared Thermography

This chapter presents a novel non-intrusive infrared thermography framework to interpret an occupant's thermal comfort by measuring skin temperature collected from different facial regions using low-cost thermal cameras. In particular, this chapter aims to resolve two limitations of the research presented in chapter 2: (1) the excessive reliance on cumbersome human feedback; and (2) the intrusiveness caused by conventional data collection methods (e.g., wrist-worn sensors). The main questions that the research addresses are: (1) is a low-cost thermal camera ($200) capable of thermal comfort prediction despite its low radiometric accuracy? (2) how to extract skin temperature features of different facial regions from the thermal image? (3) what are the significant skin temperature features to predict thermal comfort?

First, data cleaning and processing approaches are proposed to reduce the measurement error of the thermal camera. In particular, continuous thermal videos rather than a single image frame are used to extract skin temperature features. Second, facial regions (e.g., forehead) are identified through facial geometry and classic face detection algorithms. Third, machine learning algorithms are implemented to predict thermal comfort and select significant skin temperature features.

This chapter is a compilation of a research paper that has been published in the peer-reviewed journal: "Li, D., Menassa, C. C., & Kamat, V. R. (2018). Non-intrusive interpretation of human thermal comfort through analysis of facial infrared thermography. *Energy and Buildings*, *176*, 246-261."

Chapter 4 – Camera Network for Multi-Occupancy Thermal Comfort Assessment

This chapter extends the research discussed in Chapter 3 and presents a novel camera network for thermal comfort assessment in multi-occupancy scenarios. Of particular interest in this chapter is the generic and flexible camera network which can be rapidly reconfigured to adapt to various settings and capable of collecting multi-occupancy data at various angles or distances, representing real operational built environments. The main questions that the research addresses are: (1) how to detect faces and each facial region at a further distance or from a side view such that frontal facial contours are not clearly preserved in the thermal images? (2) how to compensate for the skin temperature measurements for the distance or angle from camera to occupants? (3) how to register thermal images of the same occupant captured by multiple thermal cameras at different angles/distances in a network of cameras to produce a robust prediction?

First, a dual-camera system, which consists of a low-cost thermal camera and an RGB-D sensor, is proposed to synergistically implement face detection and skin temperature extraction. Second, temperature measurements from the low-cost thermal camera at different distances or angles are calibrated by the reference infrared thermometer using linear or polynomial fit. Third, the dual-camera systems are registered using the stereo vision model to find point correspondences in different camera views.

This chapter is a compilation of a research paper that has been published in the peer-reviewed journal: "Li, D., Menassa, C. C., & Kamat, V. R. (2019). Robust non-intrusive interpretation of occupant thermal comfort in built environments with low-cost networked thermal cameras. *Applied Energy*, *251*, 113336."

Chapter 5 – Optimization of Temperature Setpoint through Personal Comfort Models and Physiological Sensing

This chapter integrates the personalized prediction of thermal comfort into the HVAC control loop to improve the overall thermal comfort in multi-occupancy spaces while observing their impact on the energy consumption. The main questions that the research addresses are: (1) how to integrate the physiological sensing approach into the HVAC systems to achieve a proactive control of the temperature setpoint? (2) given each occupant's skin temperature, how to develop personal comfort models which map skin temperature into a thermal comfort probability? (3) how to develop a physiological predictive model to interpret occupants' future thermal comfort when the setpoint is increased or decreased considering their asymmetric thermal sensitivities to cold and hot stress? (4) how to determine the optimum setpoint that improves the overall thermal comfort or reduces the energy use while maintaining comfort given occupants' comfort profiles?

First, the multinomial logistic regression is adopted to develop personal comfort models using the facial skin temperature of each occupant. Second, linear mixed models are developed to predict each occupant's skin temperature under a new setpoint. Third, three HVAC control strategies are introduced to demonstrate the setpoint selection for a given group of occupants.

Part II – Frameworks to Understand the Determinants of Occupants' Energy-Saving Behaviors

Part II, including chapters 6 and 7, describes an inter-disciplinary Motivation-Opportunity-Ability (MOA) framework combining insights from social psychology and building science to quantitively measure the determinants of occupants' energy-saving behaviors in buildings. The title and brief contents of each chapter are summarized as follows:

Chapter 6 - The Motivation-Opportunity-Ability (MOA) Framework

This chapter presents a conceptual MOA framework to identify (1) the determinants of occupants' energy-saving behaviors, and (2) occupants' energy use characteristics. In particular, this framework draws an analogy between energy intervention strategies in buildings and marketing theories in consumer science. The main questions that the research addresses are: (1) How to adapt the original MOA theory to the building context such that all possible factors defined in the energy use domain are mapped with the MOA categories? (2) How to quantitively measure one's MOA level and the influence of each factor on energy-saving behaviors? (3) How can occupants' energy use characteristics be classified based on their MOA levels for more effective and targeted intervention strategy selection?

First, a comprehensive literature review is conducted to identify the psychological definitions of the MOA factors and their corresponding measures in the building energy domain. Second, a structural equation model is developed to investigate the relationships among the MOA factors and the energy-saving behaviors of occupants from survey data. Third, clustering analysis is performed to group occupants based on their MOA levels, which represent the pre-defined energy use characteristics (e.g., prone to change behaviors). Finally, Agent-Based Modeling is conducted to demonstrate the energy-saving implications of the MOA framework.

This chapter is a compilation of a research paper that has been published in the peer-reviewed journal: "Li, D., Menassa, C. C., & Karatas, A. (2017). Energy use behaviors in buildings: Towards an integrated conceptual framework. *Energy research & social science*, *23*, 97-112."

Chapter 7 – A Unified Theory of the Motivation-Opportunity-Ability Framework with Social-Psychology Models

This chapter enhances the MOA framework discussed in chapter 6 and presents an integrated and improved MOA framework which incorporates social-psychological constructs from the Norm Activation Model (NAM) and the Theory of Planned Behavior (TPB). The model integration resolves several inherent limitations in each theory. The main questions that the research addresses are: (1) How does each construct from social-psychology theories fit into the MOA framework? (2) To what extent do these determinants influence energy-saving behaviors?

First, the NAM and the TPB theories are incorporated in the MOA framework to provide meaningful human cognitive (e.g., personal norms) and social contextual (e.g., social norms) measures for each MOA factor. Second, the strengthened MOA framework is tested based on a large-scale data collection involving multiple office buildings in the U.S. to evaluate the hypothesized relationships among each factor.

This chapter is a compilation of a research paper that has been published in the peer-reviewed journal: "Li, D., Xu, X., Chen, C. F., & Menassa, C. (2019). Understanding energy-saving behaviors in the American workplace: A unified theory of motivation, opportunity, and ability. *Energy Research & Social Science*, *51*, 198-209."

Chapter 8 – Conclusions

The dissertation concludes with chapter 8, which summarizes the significance and contributions of this research, and discusses future work directions.

CHAPTER 2

Thermal Comfort Interpretation through Wearables and Participatory Sensing

2.1 Introduction

As reviewed in Chapter 1 (Section 1.2.1.2), the current “human-in-the-loop” approach has several limitations such as the low comfort prediction accuracy due to lack of human data, requirement of continuous human participation, and absence of natural ventilation in the HVAC control strategy. To address these limitations, this chapter proposes a personalized HVAC control framework which is capable of dynamically determining the optimum conditioning model (i.e., mechanical conditioning or natural ventilation) and thermostat setpoint with reduced human participation. To achieve this, personalized comfort prediction models are developed based on the environmental and human bio-signal data collected from various sources to evaluate each occupant's thermal comfort level over time. In the mechanical conditioning mode, occupants' overall voting, as well as the predicted preference from comfort models will collectively determine the temperature setpoint. On the other hand, if comfort predictions suggest that thermal comfort can be maintained in naturally ventilated conditions, occupants will receive a notification to open the window and set back the HVAC system.

The chapter is organized to first provide a review of existing research studies on thermal comfort using human bio-signal data, followed by the contributions of this chapter. Then, components of the personalized HVAC control framework are explained in detail. Finally, two case studies (i.e., single and multi-occupancy) are presented to demonstrate the feasibility of the proposed framework.

2.2 Related Work

2.2.1 Thermal Comfort Prediction using Bio-signals

Human physiological responses, such as vasodilation and increased respiration, have been shown to be correlated with thermal sensations and discomfort (Choi and Loftness 2012, Jung and Jazizadeh 2017, Liu et al. 2008, Yao et al. 2007). Therefore, detecting these physiological responses through bio-signals (e.g., skin temperature, heart rate) provides a way to understand occupants' thermal comfort under different conditions. The benefits of applying bio-signals in the thermal comfort assessment are twofold: (1) bio-signals collected from each occupant allow researchers to develop personalized comfort models, which can improve the prediction accuracy (Li et al. 2017a, Jung and Jazizadeh 2019a); (2) bio-signals contain useful information to interpret comfort conditions and thus can reduce the dependence on human participation.

Among these bio-signals, skin temperature has been intensively investigated in prior studies. The human body maintains its core temperature at around 37 °C through the thermoregulatory control by the hypothalamus (NCBI 2009). During heat stress, vasodilation increases the flow of blood to the skin surface to dissipate excess internal heat while vasoconstriction decreases the blood flow to limit heat loss during cold stress (Charkoudian 2003). As skin temperature is directly affected by the changes in blood flow, it is often used to estimate human thermal sensation and comfort (Choi and Loftness 2012, Wang et al. 2007, Yao et al. 2007). For example, Yao et al. (2007) assessed participants' overall and local thermal sensations with respect to their mean skin temperature under three environmental conditions (i.e., slightly cool, neutral, warm) and found that skin temperature is highly correlated with thermal sensations. This study also developed linear regression models to predict overall and local thermal sensations using skin temperature. Choi and Loftness (2012) measured skin temperature of multiple body parts at different room temperatures, clothing and activity levels in a climate chamber. The result showed that the gradient of temperature on hand, wrist, and upper arm is a good indicator to predict thermal sensation. Similarly, as heart rate or heart rate variability is closely related to the metabolic level and work intensity (Perini and Veicsteinas 2003, Strath et al. 2000), researchers also investigated their role in thermal comfort prediction (Liu et al. 2008, Choi et al. 2012). For example, Liu et al. (2008) found that heart rate variability at discomfort conditions is significantly higher than that at comfort conditions.

The aforementioned studies primarily focused on identifying the correlations between different bio-signals and thermal sensations, if any. Thus, the experiments are mainly conducted in well-controlled laboratory settings using large and cumbersome measuring devices. Therefore, the feasibility of bio-signals collected from low-cost wearables as predictors in naturalistic settings is still in question and, most importantly, this knowledge has not yet been incorporated into the HVAC system to optimize its operation.

2.2.2 Ventilation Mode and Thermal Comfort

Prior studies of personalized conditioning discussed in Section 1.2.1.2 mainly focused on mechanically conditioned buildings. For buildings with operable windows, natural ventilation is an effective approach to maintain indoor thermal comfort and good air quality. Several field studies have suggested that the range of comfortable indoor temperature is wider in naturally ventilated conditions (Brager and De Dear 2000, De Dear and Brager 2002, Feriadi et al. 2003). For example, Feriadi et al. (2003) surveyed 300 households in naturally ventilated buildings and concluded that in reality people are more thermally comfortable compared to what the PMV model suggests. In general, natural ventilation at a slightly higher outdoor temperature may still be perceived as comfortable due to several reasons, such as occupant's diverse control over the environment, behavioral adjustments, increased skin evaporation rate when wind passes the human body, to name a few. On the other hand, natural ventilation can produce much higher ventilation rates than mechanical ventilation (Chartier and Pessoa-Silva 2009). Several studies investigated the concentration of air pollutants in naturally ventilated buildings and suggested that natural ventilation plays a significant role in removing indoor air pollutants and improving air quality (Santamouris et al. 2008, Hummelgaard et al. 2007).

However, natural ventilation is often an underutilized approach in practice. According to a study carried out by Canada Green Building Council, 69% of respondents revealed they have used mechanical conditioning strategies in office buildings compared to only 35% who have adopted natural ventilation (CaGBC 2016). Besides the restrictions of building code, an obstacle to the adoption of natural ventilation is that engineers often fail to distinguish when the building should solely rely on mechanical conditioning, and under what circumstances natural ventilation (or a mixed mode) outstands with equal, if not better, indoor environment but less energy consumption (Brager and De Dear 2000).

2.3 Contributions

Considering the limitations of previous literature and the benefits of natural ventilation, this chapter extends the current knowledge of personalized conditioning by incorporating human bio-signals and natural ventilation into the control loop which allows the HVAC system to dynamically determine the optimum conditioning mode and temperature setpoint based on the thermal comfort levels predicted from an integrated dataset, including both environmental data (indoor and outdoor conditions, window state) and human data (skin temperature, heart rate, activity, clothing level). The specific contributions of this chapter include:

- Validate the feasibility of using human and environmental data to predict thermal comfort levels in naturalistic settings.
- Develop a personalized control framework which integrates heterogeneous data into the operation of the HVAC system.
- Demonstrate the capabilities of the developed framework to improve overall thermal comfort in single and multi-occupancy spaces.

2.4 Methodology

2.4.1 Overview of the Personalized HVAC Control Framework

The personalized HVAC control framework leverages a range of new capabilities that have emerged in recent years such as: (1) portable and wearable health monitoring devices; (2) pervasiveness of smart mobile devices continuously available with human occupants; and (3) efficient wireless sensing, actuation, and communication networks for distributed decision and control. An overview of the operating principle of this framework is shown in Figure 2-1. One of the major contributions of this framework that differentiates it from previous studies is the integration of human physiological and behavioral data, thermal sensations and preferences with environmental data for decision making. This was realized through a smartphone application we developed for human-building interaction, which fuses heterogeneous data collected from different approaches including (1) wrist-worn health monitoring devices that measure human physiological and behavioral factors (e.g., skin temperature, heart rate, and activity level); (2) wireless sensors and probes which collect building indoor environment data (e.g., indoor temperature, humidity,

CO_2 level, window state); (3) weather station to retrieve real-time outdoor conditions (e.g., outdoor temperature and humidity).

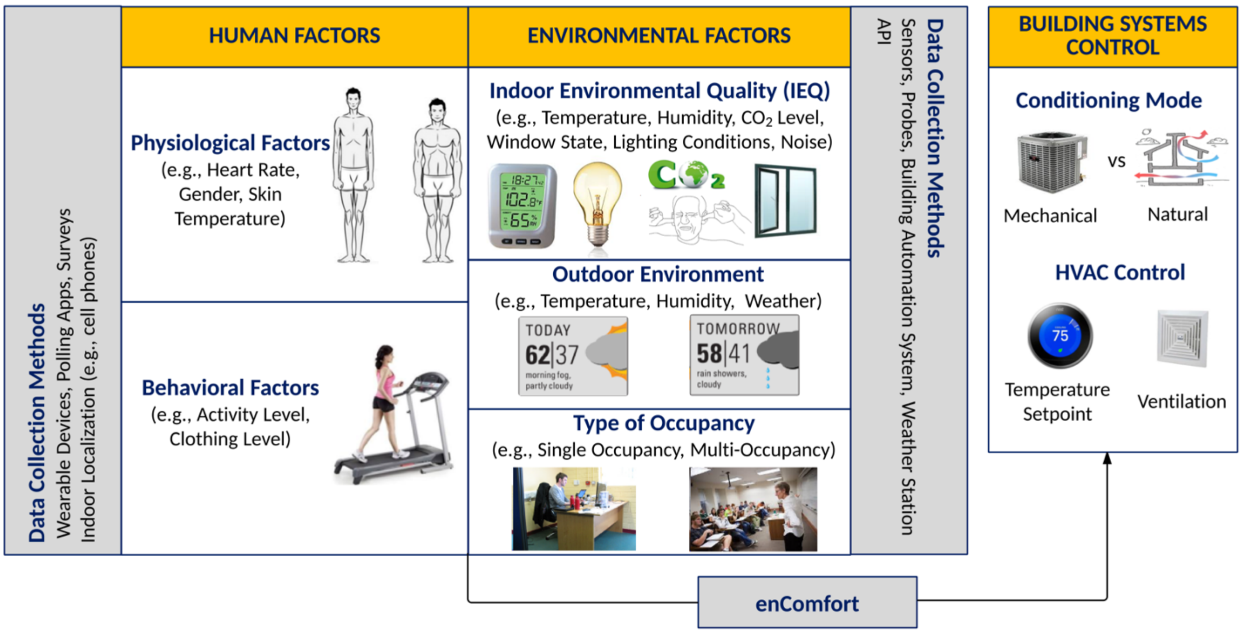

Figure 2-1 The Operating Principle of the Personalized HVAC Control Framework

2.4.2 Main Components of the Personalized HVAC Control Framework

The proposed personalized HVAC control framework has five operating components including indoor sensors and wearable devices, phone application, central database, control script, and programmable thermostat as shown in Figure 2-2. At the front-end, the phone application is paired with wearable health monitoring devices (e.g., Microsoft band) via Bluetooth to collect human physiological data (heart rate, skin temperature), behavioral data (clothing, activity level), and thermal sensations and preferences. Environmental data that are collected from indoor sensors and weather station are fused with human data in the phone application.

The human and environmental data are stored in the central database which communicates the phone application (front-end) and control script (back-end). At the back-end, the control script predicts each occupant's comfort level under different conditioning modes and setpoints. In each decision cycle, an adjustment is sent to the programmable thermostat to implement the new control strategy.

The following subsections of this chapter will discuss the details of each component as shown in Figure 2-2, including the development of software (phone app, database, control script) and the specifications of hardware (sensor, wristband, thermostat). It should be noted that this chapter aims to demonstrate a framework for personalized HVAC operation. The hardware adopted in this chapter can be replaced by any other suitable devices with similar functionalities.

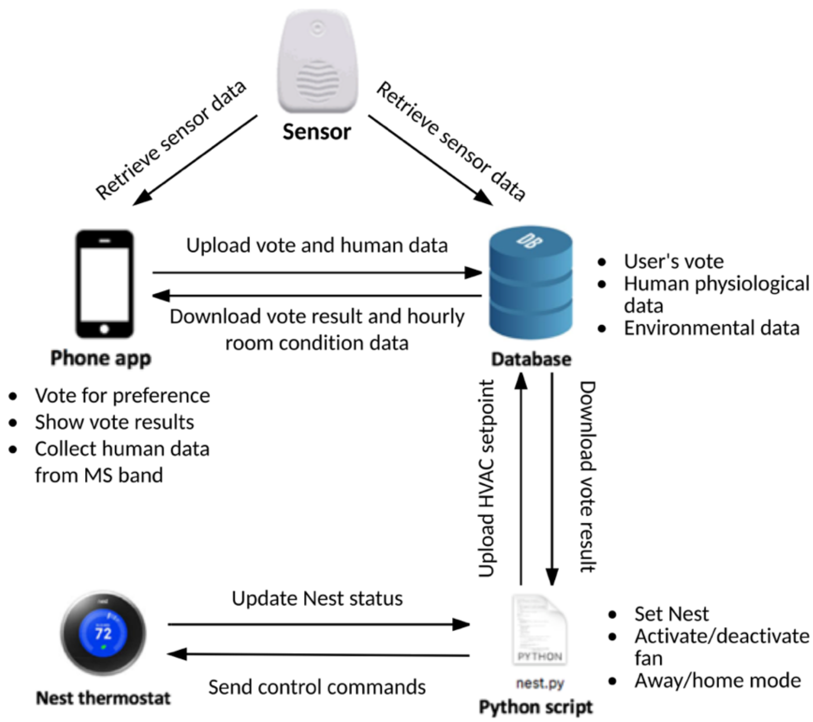

Figure 2-2 Data Flow within the Personalized HVAC Control Framework

2.4.2.1 Indoor sensors and wearable devices

Indoor environment data are collected from a set of sensors and probes as shown in Figure 2-3. In each room, we installed a Sensorist Wireless Pro temperature and humidity sensor (Figure 2-3b, temperature accuracy: ± 0.2 °C, humidity accuracy: ± 3%). A COZIR probe (accuracy: ± 50 ppm, Figure 2-3c) was adopted to measure indoor CO_2 level, which is a good indicator of indoor air quality. Operable windows were equipped with contact probes (Figure 2-3d) to monitor their states (either open or closed). All sensors and probes uploaded the data to a web server every minute through a gateway which is connected to the Internet (Figure 2-3a).

To collect human physiological and behavioral data, we compared several wearable fitness and health monitoring devices available in the market (e.g., Microsoft band 2, Fitbit, AIRO) which are popular due to powerful functionalities, affordable prices, and lightweight features. Microsoft band 2 (hereinafter "wristband", see Figure 2-4) was adopted as it embeds multiple sensors and is capable of tracking heart rate, skin temperature, light intensity, activity level, sleep quality, etc. Also, all sensors in the wristband are accessible via the application programming interface (API). Existing studies suggested the photoplethysmography (PPG) sensor in this wristband can achieve similar accuracy in heart rate measurement as the medical-grade electrocardiography (ECG) sensors for stationary subjects (e.g., Beggiato et al. 2019).

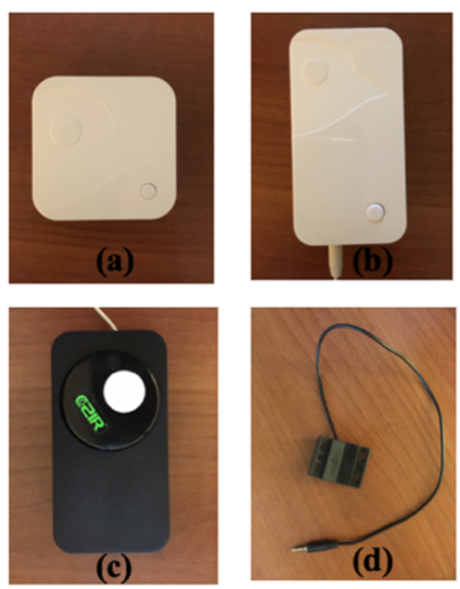

Figure 2-3 Sensors and Probes for Indoor Environment Data Collection (a) Gateway; (b) Temperature and humidity sensor; (c) CO_2 probe; (d) Window contact probe

Figure 2-4 Microsoft Band 2

2.4.2.2 Phone application

The center of the proposed framework as shown in Figure 2-2 is a smartphone application (hereinafter “app”) which enables human-building interaction. In this study, we developed an iOS app which allows users to collect physiological and behavioral data, view room conditions and HVAC settings, report actual thermal sensation and preference, check thermal votes from others sharing the room, acquire recommendation on the conditioning mode, and visualize their past efforts in using natural ventilation.

Figure 2-5 shows the steps of using this app (user-initiated actions are denoted in bold) and Figure 2-6 shows the app interfaces on an iPhone. To obtain a user's location and occupancy state (single or multi-occupancy), a marker with an encoded location is strategically placed next to each user’s desk in advance (see Figure 2-9). The app will first ask the user to scan this marker to get localized in the building. This is an improvement to prior studies where users have to manually select their location from a drop-down menu every time (Jazizadeh et al. 2013, Erickson and Cerpa 2012). This is particularly helpful in large complex buildings as users can frequently move around multiple places.

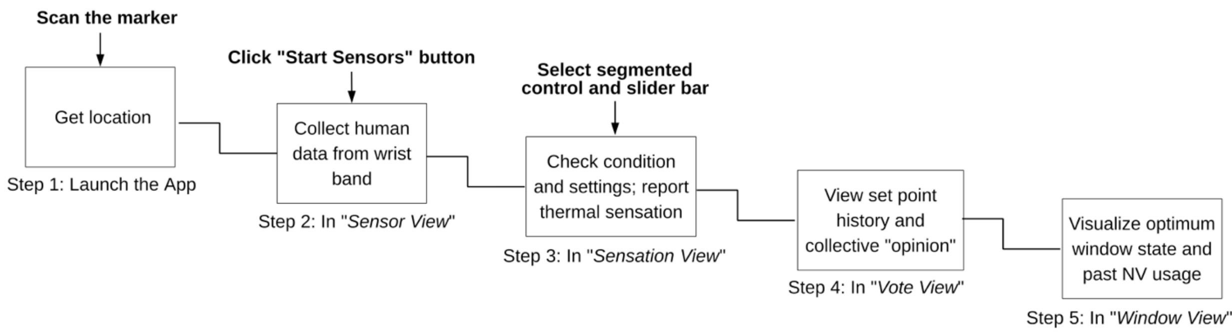

Figure 2-5 Steps of Using the Phone App

Next, the app starts to collect physiological and behavioral data including heart rate, skin temperature, activity, and clothing level through the wristband API (Figure 2-6a). Users can switch views using the tab bar located at the bottom. In the "sensation" view (Figure 2-6b), users can get current room conditions, HVAC settings, and report their actual sensation and preference through the segmented control. For the comfort scale, several designs were proposed in previous studies (e.g., ASHRAE 5-point sensation scale, McIntyre 3-point preference scale, Bedford comfort scale). For example, Jazizadeh et al. (2013) recommended a combined preference and sensation scale with 10 intensity levels. However, as the thermal preference is not necessarily associated with a certain sensation (e.g., people may consider a cooler sensation as comfortable) (Feriadi et al. 2003, Yao et al. 2007) and too many options can be confusing and thus hinder human participation. We adopted a 5-point sensation scale (i.e., cold, cool, ok, warm, hot) and a 3-point preference scale (i.e., warmer, neutral, cooler) for feedback.

In the "vote" view (Figure 2-6c), two pie charts demonstrate the collective "opinion" about the indoor thermal environment in a multi-occupancy space. This allows users to view the unresolved cold or hot requests from their peers, which aims to promote mutual understanding and mitigate the conflicts to some extent.

In the "window" view (Figure 2-6d), a bar chart displays the daily usage of natural ventilation. This feedback is anticipated to show users' efforts in adopting natural ventilation to promote long-term conservation. Users are notified by push notifications if there is an automatic adjustment of setpoint or natural ventilation is chosen as the optimum conditioning strategy (see Figure 2-7).

Figure 2-6 Application Interfaces for (a) Human physiological data; (b) Thermal sensation and preference; (c) Collective opinion; (d) Conditioning mode

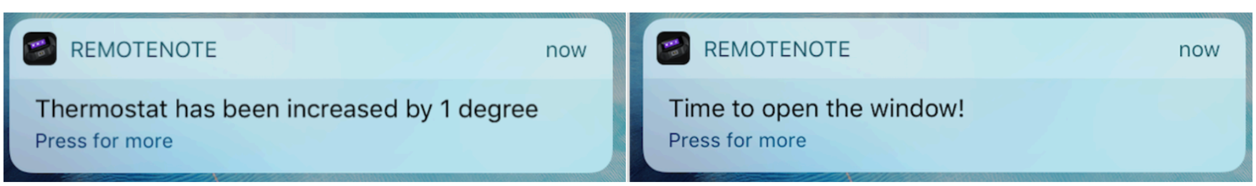

Figure 2-7 Push Notifications for Two Scenarios (left: setpoint is changed; right: time to use natural ventilation)

2.4.2.3 Database, comfort model and control script

MongoDB database is used to store and exchange information. In the database, data are organized into three main collections. "UserInfo" collection manages each user's information (e.g., username, gender). "UserData" collection stores the time-stamped human and environmental data, which are used to develop comfort prediction models. "VoteResult" collection updates users' collective thermal votes in each decision cycle. Each time a new decision cycle starts, this collection will be reset for any future requests to represent users' dynamic preferences.

As thermal preferences are categorical values (e.g., cooler and warmer), we adopted four common classification algorithms including Logistic Regression, K-nearest Neighbor, Support Vector Machine, and Random Forest. Given the data we collected in the case study, Random Forest classifier produces the highest classification accuracy. Therefore, only the result of Random Forest is discussed in the case study section. Random Forest is an ensemble method which classifies an object by averaging a large collection of decision trees and can reduce the overfitting problem originated from decision trees (Breiman 2001).

To quantify thermal comfort levels, we defined the "group comfort score" (denoted as *group_comft* in Table 2-1 and Table 2-2) as "the total number of occupants who are comfortable in current conditions". The intuition of this metric is to find the optimum HVAC strategy that can maximize the overall thermal comfort in a multi-occupancy environment. Previous studies have proposed several approaches to this question. For example, Zhao et al. (2014) implemented a geometrical solution which takes the convex hull of individual complaint regions as the group complaint region. Thus, a comfortable environment should be maintained within the complement set of the group complaint region. However, this approach will fail if the individual hot and cold complaints have a significant overlap (i.e., the comfort state is uncertain in the overlapped region). In another study, Purdon et al. (2013) proposed to directly use the net vote to determine the temperature setpoint. If more votes of a warmer environment are received, then the setpoint is increased by a fixed step and vice versa. However, this approach cannot handle the situation where some occupants do not vote because they feel comfortable in the current condition.

To overcome these limitations, we evaluated each occupant's comfort level by plugging the human and environmental data into the personalized comfort prediction model. If the predicted thermal preference is “neutral”, then this occupant is regarded as comfortable. Otherwise (i.e., “warmer” or “cooler”), this occupant is regarded as uncomfortable. As occupants are more likely to report their uncomfortable states, we assumed that if no feedback is received from an occupant, he/she is considered as comfortable in that period or has reached the comfortable state on his/her own by performing adaptive behaviors (e.g., put on a jacket). Therefore, we divided the typical working hours (from 8 am to 6 pm) into 20 segments with 30 minutes for each interval. This 30-minute decision interval is also supported by Purdon et al. (2013) and Hang-yat and Wang (2013) as occupants may not feel any changes in a shorter duration. If more than one feedback from a single occupant is received in a segment, only the last feedback is considered. This assumption guarantees that the comfort level of occupants with different feedback frequencies can be compared and computed using the same measure.

A control script was developed in Python to continuously execute decision algorithms to enable connections between the cloud data and physical HVAC system. The HVAC control loop includes two algorithms, namely the *Mode Selection Algorithm* and *Collective Decision Algorithm*. The script first executes the *Mode Selection Algorithm* (see Table 2-1) to choose the optimum conditioning mode. In each decision cycle, the *Collective Decision Algorithm* (see Table 2-2) is implemented to evaluate the highest group comfort score (the total number of occupants that are comfortable under the optimum setpoint) that can be achieved in mechanical conditioning mode. Then the *group comfort score* is evaluated again in the natural ventilation mode. The *Mode Selection Algorithm* selects natural ventilation as the optimum conditioning mode if it can produce a higher group comfort score. Otherwise, if mechanical conditioning produces a higher group comfort score in the current situation or the window is non-operable, pure mechanical conditioning is chosen as the optimum strategy and the setpoint will be determined according to Algorithm 2. In this case, ventilation is automatically activated when the indoor CO_2 level is higher than the 1000 ppm threshold specified in industry standard (ASHRAE 2010, Menassa et al. 2013b).

Table 2-1 Algorithm 1 - Pseudocode for the *Mode Selection Algorithm*

```
Algorithm 1 – Pseudo code for mode selection algorithm
Input: user_vote, human_data, envir_data, occupancy
Output: mode (MC – mechanical conditioning, NV – natural ventilation)

for every n minutes do
   if non-operable window
      run Algorithm_2
      break
   end if

   group_comft_NV = 0
   for each occupant
      individual_comft_NV = comft_model(human_data, envir_data, NV)
      // 1- comfortable, 0 – uncomfortable
      group_comft_NV += individual_comft_NV
   end for
   group_comft_MC = run Algorithm_2          // best condition achieved by
MC
   if group_comft_NV >= group_comft_MC
      return Mode_Set(NV)
   else
      return Mode_Set(MC)
   end if
end for
```

Table 2-2 Algorithm 2 - Pseudocode for the *Collective Decision Algorithm*

```
Algorithm 2 – Pseudo code for collective decision algorithm
Input: user_vote, human_data, envir_data, occupancy, set_point
Output: HVAC_Command, group_comft

if CO2 > threshold then
   return HVAC_FanOn()
else
   return HVAC_FanOff()
end if

if occupancy = 1 then      // single occupancy
   return HVAC_TempSet(user_vote)
```

```
else if user_vote < 0 (or if user_vote > 0)
   temp = set_point – 1 (or temp = set_point + 1)
   group_comft_MC = 0
   for each occupant
      individual_comft_MC = comft_model(temp, human_data, envir_data,
MC)
      // 1- comfortable, 0 – uncomfortable
      group_comft_MC += individual_comft_MC
   end for
      if group_comft_MC > ½ occupancy
         HVAC_TempSet(temp)
      else
         HVAC_TempSet(unchanged)
      end if
   reset(user_vote)
   return group_comft_MC
end if
```

2.4.2.4 Programmable thermostat

Unlike other studies which manage the HVAC system through the BACnet protocols (Pang et al. 2012), we adopted a programmable Wi-Fi enabled thermostat (e.g., Nest) and operable window sensors to allow for natural ventilation under certain conditions. By using Nest, we can directly control the HVAC system through the Python script we customized for this study without involving the details of the system (e.g., make, model). This approach requires no retrofits to the existing system, and most importantly, it allows us to develop and test the decision algorithms before accessing the physical HVAC system in a building.

2.4.3 Workflow of the Personalized HVAC Control Framework

The workflow of the proposed HVAC control framework consists of two stages (see Figure 2-8): the learning phase and the operation phase. In the learning phase, machine learning methods (e.g., Random Forest) are adopted to develop comfort prediction models using human and environmental data. In the operation phase, the decision algorithm 1 and 2 are continuously executed to determine the optimum conditioning mode and HVAC setpoint (detailed in Section 2.4.2.3). If natural ventilation is the present optimum strategy, users will be notified to open the window and turn off the HVAC system (if windows are operable). Otherwise, the HVAC system stays in the mechanical conditioning mode and adjusts the setpoint by checking users' recent votes and comfort predictions.

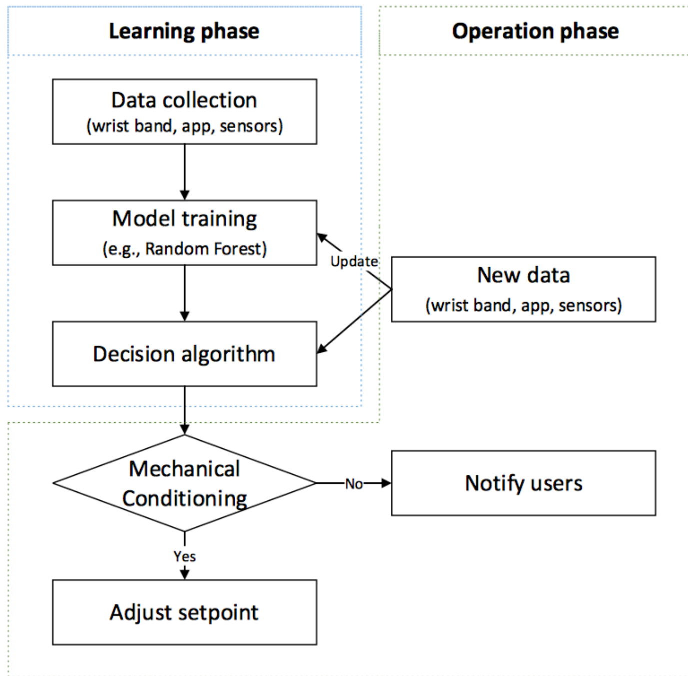

Figure 2-8 Overview of the Workflow

2.5 Case Study

Two case studies were selected to demonstrate the proposed HVAC control framework. The first case study was conducted in single occupancy rooms to demonstrate the framework's capability of determining conditioning mode. The second case study evaluated the HVAC decision algorithm in improving overall comfort in a multi-occupancy space.

2.5.1 Single-occupancy Study

The first case study was conducted in three single-occupancy rooms. The testbeds are regular residential housing units located in Ann Arbor, Michigan. Each room was equipped with operable windows and an individual HVAC unit. All participants have full control over the windows and thermostat. In each room, a set of temperature and CO_2 sensor (Figure 2-9) was installed near the desk to monitor a participant's work area. A contact probe was placed on the window frame to detect the window state. Each participant was assigned a location marker and received instructions on how to use the app and wristband before data collection.

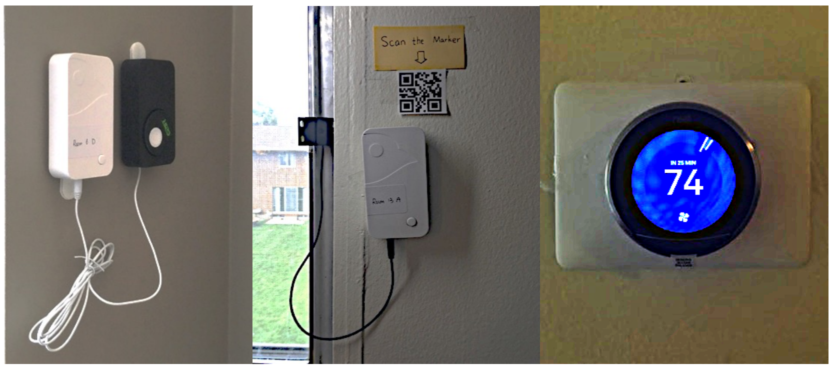

Figure 2-9 Temperature and CO_2 Sensors (left); Location Marker and Window Sensor (middle); Nest Thermostat (right)

The data collection took place during the cooling season from mid-June through July in 2016. The average daily highest and lowest temperatures were 28.9 °C and 16.7 °C respectively. Each participant was asked to provide feedback through the app under two scenarios several times a day: (1) when they feel comfortable with the indoor thermal environment; (2) when they feel uncomfortable and are about to take actions to restore the comfortable state (e.g., close the window, change the thermostat, put on a jacket).

To obtain data in the natural ventilation mode, participants were asked to open the window (also set back the HVAC system) twice per day when outdoor temperatures were acceptable (once in the morning and once in the afternoon). If participants felt uncomfortable in the natural ventilation mode, they were allowed to close the window and switch back to mechanical conditioning (feedback was provided before switching the mode). Otherwise, the indoor environment can stay in natural ventilation until participants no longer felt comfortable.

A sample dataset is shown in Table 2-3 in which the data can be categorized into three groups: (1) participant's thermal preference, which is the target variable that the comfort model will predict; (2) human data, which include clothing level (Clo, which can take L - low, M - medium, H - heavy), heart rate (HR, beats/minute), skin temperature (T_{skin}, °C), activity level (Activity, which can take idling, walking, running); and (3) environmental data, which include room temperature (T_{room}, °C), room humidity (H_{room}, %), CO_2 level (ppm), window state (NV, 0 - close, 1 open), outdoor temperature (T_{out}, °C), and outdoor humidity (H_{out}, %). A total of 271 valid thermal comfort reports were received from the three participants and the frequency of reports for each level is shown in Table 2-4.

Table 2-3 Sample Data Collected in the Learning Phase

Time	Sensation	Preference	Clo	HR	T_{skin}	Activity	T_{room}	H_{room}	CO_2	NV	T_{out}	H_{out}
06-24 17:46	Ok	Neutral	L	60	90	Idling	76	51	622	0	82	65
06-24 19:08	Hot	Cooler	L	60	92	Idling	83	54	585	0	86	72
06-24 20:14	Warm	Cooler	L	57	90	Idling	82	51	708	0	87	63
06-25 09:21	Cool	Neutral	L	70	83	Idling	75	40	1020	0	83	68
06-25 11:35	Warm	Cooler	M	80	88	Walking	77	44	827	0	85	75
06-25 16:18	Cool	Warmer	L	59	89	Idling	75	62	664	1	77	88
06-25 17:02	Ok	Neutral	L	55	89	Idling	76	65	643	1	78	73
06-26 11:37	Warm	Neutral	L	62	87	Walking	78	63	711	1	83	58
06-26 14:35	Hot	Neutral	L	62	93	Idling	81	54	425	1	90	39
06-27 10:27	Warm	Cooler	M	68	91	Idling	77	42	791	0	73	57

Table 2-4 Frequency of Reports for Each Level in the Single Occupancy Testbed (ME – Mechanical conditioning, NV – Natural ventilation)

Subject ID	Number of Data Points for Each Level - ME			Number of Data Points for Each Level - NV		
	Cooler	Neutral	Warmer	Cooler	Neutral	Warmer
1	14	24	11	6	19	6
2	22	11	14	14	19	10
3	14	21	22	16	18	10
Total	50	56	47	36	56	26

A summary of the reported room temperature and skin temperature is shown in Figure 2-10. In this figure, each row represents a participant and the four columns represent a participant's thermal preferences with respect to room temperature in mechanical conditioning, room temperature in natural ventilation, skin temperature in mechanical conditioning, and skin temperature in natural ventilation, respectively. A participant is considered comfortable if his/her preference is neutral. In general, participants tend to have a wider comfortable range in naturally ventilated conditions than in mechanically conditioned spaces. This figure also confirms prior findings that people can have different preferences under the same room temperature which suggests the need for including other factors (such as human factors) when evaluating thermal comfort.

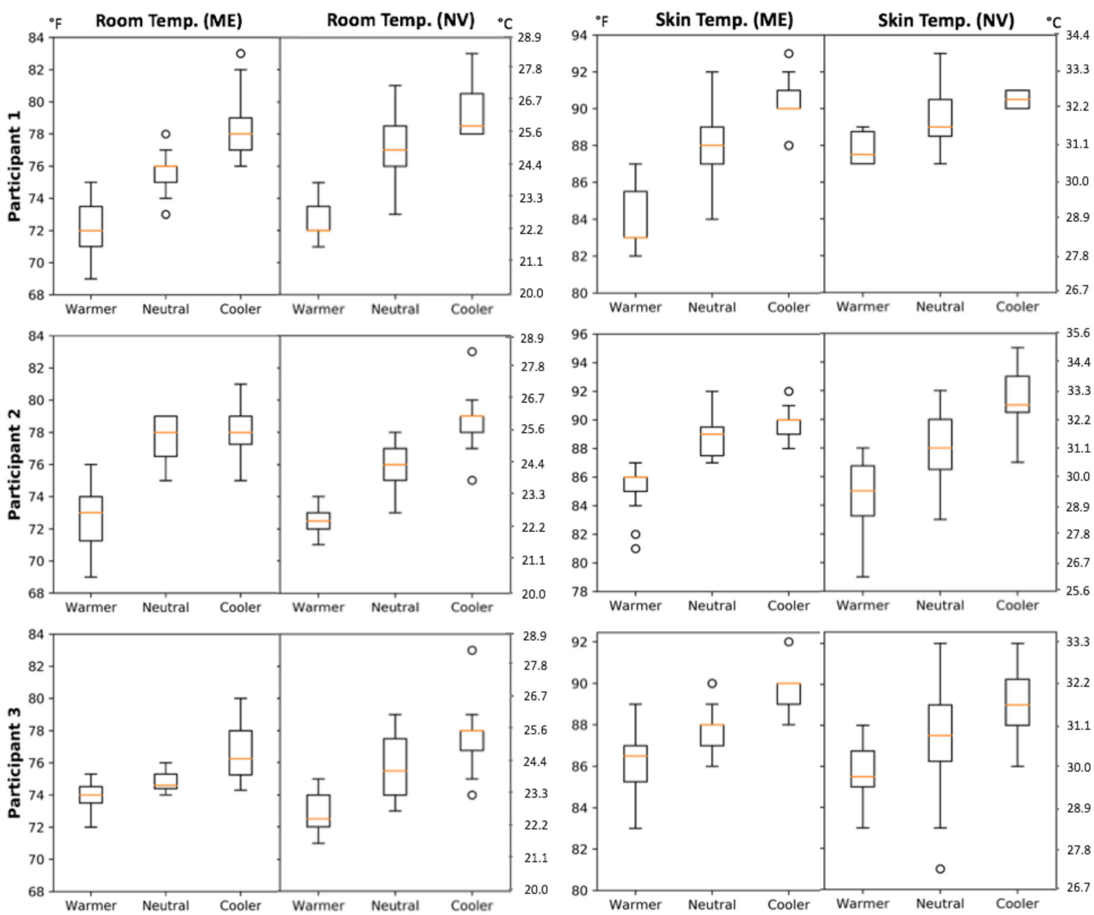

Figure 2-10 Three Participants' Reported Room Temperature and Skin Temperature at Different Thermal Preference Levels

The personalized comfort prediction models were developed using the Random Forest algorithm. Due to the lack of consensus on the appropriate dataset size, parameters were tuned to produce the highest cross-validation accuracy (we adopted the Python Scikit-learn package with the following parameters: *n_estimators* = 1000, *criterion* = “entropy”, *max_depth* = 10). Oversampling of minority classes has been adopted to address the class imbalance problem. Three feature sets were compared: the first feature set only contains environmental data (denoted as “Envir Only”), i.e., room temperature, room humidity, window state, outdoor temperature, and outdoor humidity; the second feature set only contains human data (“Human Only”), i.e., clothing level, heart rate, skin temperature, and activity level; the third feature set contains both environment and human data (“Envir + Human”). The performance of models with different feature sets was compared to determine which feature is influential in the comfort prediction.

Ten-fold cross-validation was performed to evaluate the classification accuracy of three feature sets under six scenarios (see Table **2-5**). The third feature set (“Envir + Human”) performed the best, which can achieve an approximately 80% accuracy in classifying thermal comfort which has three categorical values. Compared to the “Envir Only” and “Human Only” feature sets, the “Envir + Human” set improved the classification accuracy by 24% and 39%, respectively, indicating that integrating both environmental and human data can significantly improve the performance of comfort prediction models.

Table 2-5 Classification Accuracy of Random Forest Classifier with Different Feature Sets

Scenarios	P1 - ME	P1 - NV	P2 - ME	P2 - NV	P3 - ME	P3 - NV
Envir Only	0.595	0.635	0.700	0.654	0.602	0.667
Human Only	0.674	0.540	0.694	0.495	0.506	0.565
Envir + Human	**0.805**	**0.852**	**0.887**	**0.792**	**0.714**	**0.707**

Note: P1, P2, P3 - Participant ID; ME – Mechanical conditioning, NV – Natural ventilation

As participants' reports were continuously collected over time, the comfort prediction model can also evolve as more reports were received. Figure 2-11 shows the classification accuracy with respect to the size of the training data. Each subplot represents the prediction accuracy when 60% up to 100% training data were collected. In this case, the training data was segmented in chronological order to represent the data collected over time. For scenario (1) (2) and (3), classification accuracy improved with the size of the training data, indicating the "learning" ability of the comfort model. For scenario (4) (5) and (6), the accuracy of the whole training set was close to that when 60% of data were used. Overall, with a relatively small dataset (approximately 50 samples), the comfort model can achieve an acceptable classification accuracy. This result suggests that the proposed HVAC control framework does not heavily rely on human inputs and implies its ability to dynamically control the indoor environment without continuous voting from users.

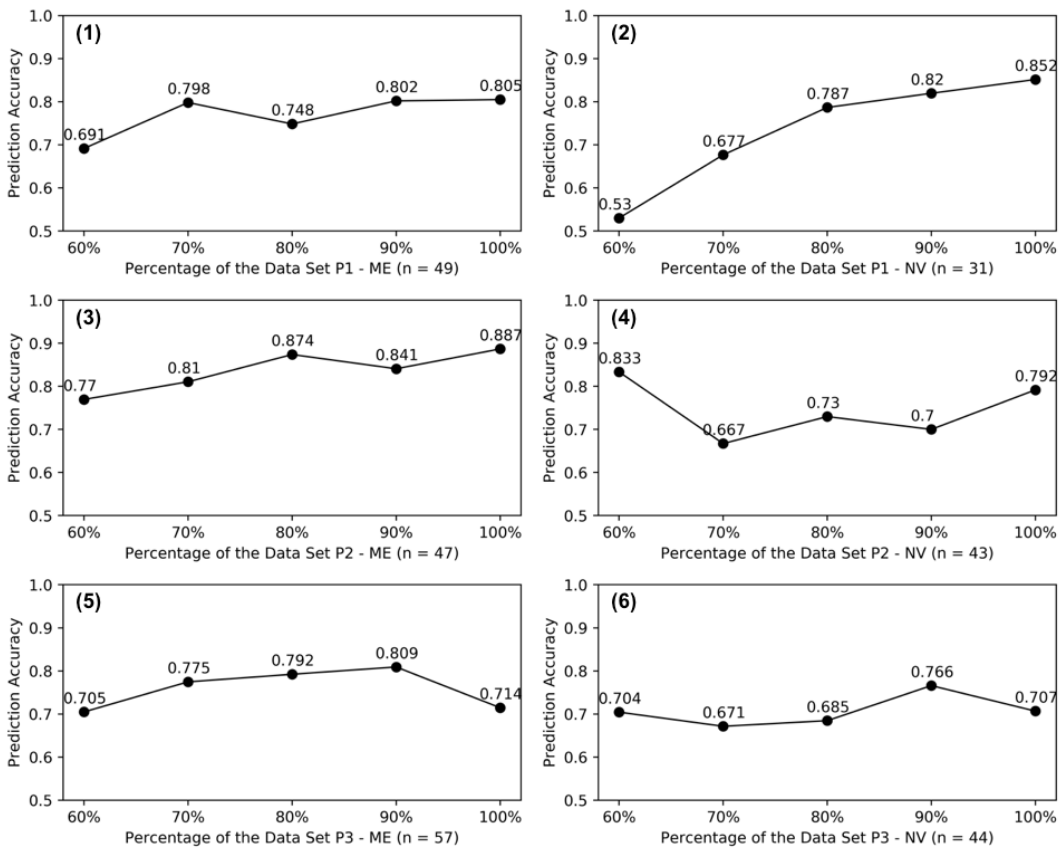

Figure 2-11 Classification Accuracy of Comfort Prediction Models with respect to Data Size (*n* represents the total number of samples in the dataset)

2.5.2 Multi-occupancy Study

Another case study was conducted in an office building located in Madison, Wisconsin which aims to evaluate the HVAC decision algorithm in a multi-occupancy space. The case study was conducted for three weeks from Nov.14th to Dec 2nd, 2016. The case study building has an open office area which accommodates twenty full-time employees (see Figure 2-12). A single programmable thermostat controls the thermal environment of this work area. During the test period, all windows were kept closed and only mechanical conditioning was considered in the decision algorithm.

Figure 2-12 Multi-Occupancy Testbed

Seven participants joined in the data collection and used the app to report their thermal preferences and the corresponding human data. Before data collection, we explained the importance of feedback and encouraged participants to vote multiple times per day. A total of 362 complete reports were collected during the test period and the frequency of reports for each level was presented in Table 2-6. Comfort prediction models were trained and evaluated using the Random Forest algorithm as discussed in the previous section. The classification accuracy of three feature sets (“Envir Only”, “Human Only”, “Envir + Human”) were shown in Table 2-7. Overall, the model can achieve an over 80% accuracy in predicting thermal comfort.

Table 2-6 Frequency of Reports for Each Level in the Multi-Occupancy Testbed

Subject ID	1	2	3	4	5	6	7
Cooler	6	7	10	11	14	9	11
Neutral	21	12	28	34	30	14	14
Warmer	16	28	17	19	23	31	7
Total	43	47	55	64	67	54	32

Table 2-7 Prediction Accuracy of the Seven Participants in the Multi-Occupancy Testbed

Subject ID	1	2	3	4	5	6	7
Envir Only	0.634	0.739	0.655	0.185	0.554	0.529	0.483
Human Only	0.373	0.434	0.601	0.696	0.712	0.679	0.634
Envir + Human	**0.932**	**0.964**	**0.839**	**0.723**	**0.744**	**0.779**	**0.748**

Figure 2-13 to Figure 2-15 show the room temperature and occupant feedback across three weeks. As shown in each figure, the data were trimmed to weekdays from 8 am to 6 pm to represent regular working hours. In each day, the bold black curve represents the room temperature over time. Participants’ thermal preference “Warmer”, “Cooler”, and “Neutral” are marked using vertical red, blue lines, and black dots, respectively. Each line or dot indicates that a participant reports his/her thermal sensation and preference at some point in the day. No reports were collected during November 23 - 25 due to the Thanksgiving holiday. Room temperature in Figure 2-13 to Figure 2-15 can vary by as much as 1.7 °C in a day. The lowest temperature usually occurred in the early morning (8 am) and gradually reached the highest value at around 2 pm. The overlap of red, blue lines and black dots indicate that participants have diverse thermal preferences in a multi-occupancy space of the same environmental condition. The frequent cold and hot reports (i.e., uncomfortable reports) represent a less than satisfied thermal environment.

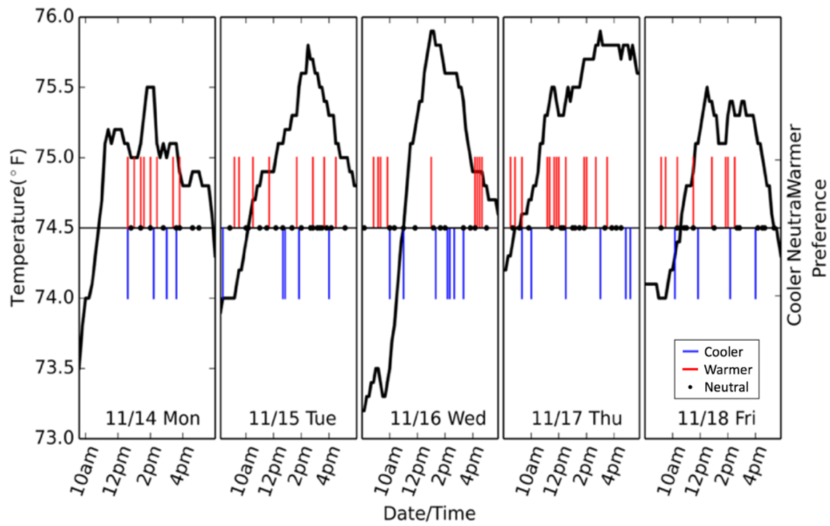

Figure 2-13 Room Temperature and Participants' Thermal Preference in Week 1

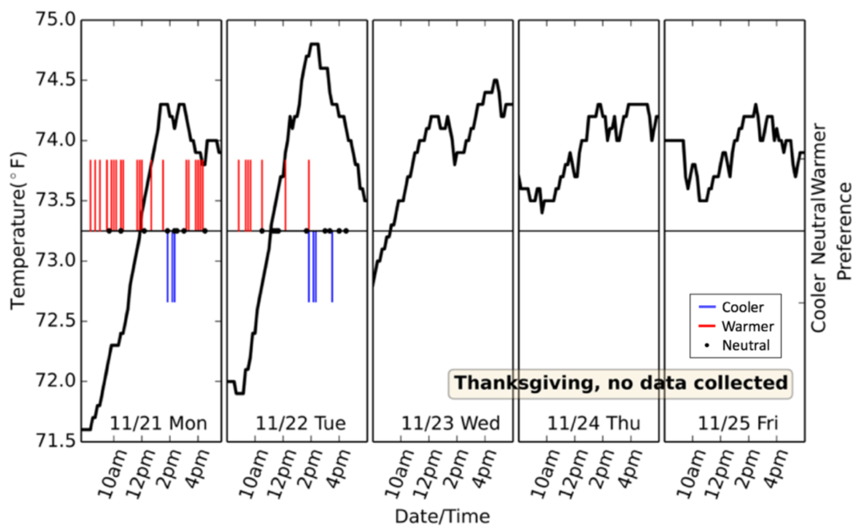

Figure 2-14 Room Temperature and Participants' Thermal Preference in Week 2

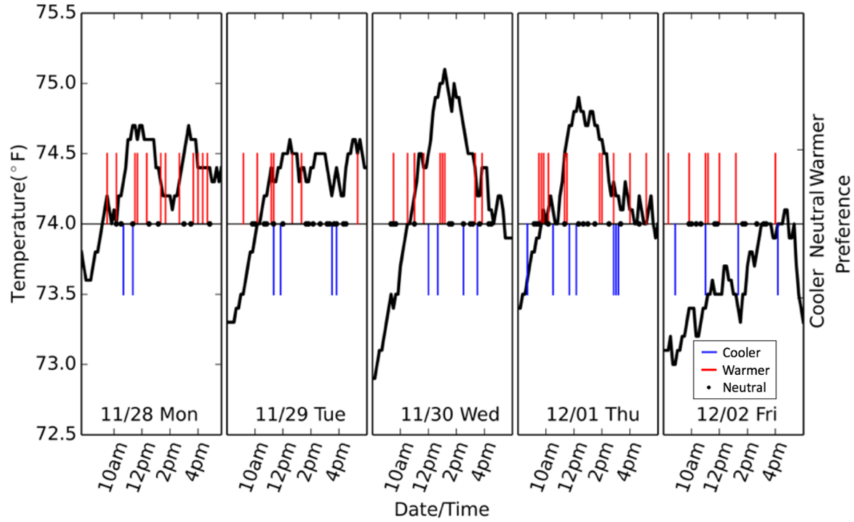

Figure 2-15 Room Temperature and Participants' Thermal Preference in Week 3

By interviewing with the participants, we found several reasons that led to the unsatisfied thermal comfort. For example, participant 5 commented that "*Even though the thermostat is next to my table, I never adjust it when I feel uncomfortable as I don't know if my colleagues have the same feelings as I do*". Participant 6 commented that "*I always feel cold in the room, but I don't know how much I should change the setpoint (if I am allowed to do so) to make me feel comfortable*". Participant 7 commented that "*I think it is a dummy thermostat as nobody ever touches it*". Therefore, to improve thermal comfort in a multi-occupancy space, it is particularly important to engage building occupants in the control loop and enable the adjustment of setpoint based on the evaluation of overall comfort levels instead of the empirical judgment.

Two scenarios were compared to demonstrate the feasibility of our proposed framework in improving thermal comfort (see Table 2-8). The scheduled scenario represents a situation where the setpoint of thermostat follows a predefined fixed schedule (as the multi-occupancy office did in the data collection). The dynamic scenario represents a situation where the Algorithm 2 – *Collective Decision Algorithm* (discussed in Section 2.4.2.3) has been implemented to dynamically adjust the temperature setpoint. In the dynamic environment, the total number of uncomfortable reports (i.e., cooler or warmer reports) were calculated from the personalized comfort models.

Table 2-8 Descriptions of Scheduled and Dynamic Environments

Scenario	Scheduled Environment	Dynamic Environment
Description	The total number of uncomfortable reports of this office is counted from the original reports as shown in Figure 2-13 to Figure 2-15. This scenario represents a scheduled environment where the thermostat setpoint is fixed and no dynamic adjustments are made over time.	The total number of uncomfortable reports of this office is calculated based on the predicted responses after implementing the HVAC decision algorithm. The responses are predicted using each occupant's comfort model when the setpoint is adjusted. This scenario represents an environment where dynamic adjustments are made according to occupants' reports and comfort predictions.

The total number of uncomfortable reports of the scheduled and dynamic scenarios are shown in Figure 2-16. On average, the total number of uncomfortable reports have been reduced by as much as 53.7% after implementing the *Collective Decision Algorithm*, which indicates the improvement of overall thermal comfort in the case study office.

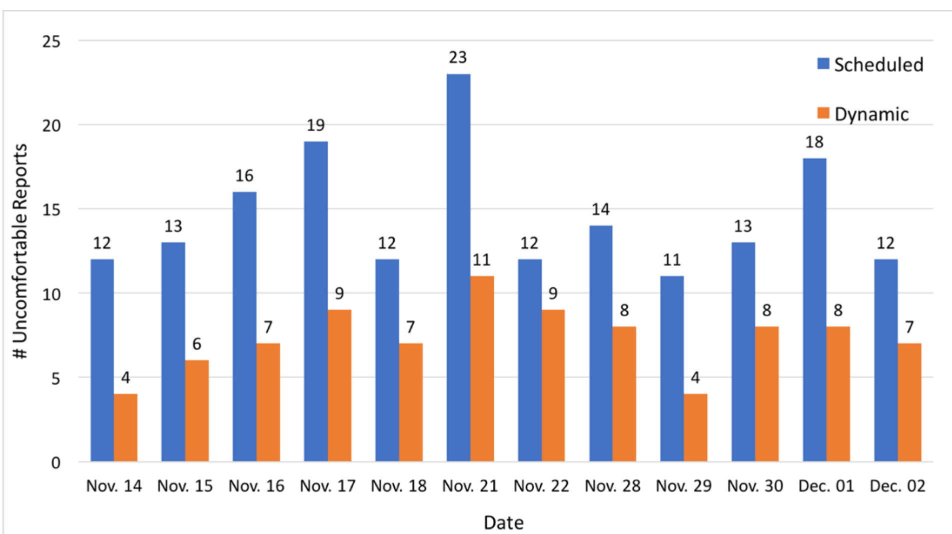

Figure 2-16 Number of Uncomfortable Reports of the Scheduled and Dynamic Environment

2.6 Conclusions

This chapter proposed an HVAC control framework which is capable of determining the optimum room conditioning mode (mechanical conditioning or natural ventilation) and HVAC settings (temperature setpoint) under different environment and human conditions. First, we introduced the major components of the personalized HVAC control framework and demonstrated its operating principles. Then, we discussed how various types of human and environmental data are integrated in the decision loop, the specifications of supporting hardware (wristband, sensors, thermostat) and the development of software (smartphone application, database, control script), as well as two HVAC control algorithms (*Mode Selection Algorithm* and *Collective Decision Algorithm*). Lastly, we demonstrated the prediction accuracy of comfort models developed from the case study and evaluated the overall thermal comfort conditions when implementing the decision algorithm. The main contribution of this chapter is the integration of human physiological and behavioral data in the HVAC control system. These additional human data can significantly improve the accuracy of predicting thermal preferences.

The main conclusions include: First, incorporating human physiological and behavioral measurements in the comfort prediction model can significantly improve its accuracy, which can be implemented in a human-focused HVAC system that dynamically controls the indoor environment. Second, the personal comfort model uses training data collected from each occupant, which accounts for the personal variations in evaluating thermal comfort. The benefits of personal models have also been discussed in later studies such as Kim et al. (2018b) and Jung and Jazizadeh (2019a). In general, personal comfort models demonstrate a better predictive power than the PMV and adaptive comfort models as they are highly customized for each occupant (Kim et al. 2018a). In addition, understanding personal thermal comfort provides insights into designing the HVAC control algorithms to optimize overall comfort in a multi-occupancy setting and also enables personalized comfort zones for each individual (e.g., through local HVAC units). From the energy's perspective, personal comfort models can be incorporated into the building energy models or Agent-Based Models for detailed energy simulation and occupant feedback (e.g., Li et al. 2017c, Thomas et al. 2017 and 2018). Third, using the identified feature set and the Random Forest model, an 80% classification accuracy can be achieved with a relatively small dataset (approximately 50 samples), indicating the reduced dependency on human inputs. Fourth, the results confirm findings from previous studies that occupants can have different thermal preferences in the same environment considering their diverse human factors, as well as the fact that occupants' comfort state can change over time due to factors such as metabolic rate and workload, making a static setpoint unable to satisfy the conflicting and dynamic thermal requirement. As discussed in the case study, the proposed *Collective Decision Algorithm* can reduce the uncomfortable reports by as much as 53.7%. Lastly, room conditioning mode can be determined by evaluating human and environmental factors identified in this chapter. The proposed mode selection capability in the HVAC control framework reveals the potential to reduce energy consumption while maintaining a satisfied indoor environment.

CHAPTER 3

Non-Intrusive Thermal Comfort Interpretation through Infrared Thermography

3.1 Introduction

Chapter 2 presents a personalized HVAC control framework which leverages integrated human and environmental data collected from multiple sources including wristbands, smartphone polling apps, commodity sensors, and weather station. The results suggest that quantitative human data, such as skin temperature and heart rate, can significantly improve the accuracy of thermal comfort prediction. However, a major limitation of this framework is the "intrusiveness" caused by the collection of human data, including: (1) the requirement of wearing wristband sensors and using phone applications which may not always be convenient or feasible in built environments (e.g., strain may arise from wearing wristbands for a long time, phone is not at hand to provide feedback); and (2) the interruption and distraction caused by the feedback mechanism during regular work time, especially over heavy workload periods or in any frustrating situations.

Therefore, in this chapter, our objective is to investigate methods to replace the "user-initiated" passive and cumbersome thermal comfort feedback and control mechanism discussed in the previous chapter with a new "non-intrusive and synchronous" approach that can result in a comfortable, data-driven thermal environment without encumbering any proactive occupant feedback. In particular, we aim to explore the premise that thermal comfort can be measured non-intrusively and reliably in real, operational, multi-occupancy-built environments. This will lead to a better understanding of the intricate characteristics of optimum setpoints given the inferenced individual comfort levels to improve the overall satisfaction of occupant groups.

The hypothesis of the proposed research is that using human facial skin temperature collected from non-intrusive low-cost infrared thermal cameras can achieve a robust prediction of thermal comfort in real-time and offer the possibility for synchronous control of indoor environments with minimal interruption of building occupants. This hypothesis will be tested by conducting research experiments to develop a new thermal comfort prediction method using the continuously collected facial skin temperature data.

The rest of this chapter is organized to first provide a detailed review of existing methods to collect skin temperature and their limitations, followed by the contributions of this chapter. Then, the main challenges of an infrared thermography-based HVAC control framework are introduced in the methodology section, including face detection, feature extraction, data cleaning, and model training and testing. Finally, the results and findings are discussed.

3.2 Related Work

In practice, skin temperature can be measured using thermocouples (Chen et al. 2011, Choi and Loftness 2012, Choi and Yeom 2017, Yao et al. 2007), infrared thermometers (Ghahramani et al. 2016), and commodity infrared thermal cameras (Abouelenien et al. 2016, Burzo et al. 2014a, 2014b, De Oliveira et al. 2007, Metzmacher et al. 2018, Ranjan and Scott 2016).

Among these devices, contact thermocouples are most widely adopted to measure skin temperature due to their high accuracy, low-cost, and easy installation. To interpret thermal sensation and discomfort, existing studies usually attach the thermocouples to a certain body region or multiple body locations and correlate the measured temperature data under different environment settings with the local or overall thermal sensation (Chaudhuri et al. 2018, Choi and

Loftness 2012, Choi and Yeom 2017, Wang et al. 2007, Yao et al. 2007). For example, Chaudhuri et al. (2018) attached thermocouples on the dorsal area of the non-dominant hand and measured skin temperature under different thermal conditions (Figure 3-1). Wang et al. (2007) measured subjects' upper extremity skin temperature, including finger, hand, and forearm (Figure 3-1) using thermocouples and concluded that skin temperature and its gradient of these regions are correlated with the overall body thermal sensation. Similar as the idea introduced in Chapter 2, Liu et al. (2019) applied wristbands (Empatica E4 and Polar V800), chest straps (for heart rate), accelerometers (for activity level), and thermocouples on the ankle area to measure subjects' physiological signals for comfort prediction (Figure 3-2).

However, as discussed earlier, this type of contact data collection method is very intrusive as the electrodes of thermocouples should be directly attached to the skin surface. This drawback limits its applicability in operational residential or office environments as it is not feasible to equip all building occupants with contact thermocouples or other wearables without interfering with their activities.

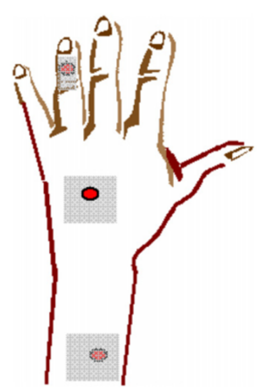

Figure 3-1 (left) Thermocouple Attached on the Dorsal Area (adapted from Chaudhuri et al. 2018); (right) Thermocouple Locations of the Upper Extremity (adapted from Wang et al. 2007)

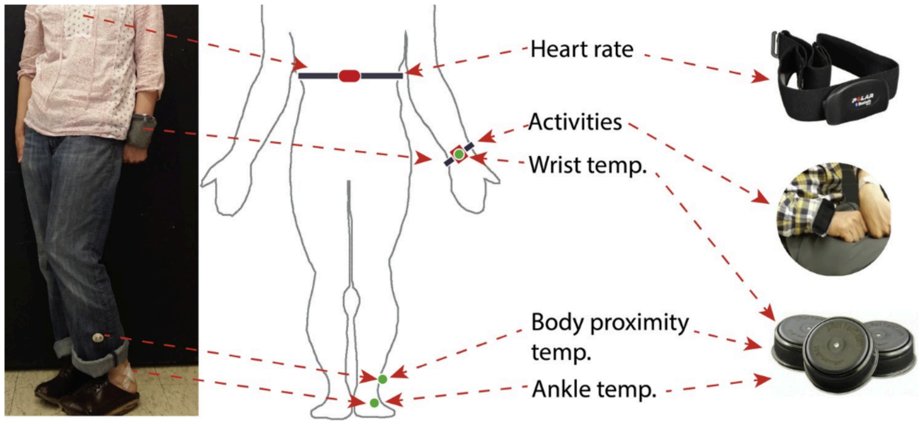

Figure 3-2 Wearable Sensors and Their Locations (adapted from Liu et al. 2019)

An infrared thermometer is a low-cost temperature sensor that can provide a non-contact measurement of skin temperature. However, in order to get an acceptable skin temperature measurement, infrared thermometers need to be placed close to the skin surface usually within a few centimeters. This is due to the fact that its field-of-view (FOV) becomes increasingly large as it moves away from the target. For example, Ghahramani et al. (2016) installed four MLX90614 infrared thermometers on an eyeglass frame to collect a subject's skin temperature of the front face, cheekbone, nose, and ear (Figure 3-3). The infrared thermometer adopted in this study has a FOV of 90° and thus for every 1 cm away from the subject, the sensing area grows by 2 cm (Sparkfun 2016), which makes the eyeglass frame an ideal (and possibly the only feasible) location to place the sensors. This study observed significant variations in skin temperature under cold and heat stresses. However, this approach has two major limitations: (1) due to its limited working range, infrared thermometers can only measure a fixed predetermined set of locations. It is unknown whether these selected sensing points are the most significant locations to measure skin temperature; and more importantly (2) this approach is not suitable in a real operational or multi-occupancy environment as it requires each occupant to wear such devices, which can be inconvenient and lacks scalability in a large space with multiple occupants such as a lounge or a conference room.

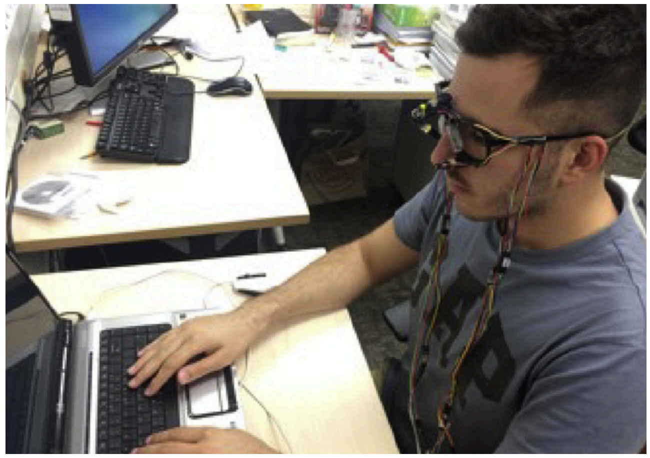

Figure 3-3 Eyeglass Frame with Infrared Thermometers (adapted from Ghahramani et al. 2016)

Using thermographic cameras, also known as thermal cameras, is an alternative way to collect skin temperature data without contacting the object. Thermal cameras have a longer and more flexible working range but usually suffer from a relatively lower accuracy compared to thermocouples and infrared thermometers (Table 3-1). However, they are able to provide a full image frame of radiometric measurements from which the users can get the temperature reading of each pixel location. Prior studies such as Abouelenien et al. (2016), Burzo et al. (2014a, 2014b), De Oliveira et al. (2007), Ranjan and Scott (2016) have used commodity thermal cameras (Figure 3-4) to collect skin temperature and correlated it with thermal sensations using different statistical methods. A recent study by Metzmacher et al. (2018) used Microsoft Kinect and a dynamically calibrated commodity thermal camera to track human faces and measure the skin temperature of different facial regions. The temperature measurements from the thermal camera were validated using a reference sensor which was attached to the skin.

Figure 3-4 Thermal Camera Models[2]: (a) FLIR A40; (b) FLIR A655sc; (c) FLIR SC6700; (d) FLIR A35; (e) FLIR T450sc; (f) FLIR Lepton 2.5

Table 3-1 Comparison of Skin Temperature Measurement Devices in Existing Studies[3]

Studies	Device	Accuracy	Resolution	Cost
Chen et al. 2011	Corte DermaLab System*	±0.2 °C	-	~$1,200
Choi and Yeom 2017	STS-BTA Surface temperature sensor*	±0.2°C at 0°C, ±0.5°C at 100°C	-	~$250 (including the hub)
Ghahramani et al. 2016	MLX90614 infrared thermometer*	±0.5°C	-	~$150 (including the Arduino)
Burzo et al. 2014a	FLIR Thermovision A40	±2°C or ±2% of Reading	320 × 240	~$6,000
Ranjan and Scott 2016	FLIR A655sc thermographic camera	±2°C or ±2% of Reading	640 × 480	~$22,000
Abouelenien et al. 2016	FLIR SC6700 thermal camera	±2°C or ±2% of Reading	640 × 512	~$15,000
Metzmacher et al. 2018	FLIR A35 thermographic camera	±5°C or ±5% of Reading	320 × 256	~$5,000
Reference Camera in Section 3.4.2.2	FLIR T450sc	±2°C or ±2% of Reading	320 × 240	~$15,000

[2] Images are collected from www.flir.com
[3] Some thermal camera models are discontinued, their costs are an estimation of the market price.

This chapter	**FLIR Lepton 2.5**	**±5°C or ±5% of Reading**	**80 × 60**	**~$200 for camera**

* denotes the intrusive data collection method

However, three significant limitations of these aforementioned studies using thermal cameras should be acknowledged: (1) the thermal camera is used as an independent tool to measure human skin temperature which is then analyzed offline in a disconnected way, rather than a built-in component of the building automation system or HVAC systems which can dynamically monitor the indoor thermal environment; (2) as these works are more exploratory studies, thermal cameras are required to be placed directly in front of the subject, usually within a fixed distance. Again, this significantly limits the applicability of thermal cameras in the real operational settings as occupants can move around at will; and (3) the commodity thermal cameras are cost-prohibitive (in excess of $5,000, see Table 3-1) and not suitable for large scale applications. It is still unknown whether low-cost thermal cameras (at the cost of accuracy) can be used for thermal comfort assessment which this chapter aims to investigate.

3.3 Contributions

In recent years, thanks to the advancements in infrared thermography, low-cost thermal cameras are available in the market and offer an ideal approach due to their capability to non-intrusively capture infrared signals emitted from the human body, their affordable price and compact size, ease of installation, and preservation of occupants' privacy. To overcome the research gaps identified in the existing body of knowledge, this chapter explores a non-intrusive and scalable framework which leverages low-cost thermal cameras to predict human thermal comfort preferences in various settings in real-time. The specific contributions of this chapter include:

- Evaluate the feasibly of using a low-cost thermal camera to collect facial skin temperature and predict thermal comfort.
- Demonstrate how to detect different regions of interest in the thermal image and process the raw skin temperature extracted from each region.
- Identify significant facial skin temperature features for comfort prediction.
- Develop a thermal comfort dataset consisting of facial thermal images, corresponding thermal sensations and preferences, and ambient room conditions to enable benchmarking of new methods in the future.

3.4 Methodology

This chapter leverages a range of techniques to develop an integrated framework for comfort assessment using low-cost and off-the-shelf thermal cameras. These techniques include (1) computer vision (e.g., Haar cascade object detection) to detect human face and extract region of interest (ROI); (2) statistical methods to clean and analyze the raw skin temperature data (e.g., smoothing); and (3) machine learning methods to develop personalized comfort prediction models and analyze significant facial skin temperature features (e.g., the Random Forest classifier). An overview of the operating principle of the proposed non-intrusive thermal comfort assessment framework is shown in Figure 3-5. In this framework, facial skin temperature is selected as the targeted bio-signal. Human faces have a higher density of blood vessels than other skin surfaces, leading to a larger skin temperature variation when the condition of the human body or ambient environment changes (Taylor 1997). As a result, facial skin temperature can be used as a physiological indicator of an individual's overall thermal comfort (Ghahramani et al. 2016, Yi and Choi 2015). Second, human faces are not covered by clothing and thus the emitted infrared energy can be directly measured by the thermal camera. In addition, human faces allow the computer vision algorithms to detect and locate ROIs in the image frame for data analysis.

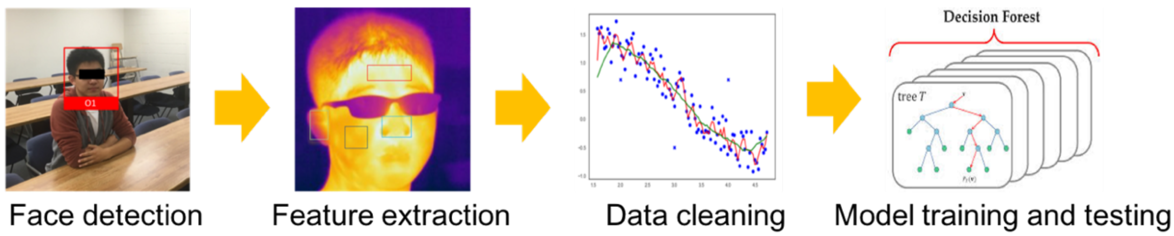

Figure 3-5 Overview of the Non-Intrusive Thermal Comfort Interpretation Framework

The remaining methodology section is organized to first introduce the sensors and devices adopted in this chapter. Second, how computer vision is applied to extract skin temperature of the ROIs is explained. Finally, the data collection experiment is presented in detail.

3.4.1 Low-Cost Thermal Camera

In this study, the FLIR Lepton 2.5 radiometric thermal camera core is used to collect skin temperature data (Figure 3-6). FLIR Lepton 2.5 is an uncooled long-wave infrared thermal imaging core with a factory-calibrated temperature value. As a result, no ad-hoc radiometric calibration is conducted, but a comparative experiment against a high-end FLIR T450SC model is performed to evaluate its measurement accuracy (see Section 3.4.2.2). Relevant specifications of Lepton 2.5 can be found in Table 3-2 (FLIR 2014).

Figure 3-6 Thermal Image Taken by the FLIR Lepton 2.5 Radiometric Thermal Camera

Table 3-2 Specifications of FLIR Lepton 2.5

Features	Descriptions
Dimensions	8.5 x 11.7 x 5.6 mm
Resolution	80(h) x 60(v) pixels
Thermal sensitivity	< 50 mK
Accuracy	±5 ˚C or ±5% of reading in the working range
Price	$199

As a low-cost thermal camera, the radiometric accuracy of Lepton 2.5 is relatively low in its full operational temperature range (-10 °C to 65 °C) compared to the high-end models or thermocouples. However, its feasibility is still worth investigation due to four reasons: (1) the actual radiometric accuracy can be higher than the nominal accuracy shown in Table 3-2 (± 5% of reading) as the measuring objects are human faces whose surface temperatures are not high (approximately 35 °C); (2) the room temperature of the experiment is set between 22 °C and 28 °C to represent a typical indoor environment rather than the full operational temperature range of the camera. As a result, the impact of environmental temperature variations on the measurement accuracy should be low (FLIR 2014); (3) continuous thermal videos rather than a single image frame are obtained to extract skin temperature. The random measurement errors can follow a Gaussian distribution and thus it is possible to reduce the error to an acceptable level for comfort interpretation by removing outliers and averaging multiple image frames; and (4) our objective is to predict a three-point thermal preference, i.e., warmer, neutral, and cooler. This is considered a classification problem rather than a regression problem which calculates a seven-point scale thermal sensation (e.g., Zhang et al. 2010). Therefore, the problem setting is more robust to the error of measurements. For example, an error of 0.5 °C might lead to a prediction error between slightly warm (+1) and warm sensations (+2); however, this error is acceptable since both are categorized into “preferring a cooler environment”. In addition, the three-point preference prediction should not be considered as a limitation as the control system can dynamically determine whether to increase or decrease the setpoint by continuously predicting one’s preferences and adjusting the ambient thermal environment.

To evaluate the radiometric accuracy of the low-cost Lepton 2.5, we conduct a comparative experiment using a FLIR T450SC thermal camera (accuracy: ±2 °C or ±2% of reading[4], approximate cost: $15,000). Facial skin temperature measurements from these two cameras (i.e., FLIR Lepton 2.5 and FLIR T450SC) are compared to evaluate the accuracy of the proposed device before conducting the following data collection experiment. Details about the comparative validation can be found in Section 3.4.2.2.

3.4.2 Face Detection and Skin Temperature Feature Extraction

To extract skin temperature features, the contour of human faces and the interested facial regions are first detected in each thermal image frame. The temperature measurements of each identified region are then extracted and processed to produce the skin temperature features, which are validated in the comparative study.

3.4.2.1 Face detection from the thermal image

Although Lepton 2.5 has a lower resolution (80 by 60), the outline of the regions of interest (e.g., forehead, nose, cheeks) are clearly preserved in the thermal image (see Figure 3-6, which was taken from 1 meter away to represent a non-intrusive distance), which makes the Haar Cascade algorithm suitable for this task. Haar Cascade is a fast and effective algorithm for frontal and profile face recognition by detecting the existence of certain characteristics in the image, such as

[4] FLIR T450SC can achieve better accuracy of ±1 °C or ±1% of reading in a limited range, see https://www.flirmedia.com/MMC/THG/Brochures/RND_059/RND_059_US.pdf

edges or changes in texture (Viola and Jones 2001). In this study, the Haar Cascade algorithm was applied to detect the existence of the facial contour, the eyes, and the nose using the OpenCV package (OpenCV 2.4.13.7). Other regions such as forehead, cheeks, ears, mouth, and neck were inferenced from their relative locations (facial geometry) to the already known regions (i.e., facial contour, eyes, and nose can help identify the location of the cheeks) during the runtime. These ROIs were selected based on prior studies such as Ghahramani (2016), Metzmacher et al. (2018), and Yi and Choi (2015). The size and location of each inferenced ROI were tuned on several subjects prior to data collection experiments to ensure the algorithm can correctly detect all features across different subjects. The measurements of each pixel located within the identified ROI were averaged to represent the corresponding skin temperature of each facial region (as shown in Figure 3-7). In each ROI, pixel values that exceeded certain thresholds (e.g., below 28 °C or above 38 °C based on the preliminary results) were filtered out as they were likely to be the background or noise, which can interfere the measurements of skin temperature features. For example, a close-by light bulb might be detected in the ROIs on faces. If not removed, the resulting high measurements can lead to a wrong prediction that the subject is too warm. Using this approach, we extracted a total of 26 facial skin temperature features, including the maximum measurement of the human face and its gradient, as well as the maximum, minimum, mean, and gradient temperature of six facial regions (i.e., forehead, nose, cheeks, ears, mouth, and neck). For the gradient temperature, the mean gradient over a five-minute period (e.g., Chaudhuri et al. 2018) was calculated using Eq. 3.1 and Eq. 3.2.

$$\nabla T_i = \frac{(T_c - T_{c-i})}{i}, \;\; i = \{1, 2, 3, 4, 5\} \tag{3.1}$$

$$\overline{\nabla T} = \frac{1}{5} \sum_{i=1}^{5} \nabla T_i \tag{3.2}$$

Where ∇T_i is the gradient temperature for time interval i; T_c is the temperature measurement at time c; $\overline{\nabla T}$ is the mean gradient temperature over five minutes which is selected as a feature.

After extracting the skin temperature of the six facial regions from each frame, the thermal image is immediately discarded to alleviate the privacy concerns.

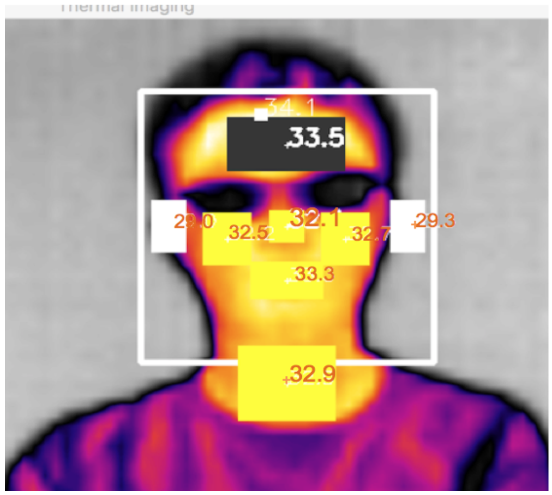

Figure 3-7 Detection of ROIs and Extraction of Temperature (for demonstration purpose, each region was highlighted in a solid rectangle)

Based on our preliminary experiments, this approach can successfully perform face detection within a camera distance of 2 meters, which is a reasonable non-intrusive distance as the thermal cameras can be mounted on the wall or a desktop in front of the users at this distance. If thermal cameras are placed further away from the subject, this approach may fail as the edges on the human face are blurred in the thermal images. To overcome this limitation, we have explored the RGB camera guided feature extraction (introduced in Chapter 4), which can achieve a robust detection of ROIs from a further distance. The results were promising but beyond the scope of this chapter.

3.4.2.2 Preliminary Accuracy Evaluation of the Low-cost Thermal Camera

As mentioned earlier in Section 3.4.1, to evaluate the accuracy of the proposed low-cost Lepton 2.5, comparative experiments were conducted in a climate chamber under three experimental conditions, i.e., cooling from 28 °C to 22 °C, heating from 22 °C to 28 °C, and steady-state condition at 25 °C. Each experiment lasted for 40 minutes and a thermal image was taken by the reference FLIR T450SC camera every 5 minutes. Each ROI in the reference image was labeled using the FLIR ResearchIR software (see Figure 3-8) which provides the mean measurement in each selected region (after removing the outliers). On the other hand, the Lepton 2.5 camera was placed at 1 meter from the participant.

We compared the reference measurements from the FLIR T450SC with the temperature retrieved from Lepton 2.5 (discussed in Section 3.4.2.1). The results showed that in most cases the differences between the two cameras were within 1 °C. A few examples of the steady-state experiment were presented in Figure 3-9. However, it should be noted that this comparison was a sanity test of the face detection and skin temperature extraction approach as discussed in Section 3.4.2.1. The temperature deviations highly depend on how each region was labeled in the ResearchIR software. For example, the forehead region in Figure 3-7 is larger and contains some low temperature pixels (e.g., the eyebrows and pixels close to hairs) compared to the corresponding region in Figure 3-8, which can be a major reason of the large difference (about 1 °C). However, the nose region in the two images look identical and the difference can be as low as 0.2 - 0.3 °C, which is acceptable given it results from a low-cost camera.

Figure 3-8 Reference Thermal Image Taken by FLIR T450SC (colored boxes represent the manually labeled ROI)

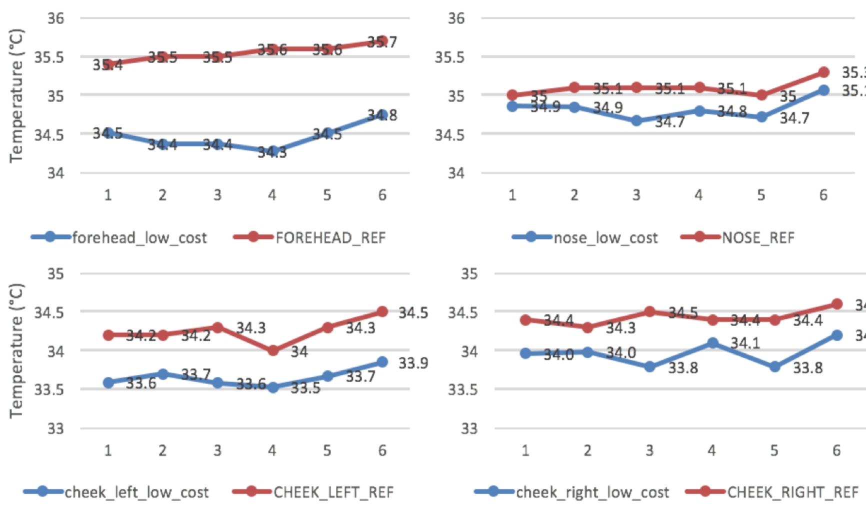

Figure 3-9 Comparison of the Low-Cost Camera with the Reference Camera

3.4.3 Data Collection Experiments

We designed an experiment to collect skin temperature data and the participants' corresponding thermal responses under three thermal conditions. The data collection experiment was conducted in a research office at the University of Michigan (UM) during the heating season from December 2017 to February 2018. During this period, the average high and low outdoor temperature was 1.6 °C and -6.7 °C, correspondingly. The data collection experiment has been approved by UM Institutional Review Board (IRB) for conducting human subjects research.

In the testbed office, one thermal camera was placed at 1 meter away from the subject which monitors the frontal face (see Figure 3-10). The testbed office had two COZIR temperature and humidity sensors (humidity accuracy: ±5%; temperature accuracy: ±1 °C) to continuously monitor the ambient conditions within the close proximity to the subject during the experiment. The two sensors were placed at the waist level (0.65 meters above the floor) which is close to the specified height of 0.6 meters for seated occupants in ASHRAE standards 55 (ASHRAE 55-2010). The testbed also had a thermostat by which the research team can freely change the indoor temperature from 20 °C to 28 °C. In the experiments, the room temperature was set between 22 °C and 28 °C, which conforms to typical indoor conditions controlled by the mechanical HVAC system (ASHRAE 55-2010).

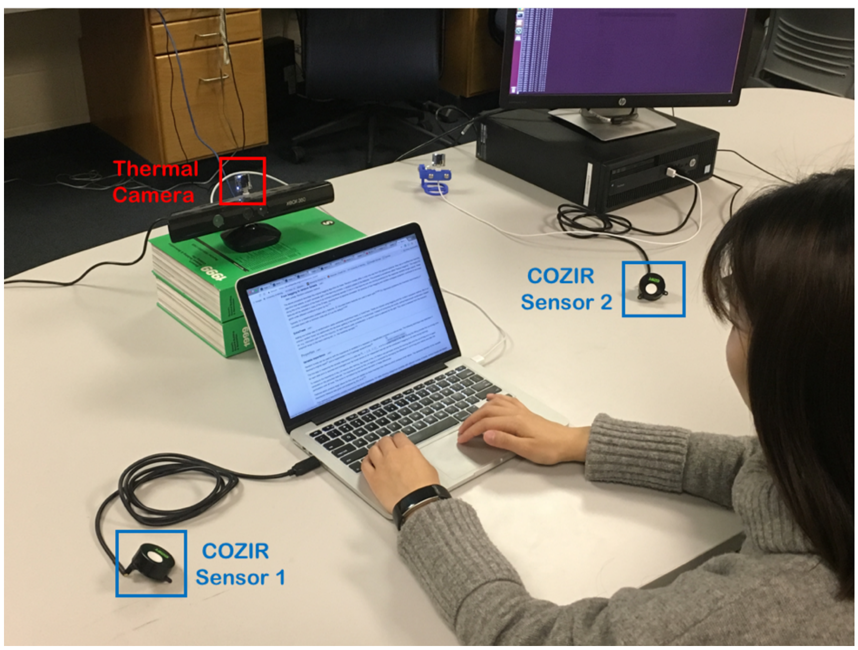

Figure 3-10 Experiment Setup

Each subject in this experiment was assigned a reference ID number for data storage and analysis. The subjects were all students from UM aged between 22 and 27 and were healthy at the time of the data collection. Subjects were asked to wear a sweatshirt and pants and keep the same clothes during the experiment as outlined in Figure 3-11. The experiment started by an interview to understand the subject's interpretation of thermal comfort (e.g., when you feel cold, do you focus on overall body sensation or the sensation of specific body parts?). Introductions about the devices, research objectives, and other related information have been provided to help subjects understand this study. Then, each subject completed an experiment consisting of four phases (see Figure 3-11). In the preparation phase, subjects were provided with a designated phone app to provide feedback about their thermal sensations (-2 to 2 for cold to hot) and preferences (i.e., warmer, cooler, neutral) (see Figure 3-12).

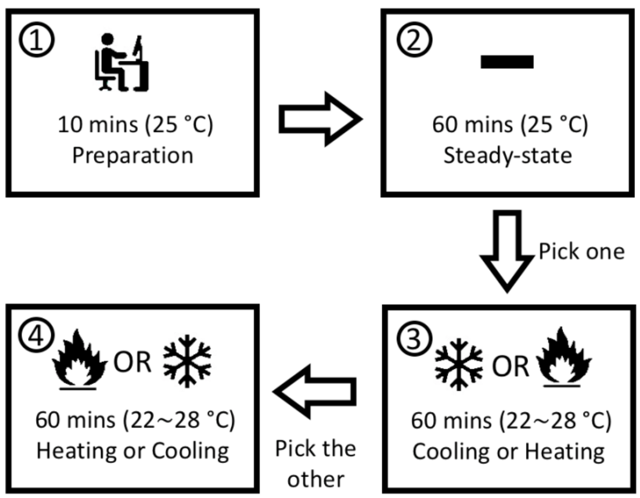

Figure 3-11 Timeline of the Data Collection Experiment

Figure 3-12 Interface of the Phone App to Collect Feedback

During the whole data collection experiment, subjects were asked to use the phone app to provide thermal feedback every three minutes, which will then be used to develop and evaluate comfort prediction models. At the same time, the facial skin temperature and environmental conditions were continuously monitored and uploaded to the database. In the 60-min steady-state phase, subjects were asked to perform daily office activities such as reading, typing, or browsing. In this phase, the room temperature was maintained at 25 °C to represent a neutral steady-state condition. Next, the cold stress or heat stress phase started in random order. In the 60-min heat stress phase, the room temperature was increased from 22 °C to 28 °C while for the cold stress phase, the room temperature was decreased from 28 °C to 22 °C. The two environment sensors showed that in both phases the room temperature was approximately changed in a linear manner with time (at a rate of ±1°C per 10 minutes). It is worth noting that subjects were not informed about the state of the experiment (cooling or heating) to eliminate potential bias towards thermal sensation. For example, if a subject knows the current room temperature is decreasing, he/she may unconsciously think he/she is getting cold.

3.5 Results

3.5.1 Data Cleaning and Processing

In the proposed approach, the measurement errors of skin temperature mainly came from three sources: (1) the thermal camera's systematic error caused by the temporal drift which accumulates over time (FLIR 2014). For example, thermal images appear blotchy due to the degrade uniformity which affects the radiometric accuracy; (2) random experiment error which may vary from one observation to another. For example, hands are detected as the mouth region when subjects drink water during the experiment, which corresponds to a spike in the raw data; and (3) random measurement error of the thermal camera which is assumed to follow a Gaussian distribution with a zero mean. For the camera's systematic error, Lepton 2.5 automatically performs a flat-field correction (FFC) every three minutes to compensate for the drift effect. During FFC, the camera closes its shutter and recalibrates the sensor based on a uniform thermal scene. For the other two random errors, we first averaged the image frames captured in each minute and removed outliers by checking the difference between adjacent measurements using Eq. 3.3.

$$d_i = \begin{cases} outlier, & if\ d_i - d_{i-1} \geq 3\sigma \\ not\ an\ outlier, & otherwise \end{cases} \tag{3.3}$$

Where d_i and d_{i-1} are the data collected at time i and $i-1$, and σ is the standard deviation of data collected from time 0 till time i. After removing the outliers, a Gaussian filter was applied to smooth the raw data. Different widths of the Gaussian filter have been compared (width = 5, 7 and 10). Considering the duration of the experiment, we chose the filter width to be 7 as it smoothed the data well and also preserved the trend of measurements. For example, Figure 3-13 shows a subject's maximum facial skin temperature in three phases (i.e., heating, cooling, steady-state) where the dashed lines represent the raw data collected directly from the thermal camera and the thick solid lines represent the processed data after removing outliers and smoothing. Through data processing, large measurement errors are removed before applying further analysis. In addition, it is easy to observe the increasing and decreasing trend of skin temperature in the heating and cooling phases while the measurements are relatively stable in the steady-state phase, which indicates that useful information is well preserved after the processing step.

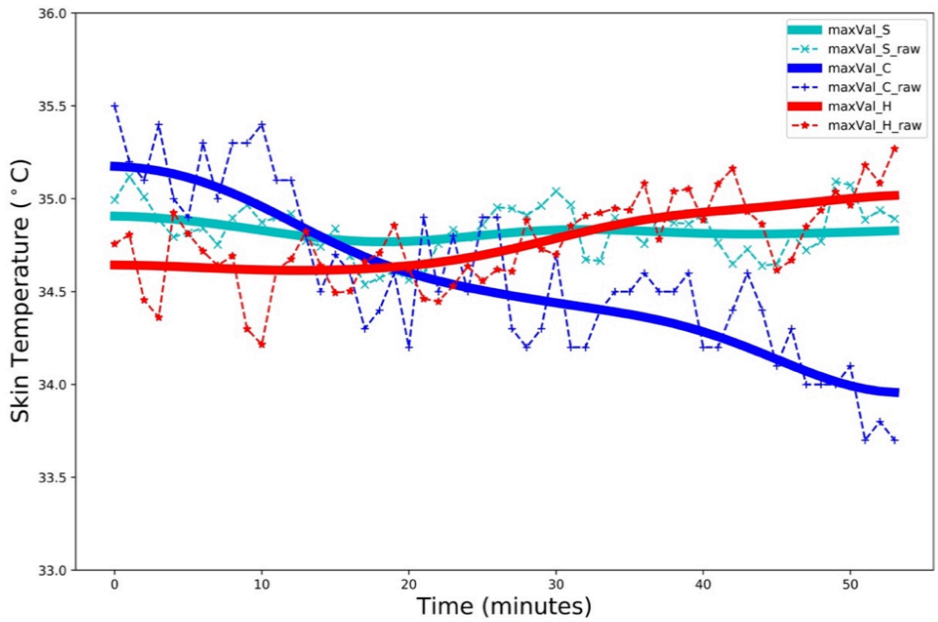

Figure 3-13 Raw and Processed Maximum Skin Temperature of a Subject in Three Phases (S: steady-state; C: cooling; H: heating)

3.5.2 Correlation Analysis between Identified Regions

A total of 12 subjects (7 males and 5 females) participated in the data collection experiments. The environmental conditions of the three phases were summarized in Table 3-3. As shown in the table, room temperature in the steady-state phase was maintained at around 25 °C with a standard deviation of ± 0.2 °C, which was close to the mean temperature of cooling and heating phases. Skin moisture level has been suggested to influence the emissivity of the skin surface, which affects the accuracy of temperature measurements (FLIR 2016). However, we did not observe obvious and excessive sweating for any subject at the high room temperature (around 28 °C), suggesting the emissivity can be assumed consistent in the experiment given the insignificant changes in skin moisture level. This is supported by the work of Owda et al. (2017) which compared the emissivity of wet skin sample (taken from a human cadaver and rinsed in water) and dry samples (dried for 4.0 hours prior to measurements). Table 3-4 shows a summary of skin temperature feature statistics in the three phases. The mean and standard deviation (SD) of each feature were calculated using Eq. 3.4 and Eq. 3.5.

$$\bar{\mu} = \frac{1}{n}\sum_{k=1}^{n} \mu_k, \quad SD(\bar{\mu}) = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(\mu_k - \bar{\mu})^2} \tag{3.4}$$

$$\bar{s} = \frac{1}{n}\sum_{k=1}^{n} s_k, \quad SD(\bar{s}) = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(s_k - \bar{s})^2} \tag{3.5}$$

Where $\bar{\mu}$ and $SD(\bar{\mu})$ are the mean and standard deviation of skin temperature of all subjects in a particular phase; $\bar{s}$ and $SD(\bar{s})$ are the mean and standard deviation of the sample standard deviation; n is the number of subjects which is 12 in this study.

Table 3-3 Summary of Environmental Conditions in Three Phases

	Cooling			Heating			Steady-State		
	Range	Mean	S.D.	Range	Mean	S.D.	Range	Mean	S.D.
T (°C)	27.5 - 22.6	25.1	1.4	22.5 - 27.7	25.3	1.5	24.5 - 25.2	24.8	0.2
RH (%)	20.2 - 33.4	27.7	3.6	32.5 - 21.4	25.8	2.2	20.6 - 26.5	23.2	0.5

In the heating and cooling phases, subjects in general demonstrated all three thermal preferences at different times of the experiment. For example, in the heating phase, a subject may initially prefer a warmer environment as the room temperature starts from 22 °C; gradually he/she feels thermally neutral as the room temperature increases; and finally, he/she may prefer a cooler environment as the room temperature exceeds the comfortable range. However, as the room temperature is controlled at a constant level in the steady-state phase, subjects usually have the same preference throughout this phase.

Table 3-4 Statistics of Skin Temperature Features in Three Phases

Features	Cooling		Heating		Steady-State	
	$\bar{\mu} \pm SD(\bar{\mu})$ (1)	$\bar{s} \pm SD(\bar{s})$ (2)	$\bar{\mu} \pm SD(\bar{\mu})$ (3)	$\bar{s} \pm SD(\bar{s})$ (4)	$\bar{\mu} \pm SD(\bar{\mu})$ (5)	$\bar{s} \pm SD(\bar{s})$ (6)
maxVal	**34.38 ± 0.84**	**0.31 ± 0.11**	**34.17 ± 0.93**	**0.12 ± 0.04**	**34.52 ± 0.62**	**0.08 ± 0.03**
∇maxVal	-.016 ± .005	.013 ± .006	.004 ± .003	.009 ± .002	-.003 ± .003	.006 ± .003
forehead_avg	**33.55 ± 0.92**	**0.34 ± 0.15**	**33.02 ± 1.50**	**0.19 ± 0.11**	**33.77 ± 0.73**	**0.07 ± 0.02**
forehead_max	34.17 ± 0.86	0.33 ± 0.13	34.01 ± 1.08	0.13 ± 0.05	34.49 ± 0.62	0.09 ± 0.03
forehead_min	30.05 ± 0.72	0.44 ± 0.25	29.58 ± 0.48	0.20 ± 0.17	30.16 ± 0.71	0.10 ± 0.09
∇forehead	-.018 ± .007	.013 ± .005	.006 ± .009	.010 ± .002	-.002 ± .002	.006 ± .003

nose_avg	**32.46 ± 1.61**	**0.60 ± 0.25**	**31.85 ± 0.66**	**0.77 ± 0.34**	**32.38 ± 1.54**	**0.22 ± 0.11**
nose_max	33.33 ± 1.20	0.45 ± 0.17	32.80 ± 0.58	0.46 ± 0.17	33.21 ± 1.07	0.17 ± 0.09
nose_min	30.87 ± 2.51	0.56 ± 0.20	30.29 ± 1.50	0.81 ± 0.33	31.15 ± 2.05	0.20 ± 0.08
∇nose	-.032 ± .012	.022 ± .009	.032 ± .021	.034 ± .015	-.007 ± .007	.017 ± .012
cheek_avg	**32.35 ± 1.84**	**0.35 ± 0.15**	**31.86 ± 1.66**	**0.31 ± 0.12**	**32.70 ± 1.46**	**0.09 ± 0.05**
cheek_max	33.62 ± 1.35	0.28 ± 0.15	33.21 ± 1.16	0.22 ± 0.08	33.73 ± 1.12	0.10 ± 0.04
cheek_min	29.47 ± 2.40	0.53 ± 0.19	29.05 ± 2.18	0.56 ± 0.23	30.32 ± 1.98	0.11 ± 0.05
∇cheek	-.017 ± .006	.018 ± .005	.016 ± .006	.010 ± .002	-.001 ± .005	.007 ± .003
mouth_avg	**33.42 ± 1.04**	**0.32 ± 0.13**	**32.54 ± 1.10**	**0.17 ± 0.05**	**33.30 ± 0.90**	**0.17 ± 0.06**
mouth_max	33.96 ± 0.95	0.28 ± 0.16	33.43 ± 0.81	0.15 ± 0.06	33.88 ± 0.81	0.12 ± 0.04
mouth_min	32.75 ± 1.28	0.42 ± 0.16	31.69 ± 1.39	0.26 ± 0.13	32.66 ± 1.10	0.20 ± 0.08
∇mouth	-.016 ± .006	.019 ± .010	.004 ± .006	.015 ± .008	.000 ± .007	.013 ± .005
ear_avg	**27.01 ± 1.36**	**0.67 ± 0.20**	**26.59 ± 1.47**	**0.71 ± 0.43**	**27.61 ± 1.51**	**0.11 ± 0.05**
ear_max	29.76 ± 1.81	0.62 ± 0.20	29.21 ± 2.02	0.70 ± 0.38	30.35 ± 1.66	0.19 ± 0.08
ear_min	25.30 ± 1.12	0.66 ± 0.25	24.69 ± 1.21	0.60 ± 0.46	25.67 ± 1.39	0.15 ± 0.10
∇ear	-.035 ± .010	.032 ± .090	.039 ± .024	.021 ± .014	.003 ± .005	.010 ± .004
neck_avg	**32.75 ± 0.83**	**0.29 ± 0.18**	**32.35 ± 0.96**	**0.24 ± 0.11**	**32.94 ± 0.92**	**0.12 ± 0.06**
neck_max	33.79 ± 0.61	0.30 ± 0.12	33.55 ± 0.64	0.14 ± 0.05	33.90 ± 0.53	0.07 ± 0.03
neck_min	29.78 ± 1.09	0.40 ± 0.29	29.50 ± 1.11	0.38 ± 0.31	30.33 ± 1.28	0.28 ± 0.21
∇neck	-.014 ± .009	.018 ± .009	.011 ± .008	.010 ± .001	.000 ± .005	.011 ± .004

Note: all numbers are in °C

As shown in Table 3-4, the standard deviations of the mean skin temperature range from 0.62 °C to 1.84 °C (see $SD(\bar{\mu})$ shown in bold in columns 1, 3, and 5), which indicate temperature variations of each facial region between different subjects. In the cooling and heating phases, the cheek region shows the highest skin temperature variation across all subjects (cooling: SD: 1.84 °C, heating: SD: 1.66 °C) and the same for the nose region (SD: 1.54 °C) in the steady-state phase. The lowest personal variations in the three phases are observed in the neck (cooling SD: 0.83 °C), nose region (heating SD: 0.66 °C), and facial maximum (steady-state SD: 0.62 °C), correspondingly. In addition, the forehead region has the highest skin temperature measurements among all identified regions (cooling: 33.55 ± 0.92 °C, heating: 33.02 ± 1.50 °C, steady-state: 33.77 ± 0.73 °C) while the ear region has the lowest measurements (cooling: 27.01 ± 1.36 °C, heating: 26.59 ± 1.47 °C, steady-state: 27.61 ± 1.51 °C). By examining columns 2, 4, and 6, the skin temperature variations in the cooling (column 2) and heating (column 4) phases are much larger than those in the steady-state phase (column 6), which implies that facial skin temperature is affected by the ambient room temperature.

On the other hand, the relatively small skin temperature deviations in the steady-state phase (column 6) suggest that the measurements are consistent when the ambient room temperature is controlled at a constant level, which also indicates accurate measurements after applying the pre-processing approach discussed in Section 3.5.1. Moreover, nose and ear region have a larger temperature variation compared to other regions in the cooling (nose: 0.60 ± 0.25 °C, ear: 0.67 ± 0.20 °C) and heating phases (nose: 0.77 ± 0.34 °C, ear: 0.71 ± 0.43 °C). These two identified regions are potentially useful features to predict thermal preferences as they are more sensitive to the change of ambient environment. As an example, Figure 3-14 shows three thermal images of the same subject captured at different time stamps in the heating phase. It is obvious that the nose region initially has a lower skin temperature which is shown in black (31.1 °C). This region gradually warms up (as shown in light red in the middle panel, 32.0 °C) and finally reaches its highest temperature (as shown in yellow in the right panel, 33.5 °C). It should be noted that the thermal images are generated based on normalized radiometric measurements to display a better temperature distribution in each frame. As a result, the colormap of thermal images is adjusted in real-time and the colors do not represent an absolute temperature scale. As shown in Figure 3-14, while the face gradually warms up (the range of temperature increases), the glasses remain at an almost identical temperature and thus become darker over time (i.e., from grey to black).

In Table 3-4, all facial regions have negative mean temperature gradients in the cooling phase. On the other hand, all the mean temperature gradients are positive in the heating phase. These results are intuitive as during these two phases, human faces are constantly losing/gaining heat to/from the ambient environment. However, it is interesting to note that some facial regions (facial maximum, forehead, mouth) are more sensitive to cold stress than heat stress. For example, in the cooling phase the forehead region has a larger gradient than in the heating phase ($|-0.018| >$

|0.006|) even though these two phases are kind of symmetric in terms of variations in environment temperature (see Table 3-3). This finding implies that the significant features to predict thermal comfort may not remain the same under hot and cold stress and thus leads to different models based on the condition of the ambient environment.

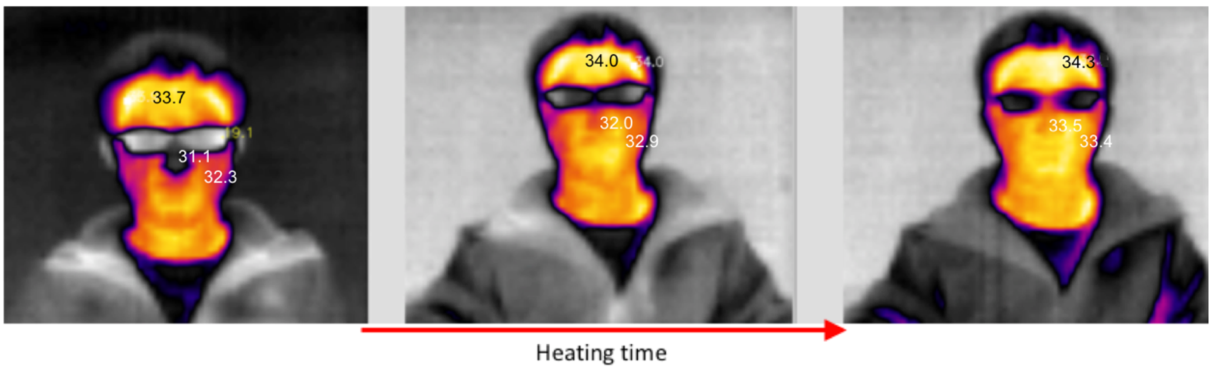

Figure 3-14 Thermal Images of the Same Subject in the Heating Phase at Different Time Stamps (absolute temperature measurements are shown in the thermal images)

To evaluate the relationship between different skin temperature features retrieved from the human face, Pearson correlation coefficients of all unique feature pairs in the three phases were calculated. Pearson correlation coefficient measures the strength and direction of the linear relationship between two variables (range between -1 and 1) where 1 represents perfect positive linear correlation and -1 represents perfect negative linear correlation (SPSS 2018). Figure 3-15 to Figure 3-17 summarize the mean Pearson correlation coefficients of the 12 subjects in each particular phase of the experiment.

In the cooling phase (see Figure 3-15), both intra-region (features extracted from a single facial region, e.g., mean, maximum and minimum of the forehead) and inter-region features (features extracted from different facial regions, e.g., features in the forehead and cheeks) are highly correlated (minimum coefficient $\rho = 0.74$). This is due to the fact that different facial regions react in the same way under the cold stress and the corresponding skin temperature features are simultaneously decreasing over time.

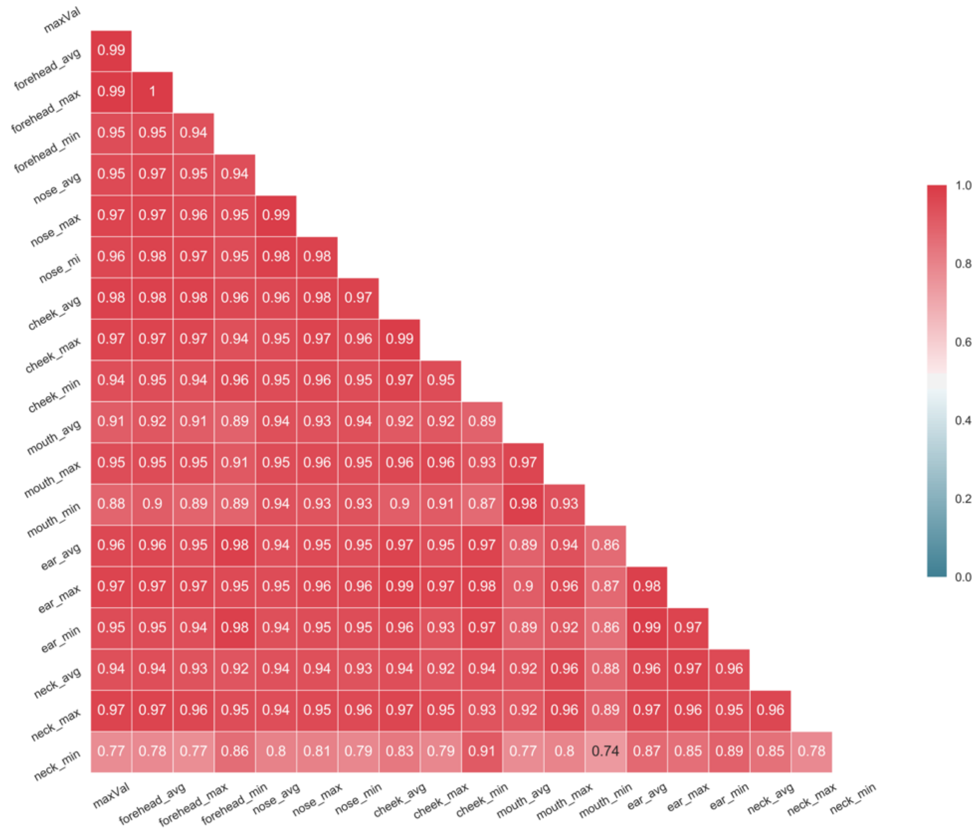

Figure 3-15 Averaged Pearson Correlation of Different Features in the Cooling Phase

However, in the heating phase (see Figure 3-16), it is important to note that only about one third of features are highly correlated with a coefficient greater than 0.7. After checking the correlation coefficients of each subject, we found out that about half of the subjects have the similar correlation coefficients as the cooling phase while the remaining have low correlations for some features, which indicates that personal variations in skin temperature responses exist in the heating phase. In the heating phase, the highly correlated features are mainly intra-region ones (e.g., the mean, maximum, minimum of nose, cheeks, and ears) and inter-regions with larger variations or gradients in skin temperature (e.g., nose: 0.77 ± 0.34 °C; ears: 0.71 ± 0.43°C; cheeks: 0.31 ± 0.12 °C, see Table 3-4). This result may be attributed to the lower sensitivity of certain facial regions (e.g., forehead) to the heat stress as discussed above. The skin temperature of these insensitive regions only varies in a limited range and may remain constant during a certain period of time in the heating phase, which leads to the low correlations.

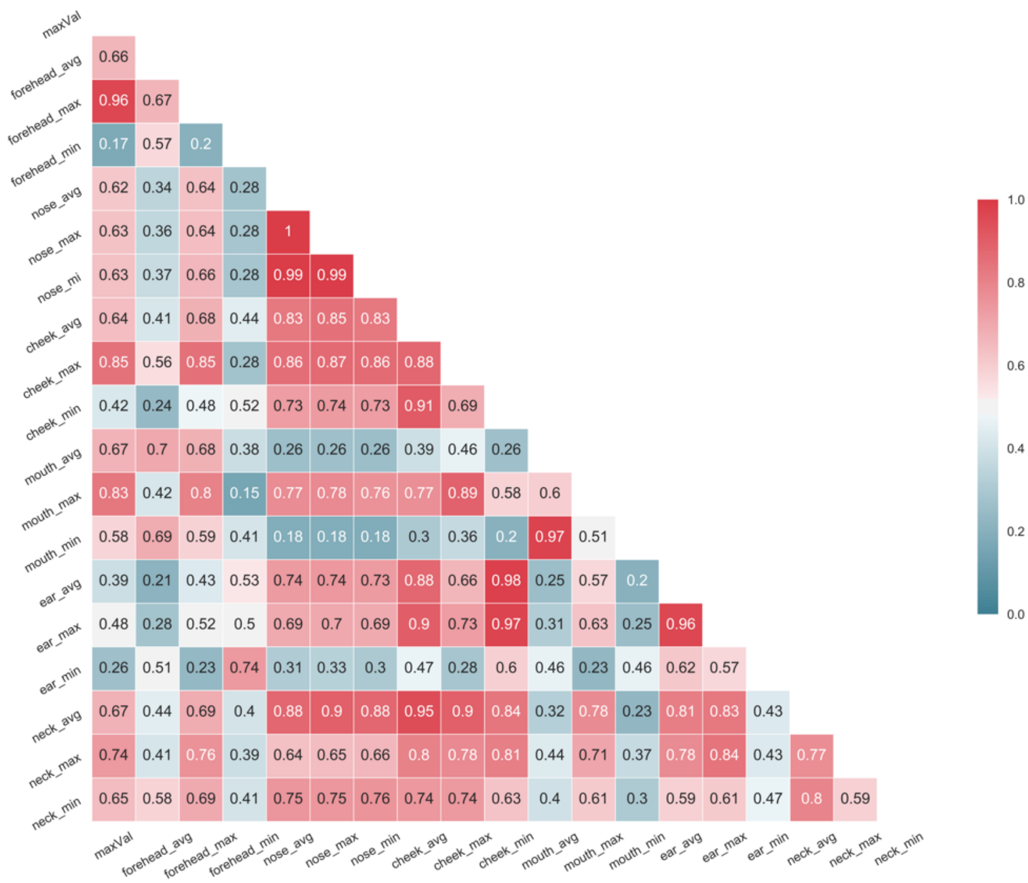

Figure 3-16 Averaged Pearson Correlation of Different Features in the Heating Phase

For the steady-state phase (see Figure 3-17) where the room temperature is maintained relatively constant, only a few features are highly correlated (this pattern is also similar across several subjects). This is due to the same reason as discussed in the heating phase while in this case, only the nose and mouth region show some temperature variations.

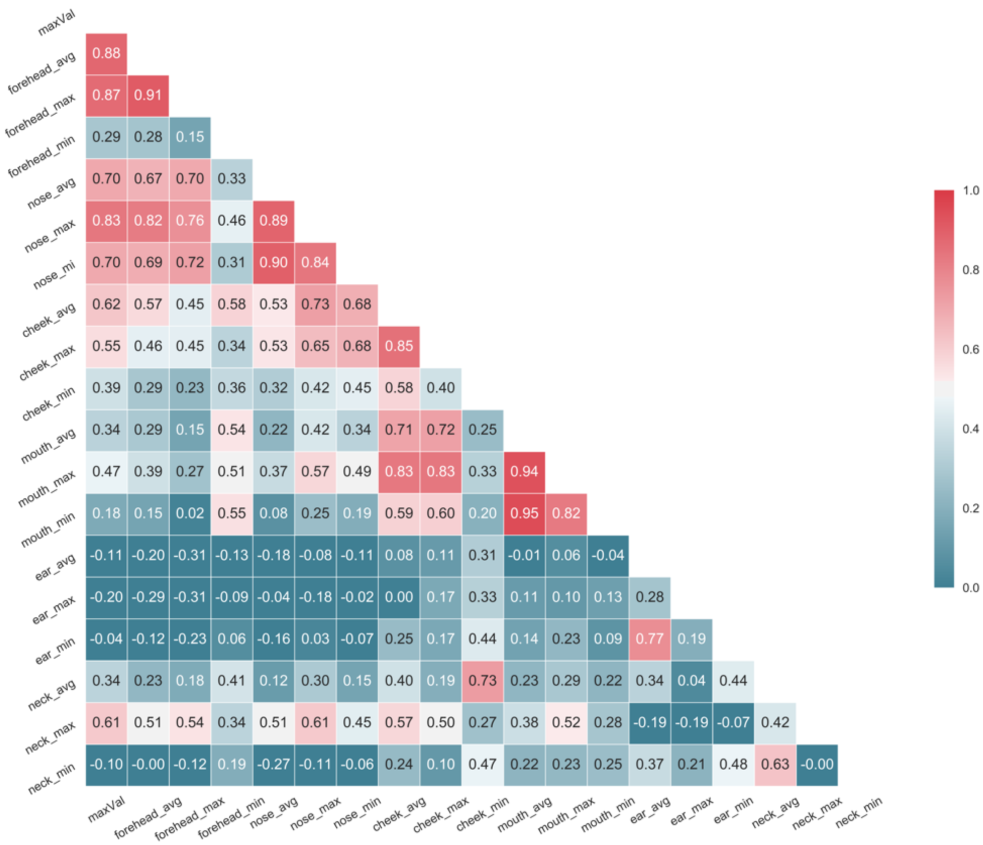

Figure 3-17 Averaged Pearson Correlation of Different Features in the Steady-State Phase

3.5.3 Thermal Comfort Prediction using the Extracted Features

Thermal comfort prediction can be translated into a classification problem where the subjects' preferences have three categorical values, i.e., warmer, cooler, and neutral. Thus, the comfort prediction model is formulated as $TC = \mathcal{F}(T_{facial}, \nabla_{facial})$, where TC is the targeted variable thermal comfort. $T_{facial}, \nabla_{facial}$ are the skin temperature features extracted from each facial region and the corresponding gradients. Common machine learning methods including Support Vector Machine, Classification Tree, and Random Forest have been investigated to classify thermal comfort (Chaudhuri et al. 2018, Kim et al. 2018a and 2018b, Li et al. 2017c, 2019d). Among these existing methods, Chaudhuri et al. (2018), Li et al. (2017c), and Kim et al.

(2018a) suggested that the Random Forest model produces the better prediction results and also provides useful interpretations (e.g., which feature is important).

Random Forest is an ensemble method which classifies an object by averaging a large collection of decision trees. This method applies bootstrap aggregating and can reduce the overfitting problem originated from decision trees (Breiman 2001). In this chapter, a total of 26 features (see Table 3-4) are considered for model training. Random Forest is an ideal method to randomly sample the training features at each split to reduce the variances in the training data. Also, it is worth noting that even though many features selected in this chapter are highly correlated (see Figure 3-15 to Figure 3-17), it does not affect the classification accuracy (James et al. 2013). Correlated features generally reduce the interpretability of the model and are usually solved by feature extraction methods such as Principal Component Analysis. However, this is beyond the scope of this chapter.

In this chapter, comfort prediction models were developed on each subject's dataset to represent personalized models. The Random Forest model was trained using the Python Scikit-learn package (Pedregosa et al. 2011). Hyper-parameters were tuned through the grid search to exhaustively evaluate the accuracy of each configuration for performance optimization (i.e., '*n_estimators*': [300, 500, 700, 1000], '*max_features*': ['auto', 'sqrt', 'log2'], '*max_depth*': [2, 3, 4, 5]). The maximum number of features allowed in the estimators and the maximum tree depth were intentionally controlled at a small size to reduce overfitting. Figure 3-18 shows the structure of a Random Forest model for a subject which consists of 500 classification trees. In this example, each tree is allowed to have a maximum depth of 3 and up to 5 features.

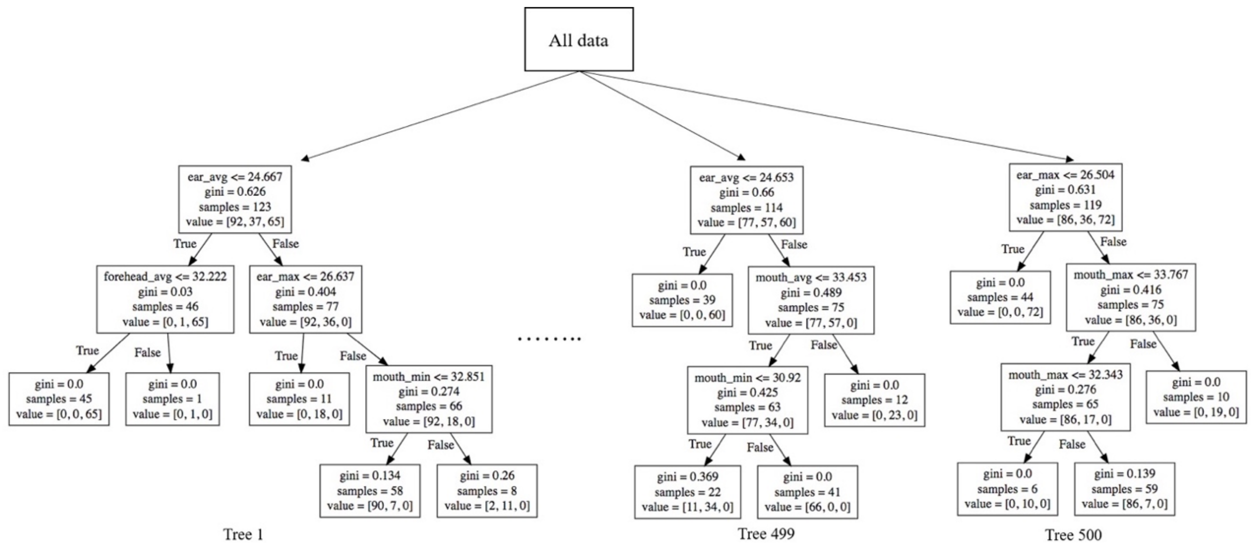

Figure 3-18 The Structure of Random Forest Model for an Example Subject

The optimal hyper-parameters for each subject's personalized comfort prediction model are shown in Table 3-5. For each subject, three prediction models were evaluated, i.e., models for the cooling phase (denoted as "cooling" in Table 3-5, which were developed using the data collected in the cooling phase); models for the heating phase (denoted as "heating", which were developed using the data collected in the heating phase); and general models (denoted as "general", which were developed using the data from all three phases). Models for the steady-state phase were not developed separately as subjects' thermal preferences generally did not change throughout that phase.

Table 3-5 Optimal Hyper-Parameters for Each Subject

Subject ID	Cooling	Heating	General
1	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 500 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto
2	• n_estimators: 500 • max_depth: 2 • max_features: sqrt	• n_estimators: 300 • max_depth: 2 • max_features: sqrt	• n_estimators: 1000 • max_depth: 2 • max_features: auto
3	• n_estimators: 300 • max_depth: 4 • max_features: log2	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 500 • max_depth: 2 • max_features: auto

4	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 1000 • max_depth: 3 • max_features: log2
5	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: log2	• n_estimators: 300 • max_depth: 3 • max_features: log2
6	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 500 • max_depth: 3 • max_features: sqrt
7	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 500 • max_depth: 2 • max_features: auto	• n_estimators: 700 • max_depth: 2 • max_features: log2
8	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 700 • max_depth: 5 • max_features: log2
9	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 700 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 5 • max_features: log2
10	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 700 • max_depth: 3 • max_features: log2
11	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 300 • max_depth: 2 • max_features: auto	• n_estimators: 700 • max_depth: 3 • max_features: sqrt
12	• ‘n_estimators: 500 • max_depth: 3 • max_features: log2	• ‘n_estimators: 500 • max_depth: 3 • max_features: log2	• ‘n_estimators: 500 • max_depth: 3 • max_features: auto

After tuning the hyper-parameters, ten-fold cross validations were conducted to evaluate the prediction accuracy of each subject’s personalized comfort prediction model, which is presented in Table 3-6. On average, using the selected facial skin temperature features, the personalized methods can achieve an 85.0% accuracy in predicting subjects’ thermal preferences and slightly higher accuracy of 91.6% and 92.7% in the cooling and heating phases, respectively.

Table 3-6 Prediction Accuracy of the Random Forest Model for Each Subject

Subject ID	1	2	3	4	5	6	7	8	9	10	11	12	Avg.
Cooling	.935	.825	.875	.921	.935	.947	.921	.946	.942	.921	.943	.882	.916
Heating	.916	.840	.932	.946	.955	.955	.942	.933	.933	.952	.942	.873	.927
General	.730	.801	.829	.921	.900	.878	.859	.854	.830	.885	.906	.812	.850

To identify the significant features for thermal comfort prediction, the selected skin temperature features were ranked according to their contributions to reducing the loss function. The five most important features for each subject are presented in Table 3-7. It can be seen that the significant features are subject-dependent. Also, these features are data-driven and may not remain identical as more data are collected in further experiments (e.g., in cooling seasons). However, features extracted from facial regions with a large skin temperature variation such as ears, nose, and cheeks are most likely to be the significant predictors, which indicates the ideal facial regions for future studies to analyze and interpret occupant's thermal preferences.

Table 3-7 Features Importance of the Random Forest Model for Each Subject

Subject ID	Cooling	Heating	General
1	• 'ear_avg' • 'ear_max' • 'nose_avg' • 'forehead_min' • 'ear_min'	• 'ear_max' • 'cheek_max' • 'nose_avg' • 'forehead_avg' • 'cheek_min'	• 'cheek_min' • 'nose_avg' • 'nose_max' • 'ear_max' • 'ear_avg'
2	• 'forehead_min' • 'forehead_avg' • 'nose_min' • 'neck_max' • 'cheek_max'	• 'ear_max' • 'mouth_min' • 'cheek_max' • 'neck_min' • 'mouth_avg'	• 'cheek_max' • 'cheek_avg’ • 'ear_max' • 'forehead_min' • 'nose_max'
3	• 'cheek_max' • 'ear_max' • 'nose_min' • 'nose_max' • 'nose_avg'	• '∇forehead' • 'ear_max' • 'cheek_max' • 'ear_avg' • 'nose_min'	• 'ear_avg' • 'ear_min' • 'ear_max' • 'forehead_avg' • 'neck_avg'
4	• 'mouth_min' • 'mouth_avg' • 'cheek_max' • 'ear_max' • 'nose_avg'	• 'ear_max' • 'cheek_max' • 'neck_min' • 'cheek_avg' • 'ear_avg’	• 'ear_max' • 'cheek_min' • 'forehead_min' • 'ear_min' • 'ear_avg'
5	• 'ear_max' • 'nose_min' • 'forehead_min’ • 'nose_avg' • 'mouth_avg'	• 'cheek_max' • 'ear_max' • 'nose_avg' • 'nose_max' • 'neck_avg'	• 'maxVal' • 'forehead_avg' • 'forehead_max' • 'cheek_min' • 'neck_avg'

6	• 'ear_max' • 'cheek_max' • 'nose_max' • 'mouth_avg' • 'mouth_min'	• 'ear_max' • 'nose_avg' • 'cheek_avg' • 'ear_avg' • 'nose_max'	• 'ear_avg' • 'ear_max' • 'cheek_avg' • 'cheek_max' • 'mouth_max'
7	• 'nose_avg' • 'nose_min' • 'ear_min' • 'forehead_min’ • 'mouth_avg'	• 'ear_max' • 'nose_avg' • 'nose_max' • 'ear_avg' • 'cheek_min'	• 'ear_max' • 'mouth_avg' • 'forehead_avg' • 'mouth_min' • 'neck_avg'
8	• 'nose_max' • 'nose_avg' • 'forehead_min' • 'forehead_avg' • 'ear_avg'	• 'cheek_max' • 'neck_min' • 'ear_avg' • 'ear_min' • 'neck_max'	• 'nose_avg' • 'ear_avg’ • 'neck_max' • 'nose_min' • 'ear_min'
9	• 'forehead_min' • 'forehead_avg' • '∇neck' • 'maxVal' • 'neck_max'	• 'ear_max' • '∇neck' • 'forehead_avg' • 'cheek_avg' • 'ear_avg'	• 'nose_max' • 'nose_min' • 'nose_avg' • 'forehead_min' • '∇neck'
10	• 'cheek_max' • 'mouth_min' • 'ear_max' • 'nose_min' • 'nose_avg'	• 'ear_avg' • 'cheek_min' • 'ear_min' • '∇ear' • 'mouth_min'	• 'mouth_max' • 'nose_max' • 'mouth_avg' • 'mouth_min' • 'cheek_max'
11	• 'forehead_min' • 'nose_max' • '∇ear' • 'forehead_avg' • 'maxVal'	• 'cheek_max’ • 'ear_max' • 'nose_avg' • 'neck_min' • 'mouth_avg'	• 'nose_max' • 'forehead_avg' • 'neck_max' • 'forehead_min' • '∇ear'
12	• ‘nose_avg’ • ‘cheek_avg’ • 'forehead_avg' • ‘ear_max’ • 'cheek_min'	• 'ear_avg • 'forehead_avg' • ‘ear_max’ • 'mouth_avg' • ‘forehead_max'	• ‘nose_avg’ • 'forehead_avg' • 'nose_max' • ‘ear_avg’ • ‘cheek_avg’

3.6 Discussion

The experimental results confirm that the subject’s facial skin temperature varies with respect to the change in environment temperature. Due to the thermoregulatory control of the human body, skin temperature tends to increase under heat stress while decrease under cold stress.

In the cooling phase, all the selected facial skin temperature features are highly correlated while for the heating phase only about one third of these features still show a similar correlation. This finding indicates different sensitivities and response behaviors of the selected facial regions in the cooling and heating phases, which might be the effect of sweating under heat stress (Parsons 2014). Another possible reason for this observation is that room temperature did not increase significantly in the heating phase (i.e., in excess of 30 °C) to observe large variations in some facial regions (e.g., forehead, nose).

In the experiments, the ambient room temperature is controlled to vary by about 5 °C (cooling phase: 27.5 - 22.6 °C; heating phase: 22.5 - 27.7 °C) as opposed to existing studies in which the room temperature variations can be as high as 10 °C (Chaudhuri et al. 2018, Choi and Loftness 2012, Ghahramani et al. 2016). Despite the relatively small changes in room temperature, statistically significant variations in skin temperature have been observed. Data from 12 subjects suggest that skin temperature of the selected facial regions react in different magnitudes, which may due to the different thickness of the subcutaneous fat layer, the density of blood vessels, and the amount of skin blood flow (Prendergast 2013). Under the cold stress, ears have the highest skin temperature variation, followed by the nose, cheeks, and forehead. Under heat stress, the nose, ears, and cheeks tend to have large temperature variations.

The significant facial regions for comfort prediction vary across subjects (Table 3-7, which can be caused by personal variations that some subjects have a relatively stable overall or regional skin temperature than others. However, in general, the susceptible facial regions to the change of environment temperature are proved to be good predictors in the Random Forest model. Except for a few cases (e.g., the general model for id 9 and id 11), temperature gradients are not very helpful in the model. This is probably due to the fact that the temperature gradient only implies how skin temperature changes but does not provide additional information about a subject's thermal comfort state. For example, a negative and substantial temperature gradient suggests that human body is losing heat to the ambient environment, however, this scenario can happen at any time during the cooling phase when the environment temperature is decreasing over time, which leads to a negative temperature gradient as observed in the data.

For the comfort prediction models, increasing the number of trees in the Random Forest model by tuning '*n_estimators*' does not always yield better performance (Table 3-5). In fact, there exists an optimal number of trees for each dataset such that more estimators will make the prediction worse and also computationally expensive. This is probably because this model randomly samples features in each tree. If the number of significant features is small compared to the non-significant ones, there is a high chance that the model is built upon non-significant features (in other words, the noise) when the number of estimators becomes larger. For the maximum tree depth (i.e., the '*max_depth*' parameter), a smaller depth (e.g., 2 or 3) is generally preferred as a deeper tree can cause overfitting.

In terms of the prediction accuracy, as shown in Table 3-6, models solely trained on the cooling and heating dataset demonstrate a higher accuracy compared to the integrated dataset which consists of all three experiment phases. This can be attributed to the different thermal sensations under cooling, heating, and steady-state conditions even though the selected skin temperatures features are numerically close in different phases, which caused seemingly "contradictory". For example, when a subject's skin temperature increases to 34 °C under heat stress, he/she may have a different thermal sensation compared to the scenario when the skin temperature decreases to 34 °C under cold stress. In this case, the temperature gradients might be a useful predictor because they help to differentiate the cold and heat stress.

It is also worth noting that personal comfort models only need to be trained once in the data collection experiment. Later, the pre-developed models can be applied to continuously predict each subject's comfort level in a non-intrusive manner. The potential applications of this non-intrusive comfort interpretation method can be adopted in a variety of thermal comfort related applications and contexts such as multi-occupancy offices, cars, trains where a promising approach to automatically and dynamically control the HVAC is much needed. During its usage, if more data are collected from the subjects (e.g., in different seasons), the prediction models can be updated using the newly received data to evolve over time.

However, this study also has some limitations. First, the single thermal camera is placed in front of the occupant, which is not suitable for multi-occupancy spaces due to the camera's limited field of view. Second, the thermal camera alone may fail to detect profile faces or frontal faces at a long distance due to its low image resolution. As a result, high resolution RGB cameras are incorporated to achieve robust face detection. Third, the thermal camera is placed at a fixed distance (1 meter) from the occupant. As an influential factor of the thermal camera's measurement, occupants' distances to the camera can vary over time in real operational settings. Thus, the viewing distance should be accounted for when measuring skin temperature.

3.7 Conclusions

This chapter presents a novel framework for real-time thermal comfort interpretation using infrared thermography. The main contribution is the proposed data collection and analysis framework to non-intrusively and automatically obtain, retrieve, and analyze facial skin temperature data and interpret thermal comfort for each occupant in real operational environments. The proposed framework leverages interdisciplinary techniques including the thermoregulatory theory, computer vision, and machine learning. Results demonstrate that facial skin temperature collected from non-intrusive low-cost infrared thermal cameras can achieve a robust prediction of thermal comfort in real-time, and offers the possibility for synchronous control of indoor environments with minimal interruption of building occupants. The resulting new knowledge has the potential to transition the current building HVAC control from a passive and user-empirical process to an automated, user-centric and data-driven mechanism that can simultaneously improve occupant satisfaction and well-being in indoor environments. Future research can also investigate if the non-intrusive thermography can evaluate occupants' mental workload and performance in different thermal environments (Wang et al. 2019c).

The main conclusions from this chapter include: first, facial skin temperature is a useful bio-signal to analyze subjects' thermal comfort. In the experiment, a variation of 5 °C in the room temperature shows statistically significant impacts on the facial skin temperature. Second, the data suggest that facial skin temperature is more sensitive to cold stress than heat stress. A higher correlation of facial skin temperature features has been observed in the cooling experiments. Third, ears, noses, and cheeks suggest a large skin temperature variation. Features retrieved from these regions are the most significant predictors for thermal comfort. Fourth, despite the low-cost thermal camera has a lower accuracy compared to the contact thermocouples or infrared thermometers adopted in other studies, by incorporating features collected from different facial regions, subjects' thermal comfort can be predicted with an 85% accuracy in the proposed framework.

CHAPTER 4

Camera Network for Multi-Occupancy Thermal Comfort Assessment

4.1 Introduction

Chapter 3 presents a "non-intrusive" approach which leverages a low-cost thermal camera to assess occupants' thermal comfort through the skin temperature of six facial regions (e.g., forehead, nose). This approach can automatically and continuously detect human faces, measure the skin temperature of each facial region, clean and process raw data, and interpret thermal comfort using personal comfort models. At the end of Chapter 3, three limitations of this approach have been acknowledged, including unsuitable to simultaneously monitor multiple occupants in the built environment due to the limited camera FOV, incapable of detecting occupants at a long distance (over 2 meters) due to the low camera resolution, and lack of calibration of the camera viewing distance which affects the radiometric measurement. In this chapter, we will introduce a new approach that addresses these limitations.

On the other hand, the word "non-intrusiveness" has become a buzzword in thermal comfort studies in recent years (e.g., Chaudhuri et al. 2018, Cheng et al. 2017, Cosma and Simha 2019, Ghahramani et al. 2016, Jazizadeh and Jung 2018, Jung and Jazizadeh 2017, Li et al. 2018, 2019a, 2019c, Liu 2018, Lu et al. 2019, Metzmacher et al. 2018, van der Valk et al. 2015). However, the existing body of knowledge lacks a consistent and comprehensive description of the characteristics that a non-intrusive approach should possess. In Chapter 3, the "non-intrusiveness" is mainly reflected by the "non-contact" manner in physiological data collection and the reduced human engagement to resolve the dependency on wearables and interruptions caused by the frequent human input. These two characters are supported by studies such as Jazizadeh and Jung (2018), Cosma and Simha (2019), and Lu et al. (2019). For example, Jazizadeh and Jung (2018) adopted a regular RGB camera to analyze color variations (which is a proxy of blood perfusion) in facial skin under hot and cold environments. In this study, the camera is mounted on a computer display to capture images of the frontal face. However, this approach requires subjects to stay still without any body movement for two minutes during the image collection. Otherwise, the color information will be corrupted. In this case, the inconvenience may still arise from the claimed "non-intrusive" approach. However, existing studies also have different interpretations of "non-intrusiveness". For example, Ghahramani et al. (2016) considered an eyeglass frame with mounted infrared thermometers is a non-intrusive approach, despite subjects are required to wear it during the data collection. Similarly, Liu et al. (2018) treated wearables, such as chest strip and wristband, as non-intrusive as they do not disturb subjects for survey input. Chaudhuri et al. (2018) claimed using contact thermocouples attached to the skin surface by tapes is also non-intrusive when they are attached to the non-dominant hand rather than multiple body locations. Therefore, a comprehensive description of a truly "non-intrusiveness" approach for thermal comfort assessment is much needed to fill the knowledge gap and promote their applications in real operational environments.

Considering the limitations of each study reviewed in Section 1.2.1.2 Participation Oriented Thermal Comfort Assessment Section 2.2.1 Thermal Comfort Prediction using Bio-signalsand Section 3.2 Related Work, a truly non-intrusive approach which can be readily adopted in real operational multi-occupancy environments should have specific characteristics summarized as follows:

- The approach should continuously collect human physiological data for real-time and robust thermal comfort assessment. Therefore, approaches that require manual data collection and offline processing fail this criterion.
- The collection of human physiological data should not require wearable devices, personal equipment, or excessive human feedback, which can cause discomfort, inconvenience or interruptions of building occupants.
- Occupants can have flexible and relaxed postures and possibly move around in the built environment. In other words, occupants are not required to remain at a static posture while the approach is in operation.
- The approach should have high scalability potential such that it can be flexibly configured to various built environments, especially in multi-occupancy spaces where multiple occupants' thermal comfort can be simultaneously assessed without incurring additional adjustments. Typically, studies that require personal equipment fail this criterion due to their hardware dependency. For example, each occupant has to wear a wristband or use the phone app for data collection, which can be cumbersome in large multi-occupancy spaces. If some occupants do not have access to such devices, their comfort preferences are not taken into account.
- The approach should be robust against variations in ambient conditions, such as the lighting intensity. Studies that rely on analyzing different channels of RGB images may fail this criterion due to their sensitivity to lighting variations. For example, a dimmer room or background reflection can substantially change the value of each pixel in an image.

These five significant characteristics of a non-intrusive approach for thermal comfort assessment are summarized in Table 4-1 and Table 4-2 summarizes the unaddressed characteristics of each related study reviewed in previous sections.

Table 4-1 Characteristics of the Non-Intrusive Thermal Comfort Assessment

Serial number	Characteristics
1	Continuous collection of human physiological data
2	Does not require personal devices or human feedback
3	Flexible postures or body movements
4	High scalability in multi-occupancy scenarios
5	Robust against variations in ambient conditions

Table 4-2 Limitations of Existing Studies in Thermal Comfort Assessment

Sources	Devices	Input variables	Unaddressed characteristics
Feldmeier and Paradiso (2010)	Wearable sensor nodes (wrist, neck)	Local temperature and humidity, thermal vote	1, 2, 4
Erickson and Cerpa (2012)	Phone application	Room temperature, thermal vote (rectify the PMV model)	1, 2, 4
Purdon et al. (2013)	Phone application, passive infrared sensor, environment sensor	Thermal vote, setpoint	1, 2, 4
Jazizadeh et al. (2013), Hang-yat and Wang (2013)	Phone application, environment sensor	Room temperature and humidity, thermal vote	1, 2, 4
Gao and Keshav (2013)	Infrared thermometer, Kinect, environment sensor	Clothing temperature, Room temperature and humidity, thermal vote (rectify the PMV model)	1, 2, 3, 4
Kim et al. (2018a)	Personal comfort chair equipped with environment sensors	Control behavior, indoor and outdoor environmental factors	1, 2, 4
Chaudhuri et al. (2018), Choi and Loftness (2012), Choi and Yeom (2017),	Thermocouples	Skin temperature of one or multiple body regions	2, 3, 4

Wang et al. (2007), Yao et al. (2007)			
van der Valk et al. (2015)	Wristband sensor, environment sensor	Bio-signals such as heart rate, galvanic skin response and environmental factors such as temperature, humidity, illuminance, noise.	2, 4
Li et al. (2017a, 2017c)	Wristband sensor, phone application	Skin temperature, heart rate, activity level, clothing level, indoor and outdoor environmental factors	2, 4
Liu et al. (2018) and Liu et al. (2019)	Wristband sensor, accelerometers, thermocouples	Skin temperature, heart rate, activity level, ambient temperature	2, 4
Ghahramani et al. (2016)	Infrared thermometers on an eyeglass frame	Skin temperature of the front face, cheek, nose, and ears	2, 4
Jung et al. (2019)	Heat flux sensor	Heat exchange rates between the human body and ambient environment	2, 4
Abouelenien et al. (2016), Burzo et al. (2014a, 2014b), De Oliveira et al. (2007), Metzmacher et al. (2018), Lu et al. (2019)	Commodity thermal cameras	Skin temperature of one or multiple facial regions	3, 4
Ranjan and Scott (2016)	Commodity thermal camera	Skin temperature of multiple body regions (image was manually taken by researchers)	1, 3, 4
Cosma and Simha (2019)	Low-cost thermal camera	Clothing temperature from the arms, torso, and head	3, 4
Li et al. (2018)	Low-cost thermal camera	Skin temperature of forehead, nose, cheeks, mouth, ears, and neck.	3, 4
Kwon et al. (2012)	RGB camera	RGB videos to infer heart rate	3, 4, 5
Cheng et al. (2017), Jung and Jazizadeh (2018)	RGB camera	RGB videos to infer blood perfusion	3, 4, 5
Jung and Jazizadeh (2017)	Doppler radar	Chest and abdomen movement to infer respiration rate	3, 4

Therefore, the objective of this chapter is to develop a truly non-intrusive physiological sensing approach which satisfies the five main requirements as summarized in Table 4-1. To this end, this chapter extends the single camera study in Chapter 3 and proposes a camera-occupant network. The main challenges of the proposed approach, such as the network formation, camera registration, and skin temperature extraction, are detailed in Section 4.3.

4.2 Contributions

This chapter explores a camera-occupant network consisting of multiple low-cost thermal and RGB-D cameras to achieve good viewing coverage of the environment and simultaneous interpretations of thermal comfort in operational multi-occupancy-built environments. The specific contributions of this chapter include:

- Develop a comprehensive description of the characteristics of a non-intrusive thermal comfort assessment approach.
- Design a generic and robust thermal camera network which can be rapidly reconfigured to adapt to various settings and has little or no hardware infrastructure dependency.
- Demonstrate a dual camera system in which skin temperature can be extracted from facial regions from a low-resolution thermal camera with the help of an RGB-D sensor.
- Demonstrate methods to dynamically calibrate skin temperature with respect to the camera viewing distance.
- Demonstrate methods to register occupants from different camera nodes in the network.

4.3 Methodology

The networked camera system leverages a range of cutting-edge techniques, such as deep neural network to robustly detect multiple occupants from different angles and distances, computer vision to register and track occupants in different camera views and stitch indoor scenes, signal and data processing approaches to remove outliers and smooth the data, and machine learning to develop personal comfort models using skin temperature data. Figure 4-1 presents an overview of the thermal camera network.

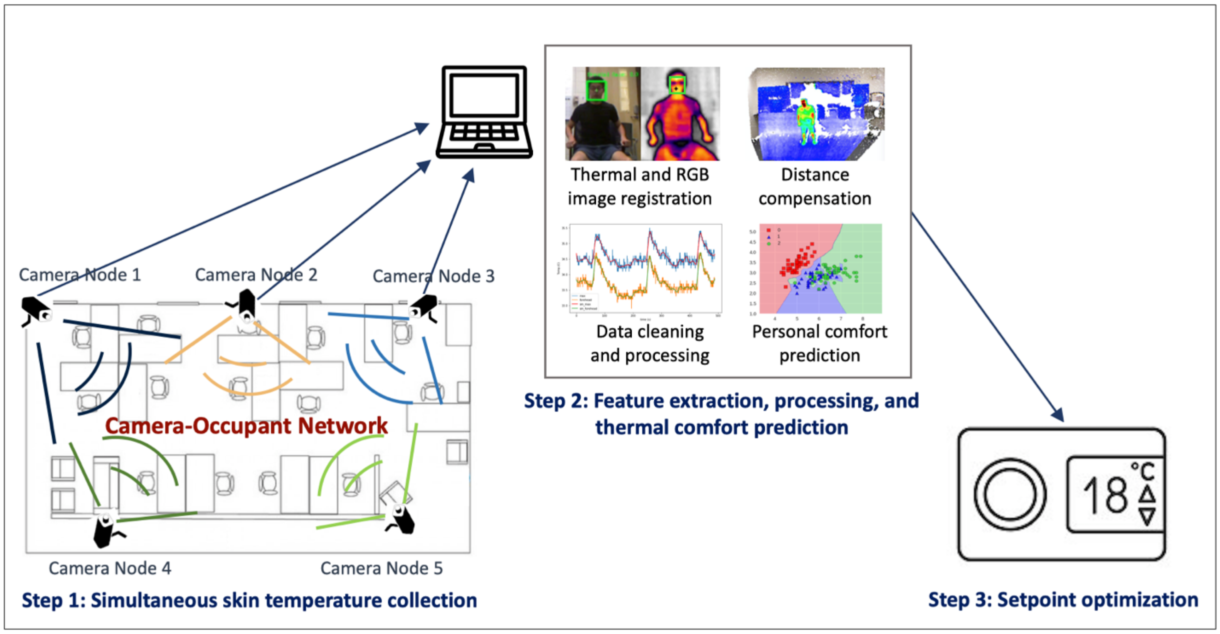

Figure 4-1 Overview of the Proposed Thermal Camera Network

Table 4-3 summarizes the main improvements in the current chapter. Details in the table are explained in the following subsections which are organized to first introduce the component of the camera network – that is, a single camera node; followed by descriptions of the camera-occupant network including its graph abstraction, occupant registration, data communication, data cleaning, and feature extraction.

Table 4-3 Comparisons of the Proposed Thermal Camera Network and the Single Camera Approach Introduced in Chapter 3

Descriptions	Prior work (Chapter 3)	This Chapter
Intended application	Single occupancy	Multi-occupancy
Type of camera	Thermal camera only	Fusion of thermal and RGB-D cameras
Number of cameras	Single camera node	Multiple camera nodes
Face detection approach	Haar cascade algorithm	Can apply various state-of-the-art algorithms
Camera placement	In front of the occupant	Flexible camera placement
Occupant posture and body movement	Refrain from large movements (avoid being out of the camera view)	No constraints
Camera-occupant Distance	Not considered	Compensated for distances
Feature selection	Local skin temperature features from each facial region	Global skin temperature features from the whole facial area

4.3.1 Thermal and RGB-D Dual Camera System

The camera network shown in Figure 4-1 consists of multiple camera nodes that are placed at different locations in a built environment. Each camera node is a low-cost dual camera system comprised of a FLIR Lepton 2.5 thermal camera module and a Microsoft Kinect (an RGB-D camera). As shown in Figure 4-2, the thermal camera is rigidly mounted on top of the Kinect.

Figure 4-2 The Dual Camera System

This dual camera system performs a synergistic function where the Kinect implements the human detection (by its RGB camera) and provides distance information (by its depth sensor) to register the dual camera system and complement temperature measurements taken at different distances by the thermal camera. Table 4-4 shows the specifications of these two cameras.

Table 4-4 Specifications of the Thermal Camera and Microsoft Kinect

FLIR Lepton 2.5	Dimensions	8.5 x 11.7 x 5.6 mm
	Resolution	80 (h) x 60 (v) pixels
	Thermal sensitivity	< 50 mK
	Accuracy	±5 ˚C or ±5% of reading in the working range
	Field of view	51° (h) and 42° (v)
	Price	$ 199
Microsoft Kinect	RGB camera resolution	640 (h) x 480 (v) pixels
	Field of view	57° (h) and 43° (v)
	Effective range of depth sensor	0.8 – 5 m
	Depth accuracy	± 4 cm at the maximum working range (5 meters)
	Price	$ 48

4.3.1.1 Kinect face detection

As introduced previously, the human face is selected as the region of interest as it has a higher density of blood vessels where the skin temperature variations due to thermoregulatory behaviors are more significant, and the infrared energy emitted by the human face can be directly detected as it is not covered by clothing. To detect human faces in thermal images, prior work in Chapter 3 tested the Haar Cascade algorithm (Viola and Jones 2001), Histogram of Oriented Gradients (Dalal and Triggs 2005), and Eigenfaces (Turk and Pentland 1991) and found that the Haar Cascade algorithm to be the only feasible method to detect frontal faces as only certain edges (e.g., nose) are preserved in the low-resolution images (80 by 60) (Li et al. 2018). In terms of profile faces, however, none of these methods work robustly due to the blurred edges, which limits the application of such single thermal camera system in real built environments as occupants' poses and locations can be very flexible over time. To address this limitation, in this chapter, we adopted a Kinect (RGB-D camera) to assist the thermal camera in face detection. Kinect is suitable for this task as the high-resolution RGB images (640 by 480) contain more color information than thermal images and thus support the state-of-art face detection algorithms. Specifically, we adopted the deep neural network (DNN) based face detectors implemented in the OpenCV library (OpenCV 3.3). Based on our preliminary test, the DNN detector demonstrates a much higher accuracy than the Haar Cascade algorithm in both frontal and profile face detections at distances between 0.8 to 5 meters, distances typically encountered in indoor environments. However, other algorithms such as the Faster R-CNN and DeepFace (e.g., Jiang and Learned-Miller 2017) can also be applied to assist the thermal camera to locate human faces.

4.3.1.2 Occupant tracking in a single dual camera node

As more than one occupant can be observed by a single camera node in a multi-occupancy environment, we implemented the centroid tracking algorithm to track occupants across image frames. This algorithm assumes that centroids of the same object in the two consecutive frames will have the closest distance (Rosebrock 2018). In the first frame, the centroid of each face can be detected using the face detection algorithm introduced in Section 4.3.1.1. In the subsequent frame at time t+1, the Euclidean distances between each pair of centroids in the current frame t+1 and the previous frame t are calculated and each occupant in frame t+1 is assigned to the ID of its closed centroid in the previous frame t (see Eq. 4.1).

$$Occupant\ ID = \underset{m \in M_t}{\operatorname{argmin}} \|x_{t+1} - m\| \tag{4.1}$$

Where M_t is a set of the centroids of all subjects at time t; m is the centroid of one subject in the set M_t; x_{t+1} is the centroid of a subject at time $t+1$ (which needs to be updated), and $\|\cdot\|$ is the $L2$-norm. This recursive subject tracking process is illustrated in Figure 4-3 with an example of two occupants. As shown in Figure 4-3a, at time $t+1$ the unknown centroids i and j (denoted in triangles) are updated based on their closest Euclidean distances to the centroids at time t (denoted in circles). The unknown centroids at time $t+2$ (denoted in squares) are updated accordingly (Figure 4-3b).

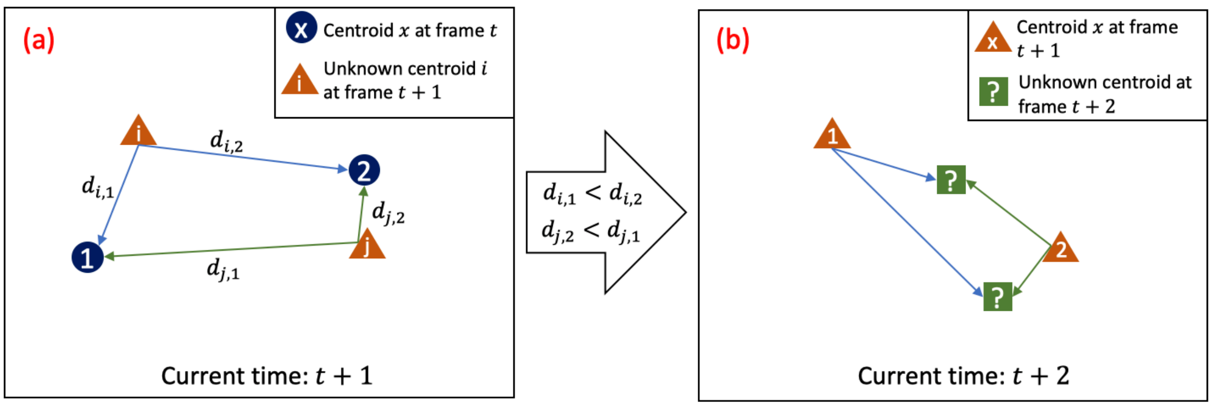

Figure 4-3 The Centroid Tracking Algorithm: (a) Update at Time t+1; (b) Update at Time t+2

4.3.1.3 Kinect and thermal camera registration

As the Kinect and thermal camera have different FOV and resolutions, these two cameras should be registered to find point correspondences such that face coordinates detected in the RGB images can be mapped to thermal images. In this case, both Kinect and thermal camera can be modeled as a pinhole camera which projects the 3D world scene into a 2D image plane through the perspective transformation shown in Eq. 4.2 (OpenCV 2018).

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{4.2}$$

Alternatively, in a more concise form,

$$s\,m = K[R|T]M$$

Where M is a 4 × 1 vector representing the homogeneous coordinate of a 3D point in the world coordinate space; m is a 3 × 1 vector representing the homogeneous coordinate of a 2D point in the image coordinate; K is the 3 × 3 intrinsic matrix of the camera consisting of the focal lengths (f_x, f_y) and principal points (C_x, C_y); $[R|T]$ is the 3 × 4 extrinsic matrix consisting of a rotation R and a translation T; and s is a scaling factor.

In the dual camera system, the registration process is to estimate the intrinsic matrix of the thermal camera K_{IR}, the intrinsic matrix of the RGB camera K_{RGB}, and the homogeneous transformation matrix $[R|T]$ between the thermal and RGB cameras (see Figure 4-4). Once these three unknown matrices are estimated, the point correspondences in two cameras (e.g., (u_1, v_1) and (u_2, v_2)) can be determined according to the pinhole camera model in Eq. 4.2. In practice, such a dual camera system can be calibrated using the stereo vision calibration process. As shown in Figure 4-4, the calibration requires both cameras to observe a planner and predefined pattern, such as a checkerboard or a square grid, from at least two different orientations to determine the unknowns using the maximum likelihood estimation (Zhang 1999).

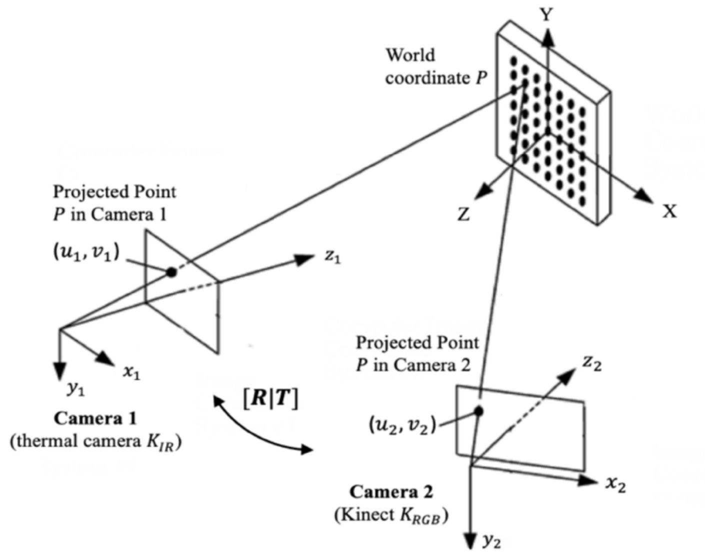

Figure 4-4 Stereo Vision Calibration for Kinect and Thermal Camera Registration

However, thermal cameras typically cannot detect the regular black-and-white calibration patterns printed on the paper as the infrared energy emitted is uniform across the patterns. Therefore, we made a special 6 × 7 checkerboard pattern from the aluminum foil (shown in silver) and the vinyl polymer (shown in black) (Figure 4-5a). Each black or silver square has a dimension of 62.5 mm. Due to the color differences, the checkerboard pattern can be detected by the RGB camera to extract corner points (Figure 4-5a and c). On the other hand, as the aluminum foil has a higher emissivity, it emits more infrared energy and thus looks brighter in thermal images. As shown in Figure 4-5b and d, the checkerboard corner points can be easily observed by a thermal camera, especially when the pattern is heated up by a hairdryer.

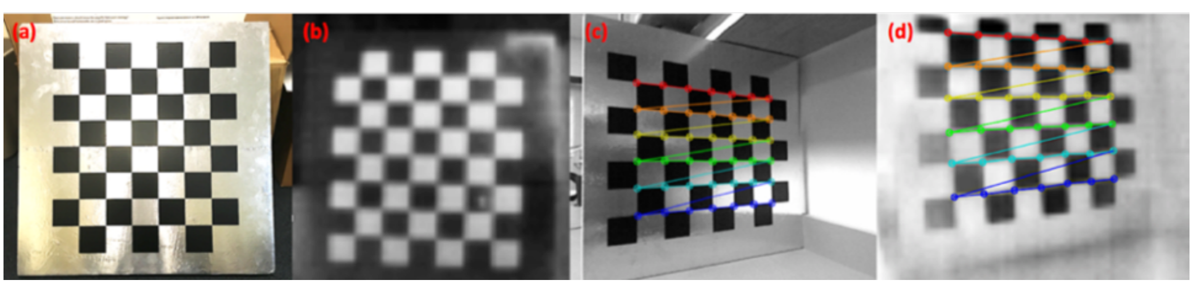

Figure 4-5 Special Checkerboard for the Dual Camera Registration: (a) RGB Image of the Checkerboard (b) Thermal Image of the Checkerboard (bright squares have higher infrared energy); (c) Corner Detection using the Kinect; (d) Corner Detection using the Thermal Camera

We captured twenty pairs of RGB and thermal images from different orientations relative to the dual camera system and implemented the calibration using the Matlab Stereo Camera Calibrator (Mathworks 2016). Although the thermal camera has a low resolution, results showed that the re-projected points are close to the detected points (Figure 4-6a), and the mean re-projection error is 1.02 pixels (Figure 4-6b), which is acceptable for this application. It is also worth noting that the three unknown matrices only depend on the intrinsic properties of two cameras and their relative pose (how thermal camera is mounted), which are not affected by the distance between the camera and the checkerboard pattern. As a result, the registration process only needs to be done once when configuring the dual camera system.

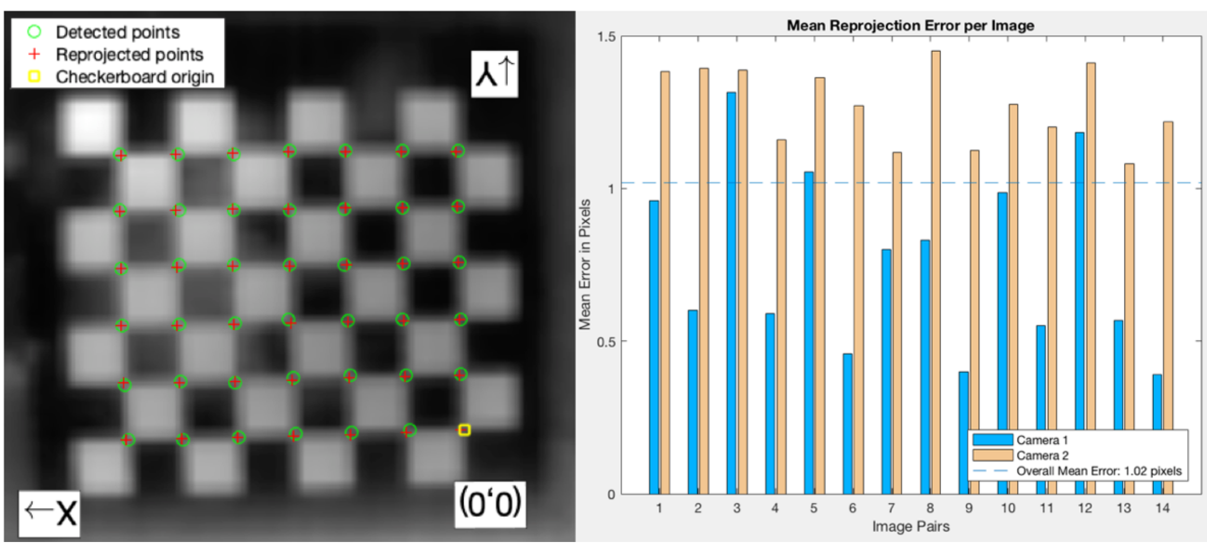

Figure 4-6 Dual Camera Registration Results: (a) Detected Corner Points and the Re-projected Points after Registration; (b) The Mean Re-projection Error in Pixels

Figure 4-7 shows the result of dual camera registration where the face in the thermal image (labeled in the bounding box, see Figure 4-7c) is located based on the face coordinates detected in the RGB image (Figure 4-7b) and its corresponding depth data from the Kinect (Figure 4-7a).

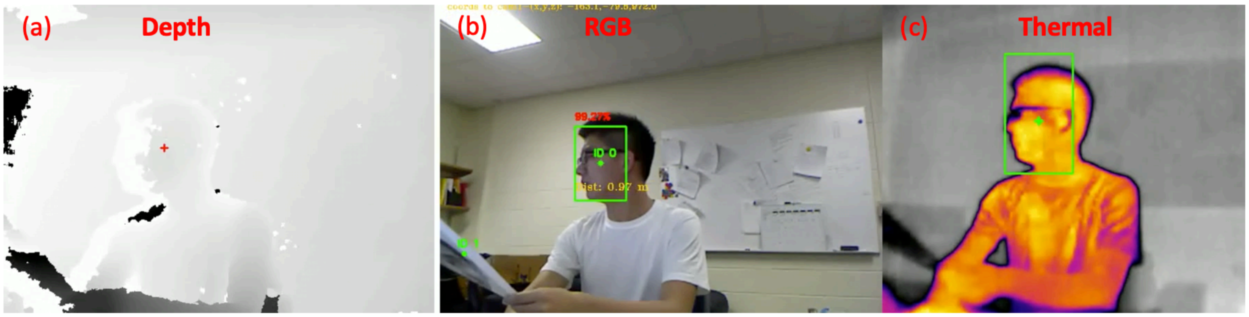

Figure 4-7 Dual Camera Face Detection: (a) Depth Data from the Kinect; (b) RGB Images from the Kinect (for face detection); (c) Thermal Images from the Thermal Camera (bounding box is mapped from the RGB image)

4.3.1.4 Distance calibration of the thermal camera

The infrared energy reaching the thermal camera is affected by the distance between the camera and the object surface (FLIR 2016). Thus, the real-time distance of the camera and each occupant should be measured to fuse the skin temperature data collected from multiple camera nodes. To calibrate distances, we conducted an experiment using the low-cost thermal camera to collect the mean temperature of the frontal face at different distances from 0.8 to 2 meters with a step size of 0.05 meters (room temperature: 26.0 °C, relative humidity: 28.5%). The facial mean temperature was calculated by averaging the measurements of all pixels that exceed a predefined threshold (e.g., measurements below 27 °C were excluded) within the bounding box. The distance was calculated from the point cloud produced by the Kinect. The depth measurement of the Kinect has an accuracy of ± 4 cm within its working range of 5 meters which is considered sufficient for this study (Khoshelham and Elberink 2012). At each distance, three thermal images of a subject's frontal face were collected and averaged to represent the measurement at that distance. The whole experiment is conducted within one minute thus the facial skin temperature can be assumed constant during this short period. This calibration experiment was repeated on five different subjects to quantify the impact of distances on temperature measurements and the averaged slope was retained. It is worth noting that the viewing angle is fixed during the calibration (i.e., perpendicular to the face). However, adjusting the angles also affects the facial regions observed by the camera, which will lead to different temperature measurements. For example, an image capturing the frontal face can have a higher measurement than that of a profile face as the forehead region (which has a high temperature) is well captured in the former image.

As shown in Figure 4-8a, a linear relationship can be observed from the samples ($\hat{y} = -0.50x + 35.02$, adjusted R-square = 0.96, RMSE: 0.04), which implies that skin temperature measurements will drop by 0.5 °C for every one-meter increase in distance for the low-cost thermal camera. Figure 4-8b shows the residual plots of the linear fit. It can be seen that the residuals are symmetrically distributed around zero and no clear patterns are observed, which also indicates a good fit of the linear model.

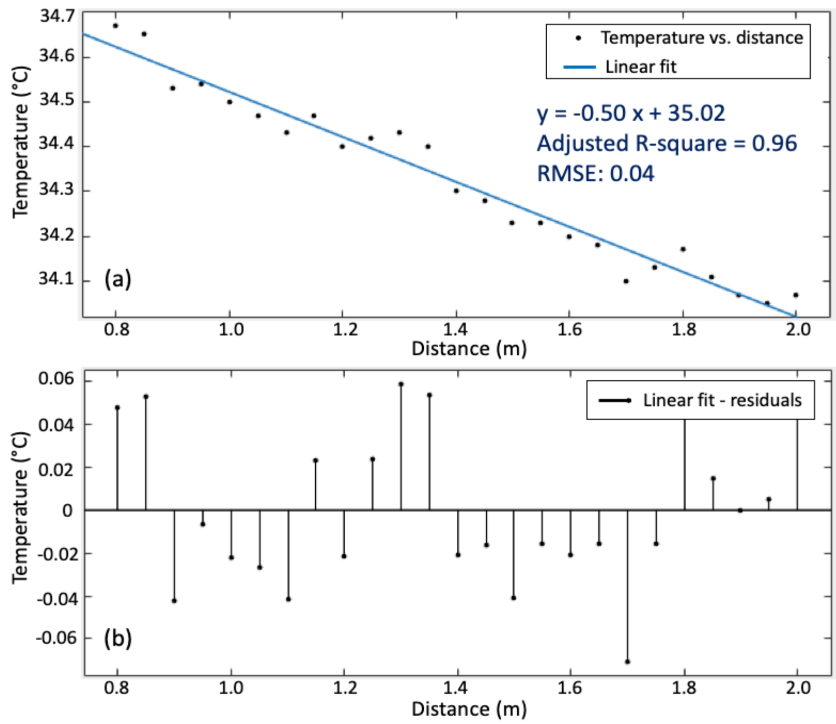

Figure 4-8 A Linear Fit of Distance and Temperature Measurements: (a) Linear Regression Line; (b) Residuals

4.3.2 The Camera-Occupant Network

The camera-occupant network is proposed to non-intrusively and simultaneously interpret occupants' thermal comfort in real multi-occupancy spaces. Specifically, this network aims to achieve comprehensive coverage of the environment such that all the occupants can not only be seen by cameras but also have flexible postures and movements during the data collection. It should also be noted that cameras in the network are not placed in front of faces as Chapter 3 and the images are discarded immediately after retrieving skin temperature data to address the privacy concerns that may arise from any camera systems. This sub-section is organized to first introduce the configuration of the camera network, including its graph abstraction, occupant registration of different camera views, and the data communication between camera nodes.

4.3.2.1 Graph abstraction of the network

The camera-occupant network is an observation system which contains multiple camera nodes to observe one or more occupants from arbitrary angles and distances. This network can be represented in a graph abstraction adapted from Feng et al. (2018) consisting of *nodes* and *edges*. Figure 4-9 is an example network which contains three subjects and two camera nodes. In this graph abstraction, there exist three types of nodes including a *camera node* (denoted as two triangles bounded by a rectangle which represent the dual camera system), an *occupant node* (denoted as a square), and a *world coordinate node* which represents the origin in the 3D world (denoted as a circle). In addition, there are two types of edges connecting each pair of nodes including *observations* (denoted as solid lines) and *constraints* (denoted as dashed lines). The observation represents the pose between a camera node and an occupant node which can vary over time as occupants change their posture or move around. The observation edges can be estimated using the pinhole camera model introduced in Section 4.3.1.3. As shown in Figure 4-9, occupant nodes 1 and 2 are both observed by camera nodes 1 and 2, while occupant node 3 is only observed by camera node 2.

On the other hand, the constraint edges represent a known geometric relationship within a dual camera system (i.e., the relative pose between the thermal camera and the Kinect) or between dual camera systems (i.e., the relative pose between two dual camera systems mounted in an environment). The constraints can be determined when the camera network is configured upfront through the calibration process introduced in Section 4.3.1.3 and will not be affected by the number, poses, and locations of occupants in the environment. In addition, the origin in the 3D world can be assigned to the location of a camera node and thus their relationship is also represented as a constraint.

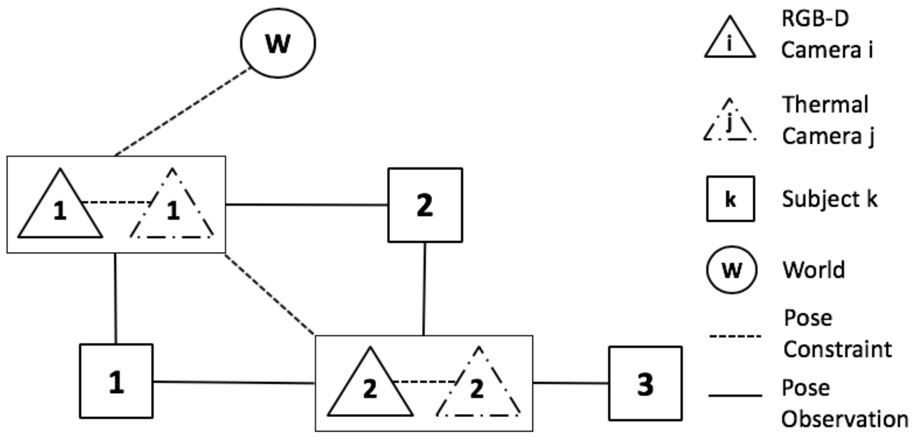

Figure 4-9 Graph Abstraction of the Camera-Occupant Network

To scale up the camera-occupant network in a large multi-occupancy space, more camera nodes can be added to the network. The camera network will be configured such that any occupant node is connected to at least one camera node. Therefore, the skin temperature of each occupant is guaranteed to be collected. To achieve this, the camera network can be recursively configured to maximize the aggregate observability of facial regions of occupants, which is an optimization problem that is subject to a series of constraints such as the number of camera nodes, and distances between cameras and occupants. However, this is beyond the scope of this chapter.

4.3.2.2 Occupant registration among different camera nodes in the network

In Section 4.3.1.2, we introduced the centroid tracking algorithm (which was implemented in a single camera node) to track multiple occupants across video frames. However, in a camera-occupant network, thermal profiles collected by multiple camera nodes from different viewpoints should be associated with the same occupants in the 3D world coordinate system. This process is called occupant registration. For example, as shown in Figure 4-9, camera node 1 observes only two of three occupants (occupant 3 is outside of the view), while camera node 2 observes all three of these three occupants. In this case, the network should correctly associate the two thermal profiles in camera node 1 with the two corresponding occupants in camera node 2. Typically, the registration can be achieved by calculating the descriptors of feature points of occupants in different viewpoints and then mapping these feature points according to their similarities (Lowe 2004). However, this feature-based method is not suitable for the camera-occupant network as (1) feature points detected from two viewpoints in the network can be very different, e.g., one camera node observes the fontal face while another observes a profile face; and (2) calculating the feature descriptors can be computationally expensive, which is not optimal for real-time registration.

Therefore, we implemented the location-based occupant registration using the stereo vision and the pinhole camera model introduced in Section 4.3.1.3. In this case, instead of registering a thermal camera with an RGB camera (Figure 4-4), each pair of RGB cameras are registered through the same stereo vision calibration process to get the transformation matrix $[R|T]$ using a paper printed checkerboard pattern. Then, the 3D world coordinate $[X\ Y\ Z\ 1]^T$ of each occupant with respect to the world origin can be calculated from Eq. 4.2. Finally, the occupant ID in the camera node i can be mapped to that from a different viewpoint j based on the closest distance using Eq. 4.3, which is a modified version of Eq. 4.1.

$$Occupant\ ID = \underset{m \in M_j}{\operatorname{argmin}} \|x_i - m\| \tag{4.3}$$

Where M_j is a set of world coordinates of all subjects in the camera node j; m is the world coordinate of a subject in the set M_j; x_i is the world coordinate of a subject in the camera node i (which needs to be registered); $\|\cdot\|$ is the $L2$-norm. Thus, the camera network can recursively register all occupants observed by different camera nodes.

4.3.2.3 Data communication among camera nodes

In the camera network, camera nodes need to exchange occupants' world coordinates and register the same occupant from different viewpoints. For the scalability purpose, the program was coded for each single camera node such that the network can be quickly configured when adding or removing camera nodes. The data communication was implemented using the User Datagram Protocol (UDP). UDP has advantages of low latency and loss-tolerating, which are suitable for real-time video streaming.

4.3.3 Data Cleaning and Feature Extraction

The facial skin temperature collected directly from each bounding box in thermal images are the raw data which can contain several types of random noises such as the false detection of background as faces, inaccurate face coordinates mapping due to occlusions, and interference of a high temperature object in the environment (e.g., hot water cup). These noises are typically shown as out-of-range isolated noises in the measurements. As a result, we applied the median filter shown in Eq. 4.4 to remove such noises before data analysis.

$$y[k] = median\ \{x[i], i \in w\} \tag{4.4}$$

Where $y[k]$ is the kth value after filtering; w is a neighborhood defined by the user; $x[i]$ is the raw data in the neighborhood w.

Then, the moving average filter as shown in Eq. 4.5 was applied to further filter out noises from fluctuations.

$$y[k] = \frac{1}{2n+1} \sum_{i=-n}^{i=n} y[k+i] \tag{4.5}$$

Where $y[k]$ is the k th value after filtering; $2n + 1$ is the window size of the moving average; $y[k + i]$ is the raw data in the sliding window.

As images of frontal faces are not guaranteed in the camera network, unlike Chapter 3 which segmented the frontal face into six local facial regions (e.g., forehead, nose) and extracted skin temperature from each local region as the features of personal comfort models, we extracted the skin temperature from the whole facial region which consists of both frontal and profile faces. The features collected from the detected facial region are summarized as follows:

- The mean, first quartile, third quartile, and maximum of all pixels in the detected facial region. These features describe the distribution of skin temperature over a facial region.
- The skin temperature variance of all pixels in the detected facial region. As suggested in Chapter 3, the nose, ears, and cheeks regions have larger skin temperature variations than other regions when the ambient air temperature changes. Therefore, large skin temperature variations over the whole facial region can imply that an individual is experiencing cold stress (as some local regions become significantly colder than others).
- The skin temperature gradients of every minute. As suggested in Chapter 3, the gradients can imply the heat or cold stress in the environment which is useful to predict an occupant's thermal comfort state.

4.3.4 Experimental Setup and Protocol

The proposed camera network was experimentally tested in a transient heating environment to verify its applicability in real operational built environments. The experiment included a 20-minute preparation phase and a 50-minute data collection phase to collect subjects' facial skin temperature. The experiment was conducted in a research office at the University of Michigan (UM) during the heating season in 2018. The experiment office has equipped a thermostat which can control the indoor temperature from low (23°C) to high (27 °C) through two HVAC diffusers. As shown in Figure 4-10, two dual camera nodes were placed approximately 1.3 meters away from a table where subjects sat at during the experiment to represent a simplified camera network. Two temperature and humidity sensors (humidity accuracy: ±5%, temperature accuracy: ±1 °C) continuously monitored the ambient environmental conditions. The two sensors were placed at the waist level (0.65 meters above the floor) which was close to the specified height of 0.6 meters for seated occupants in ASHRAE standards 55. To represent a multi-occupancy scenario, 2 subjects were required to participate in the experiment each time. In total, 16 subjects (10 males and 6 females for a total of 8 experiments) were recruited. All subjects were UM students and were healthy at the time of the experiment. The experiment has been approved by the UM Institutional Review Board for conducting human subjects research.

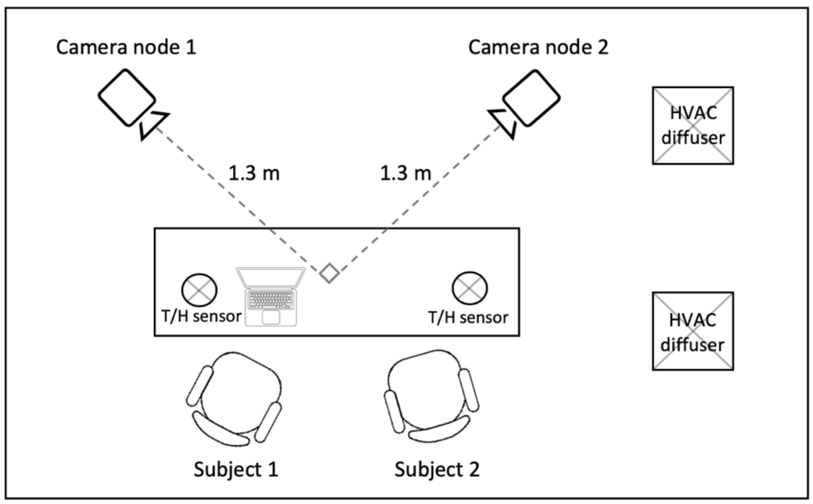

Figure 4-10 The Experimental Setup

Before the experiment started, the room temperature was set at 23 °C to represent a cool environment. During the 20-minute preparation phase, subjects were asked to remain seated in the testbed to reach steady-state skin temperature. Then, during the following 50-minute data collection phase, the thermostat was set at 27 °C to create a transient heating environment (see Figure 4-11). During this period, subjects were asked to perform daily office activities such as reading, typing, browsing, or chatting with each other while their facial skin temperature was extracted by the camera network. To collect the ground truth thermal comfort, subjects were required to report their thermal sensations in a five-point scale (from “cold” to “hot”) and preferences in a three-point scale (from “prefer warmer” to “prefer cooler”) through a phone application and also wear a wristband sensor (Microsoft Band 2) to record the wrist skin temperature, which is only used for comparison. For more details about the phone application and the wristband, please refer to Chapter 2. After the experiment, subjects participated in a survey to evaluate their experience regarding the user acceptance, privacy concern, and level of intrusiveness of the camera network.

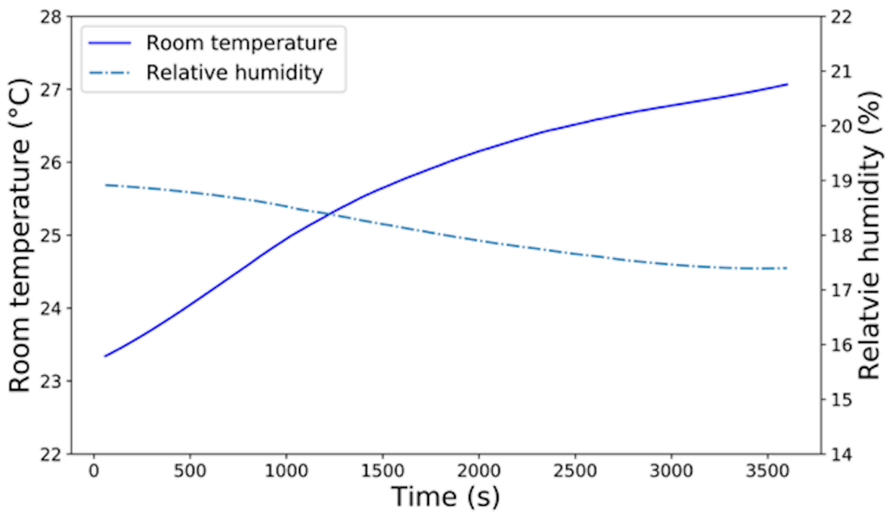

Figure 4-11 Room Condition in a Transient Heating Experiment

It is worth noting that unlike existing experimental studies which typically require subjects to stay in the same posture and refrain from body movements during data collection (e.g., Jung and Jazizadeh 2018, Metzmacher et al. 2018), subjects in this study were allowed to move their body (e.g., stretching), change their postures and facing directions, or even move around in the room to represent scenarios in real office settings and also make them feel as comfortable as possible (to achieve the least intrusiveness caused by the system). We believe such an experimental study verifies the applicability of the proposed system.

Figure 4-12 shows the image frames collected in the experiment. The two rows of images are the views of camera nodes 1 and 2, respectively. The three columns are the depth images, RGB images, and thermal images collected from the dual camera nodes. It can be seen that for the right subject (denoted in a green bounding box), camera node 1 detects the profile face at a distance of 1.11 meters while camera node 2 detects the frontal face at a distance of 1.30 meters. This demonstrates the idea of a camera network which observes each subject from different angles and distances to overcome the limitations of a single camera. Skin temperature features (discussed in Section 4.3.3) are automatically and continuously extracted from the identified facial region and compensated by viewing distances (discussed in Section 4.3.1.4) for data analysis.

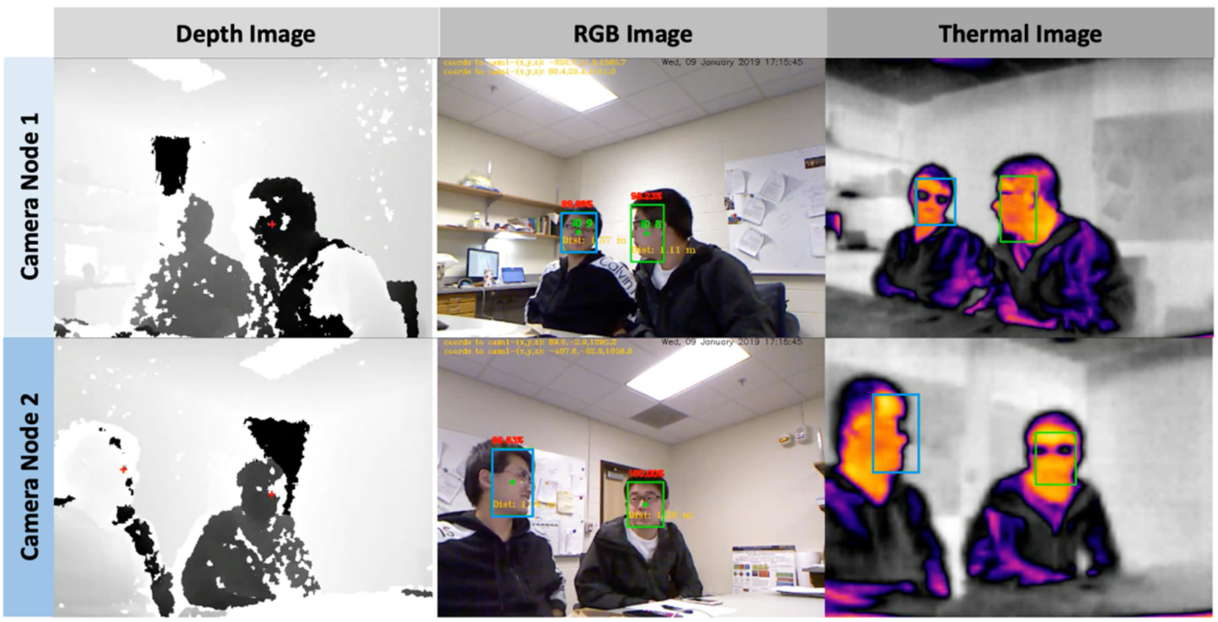

Figure 4-12 Image Frames Collected in the Experiment (first row: views from camera node 1; second row: views from camera node 2)

4.4 Results and Discussion

In this section, we presented the statistics of facial skin temperature features and their correlations during the thermoregulation process. Correlations between the facial mean skin temperature and wrist skin temperature were also evaluated to validate the proposed networked camera system. Then, we mapped facial mean skin temperature to each subject's feedback and explored if an individual's thermal comfort state can be reflected by the facial skin temperature.

Finally, a post-experiment survey was conducted to evaluate subjects' experience with the proposed approach.

4.4.1 Summary of Facial Skin Temperature Features and Gender Differences

Table 4-5 and Table 4-6 present a summary of skin temperature features collected by camera node 1 and 2, correspondingly. The mean ($\bar{\mu}$) and standard deviation ($\bar{s}$) of each feature are calculated using Eq. 4.6 and 4.7 as shown below.

$$\bar{\mu} = \frac{1}{n}\sum_{k=1}^{n}\mu_k, \quad SD(\bar{\mu}) = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(\mu_k - \bar{\mu})^2} \tag{4.6}$$

$$\bar{s} = \frac{1}{n}\sum_{k=1}^{n}s_k, \quad SD(\bar{s}) = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(s_k - \bar{s})^2} \tag{4.7}$$

Where $\bar{\mu}$ and $SD(\bar{\mu})$ are the mean and standard deviation of skin temperature features; $\bar{s}$ and $SD(\bar{s})$ are the mean and standard deviation of the sample standard deviation; n is the number of subjects which is 16 in this study.

Statistics in Table 4-5 and Table 4-6 are divided into three categories: all subjects, all males, and all females, respectively. For each category, two statistics $\bar{\mu} \pm SD(\bar{\mu})$ and $\bar{s} \pm SD(\bar{s})$ are calculated for each feature: $\bar{\mu} \pm SD(\bar{\mu})$ indicates the mean value of each feature and its variations across different subjects, and $\bar{s} \pm SD(\bar{s})$ reflects how much each feature changes in the experiment and its variations across subjects. As shown in Table 4-5 and Table 4-6, the first quartile temperature of the facial region has a higher variation (node 1: 0.72 ± 0.16 °C, node 2: 0.63 ± 0.20 °C) than all other features while the maximum temperature feature has a smaller variation (node 1: 0.43 ± 0.10 °C, node 2: 0.41 ± 0.10 °C). This result suggests that as room temperature gradually increases in the experiment, a subject's facial skin temperature increases correspondingly due to the thermoregulation, however, gaps between the baseline temperature and high temperature regions tend to become narrower over time. This finding is also partially reflected by the facial temperature variances (node 1: 0.40 ± 0.16 °C, node 2: 0.59 ± 0.26 °C) as 9 out of 16 subjects observe a slight decrease in the variances over time, which is supported by Chapter 3 where low skin temperature regions such as nose and checks change more significantly than high temperature regions like forehead under heat stress. For the rest of subjects who hold steady or increasing variances, this may be caused by the frequent changes of their facing directions and body movements such that a camera node does not observe the same facial region over time.

Table 4-5 Statistics of Skin Temperature Features Collected by Camera Node 1

Features	All subjects		Males		Females	
	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$
Mean	32.76 ± 0.38	0.55 ± 0.12	32.64 ± 0.38	0.51 ± 0.12	32.98 ± 0.31	0.60 ± 0.12
1st quartile	32.12 ± 0.46	0.72 ± 0.16	31.99 ± 0.45	0.66 ± 0.16	32.35 ± 0.42	0.82 ± 0.10
3rd quartile	33.86 ± 0.40	0.55 ± 0.15	33.75 ± 0.43	0.53 ± 0.15	34.04 ± 0.29	0.58 ± 0.15
Max	35.02 ± 0.31	0.43 ± 0.10	34.93 ± 0.31	0.43 ± 0.11	35.18 ± 0.27	0.44 ± 0.11
Variance	2.53 ± 0.32	0.40 ± 0.16	2.54 ± 0.38	0.39 ± 0.16	2.51 ± 0.23	0.41 ± 0.19

Note: All numbers are in °C

Table 4-6 Statistics of Skin Temperature Features Collected by Camera Node 2

Features	All subjects		Males		Females	
	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$	$\bar{\mu} \pm SD(\bar{\mu})$	$\bar{s} \pm SD(\bar{s})$
Mean	32.16 ± 0.22	0.47 ± 0.16	32.08 ± 0.21	0.45 ± 0.15	32.29 ± 0.16	0.49 ± 0.18
1st quartile	31.44 ± 0.32	0.63 ± 0.20	31.32 ± 0.29	0.60 ± 0.19	31.65 ± 0.27	0.68 ± 0.22
3rd quartile	33.17 ± 0.31	0.48 ± 0.13	33.12 ± 0.35	0.47 ± 0.13	33.26 ± 0.22	0.50 ± 0.15
Max	34.32 ± 0.27	0.41 ± 0.10	34.29 ± 0.33	0.40 ± 0.09	34.37 ± 0.14	0.42 ± 0.13
Variance	2.24 ± 0.79	0.59 ± 0.26	2.26 ± 0.82	0.58 ± 0.29	2.20 ± 0.81	0.62 ± 0.22

Note: All numbers are in °C. Grey shading indicates the means of two groups are statistically different.

As shown in Table 4-5 and Table 4-6, females generally have a slightly higher skin temperature and larger variations than males. To evaluate if there exist significant gender differences in each feature, the *t*-test is conducted (two-sided 95% confidence interval). The result suggests that except one group (denoted in the light grey shading in Table 4-6), males and females do not show significant differences in the selected skin temperature features.

By comparing Table 4-5 and Table 4-6, it can be found that the facial skin temperature ($\bar{\mu}$) and variation ($\bar{s}$) of each feature collected by the camera node 1 are slightly higher than those by the camera node 2. This difference can be caused by the fact that one camera node captures more warmer regions than the other in the experiment (i.e., node 1 observes more frames of the frontal face which contains the forehead region that is typically warmer than cheeks). However, the trends of skin temperature features from the two camera nodes are both increasing over time, which can be used to interpret an individual's comfort state. This will be further discussed in Section 4.4.2 and 4.4.3.

4.4.2 Correlation Analysis between Different Skin Temperature Features

Correlation analysis is conducted to further investigate the relationships between different features. As shown in Table 4-7 and Table 4-8 the Pearson correlation coefficients of all features except for variances suggest a strong positive correlation between each feature pair (ranged from 0.63 to 0.94). The weak correlations between variances and other features indicate that variances are relatively steady in the experiment compared to others. To reduce the dimensionality of features, we adopt the facial mean skin temperature of the whole facial region detected in the cameras as the main feature for further analysis because it is representative of other features (due to the high correlations) and also more precise than others due to averaging.

Table 4-7 Correlations between Skin Temperature Features collected by Camera Node 1

	Mean	1st quartile	3rd quartile	Max	Var
Mean	1.00	0.92	0.91	0.88	- 0.00
1st quartile	0.92	1.00	0.78	0.75	- 0.16
3rd quartile	0.91	0.78	1.00	0.94	0.15
Max	0.88	0.75	0.94	1.00	0.19
Var	- 0.00	- 0.16	0.15	0.19	1.00

Table 4-8 Correlations between Skin Temperature Features collected by Camera Node 2

	Mean	1st quartile	3rd quartile	Max	Var
Mean	1.00	0.88	0.83	0.82	-0.11
1st quartile	0.88	1.00	0.63	0.63	-0.35
3rd quartile	0.83	0.63	1.00	0.94	0.13
Max	0.82	0.63	0.94	1.00	0.20
Var	-0.11	-0.35	0.13	0.20	1.00

4.4.3 Correlation Analysis between the Facial Mean Skin Temperature and Wrist Skin Temperature

Skin temperature from a wristband sensor is used to validate the proposed camera network. The wristband sensor has a resolution of 1 °C and takes a measurement every 30 seconds. Due to the differences between the wrist and facial skin temperature and the systematic error of different instruments, measurements from these two sources are not directly compared. Instead, we analyze their correlations as room temperature increases. As shown in Table 4-9, all coefficients, except one (subject 16, node 2), suggest moderate to strong positive correlations between the facial mean skin temperature and wrist temperature (ranged from 0.45 to 0.92), which indicates the non-intrusive camera network can capture the same thermoregulatory responses as the wearables. Also, for the same subject, it can be seen that the coefficient from one camera can be much higher than that of the other (e.g., subject 10). This finding suggests that despite an occupant can be observed by multiple camera nodes, data from different cameras may not be equally important in assessing changes in their skin temperature. Therefore, future studies will assign different weights to cameras in the comfort assessment according to their viewing distances and angles.

Table 4-9 Pearson Correlation Coefficients between the Facial Mean Skin Temperature and Wrist Skin Temperature

Subject ID	1	2	3	4	5	6	7	8
Node 1	0.78	0.74	0.84	0.71	0.77	0.80	0.62	0.62
Node 2	0.77	0.77	0.73	0.71	0.75	0.79	0.60	0.64
Subject ID	9	10	11	12	13	14	15	16
Node 1	0.47	0.82	0.70	0.64	0.84	0.92	0.77	0.77
Node 2	0.50	0.52	0.49	0.45	0.65	0.64	0.59	-0.21

4.4.4 Mapping Facial Mean Skin Temperature to Thermal Comfort State

To visualize the changes of skin temperature in the transient heating experiment, each subject's facial mean skin temperature is fitted using the polynomial regression. Specifically, the lower degree of polynomials is selected if the coefficient of determination R^2 does not increase significantly with a higher degree of polynomials (we used 5% as a threshold). As shown in Figure 4-13, each subplot shows the result of an experiment measured by a camera node. In each subplot, the two dotted lines denote the processed skin temperature data of two subjects, which are then fitted by polynomials of degree ranged from 1 to 3. All fitted curves (denoted in solid lines of the corresponding colors) in Figure 4-13, except subject 16, demonstrate an increasing trend of skin temperature over time, which implies the increases in skin blood flow under heat stress.

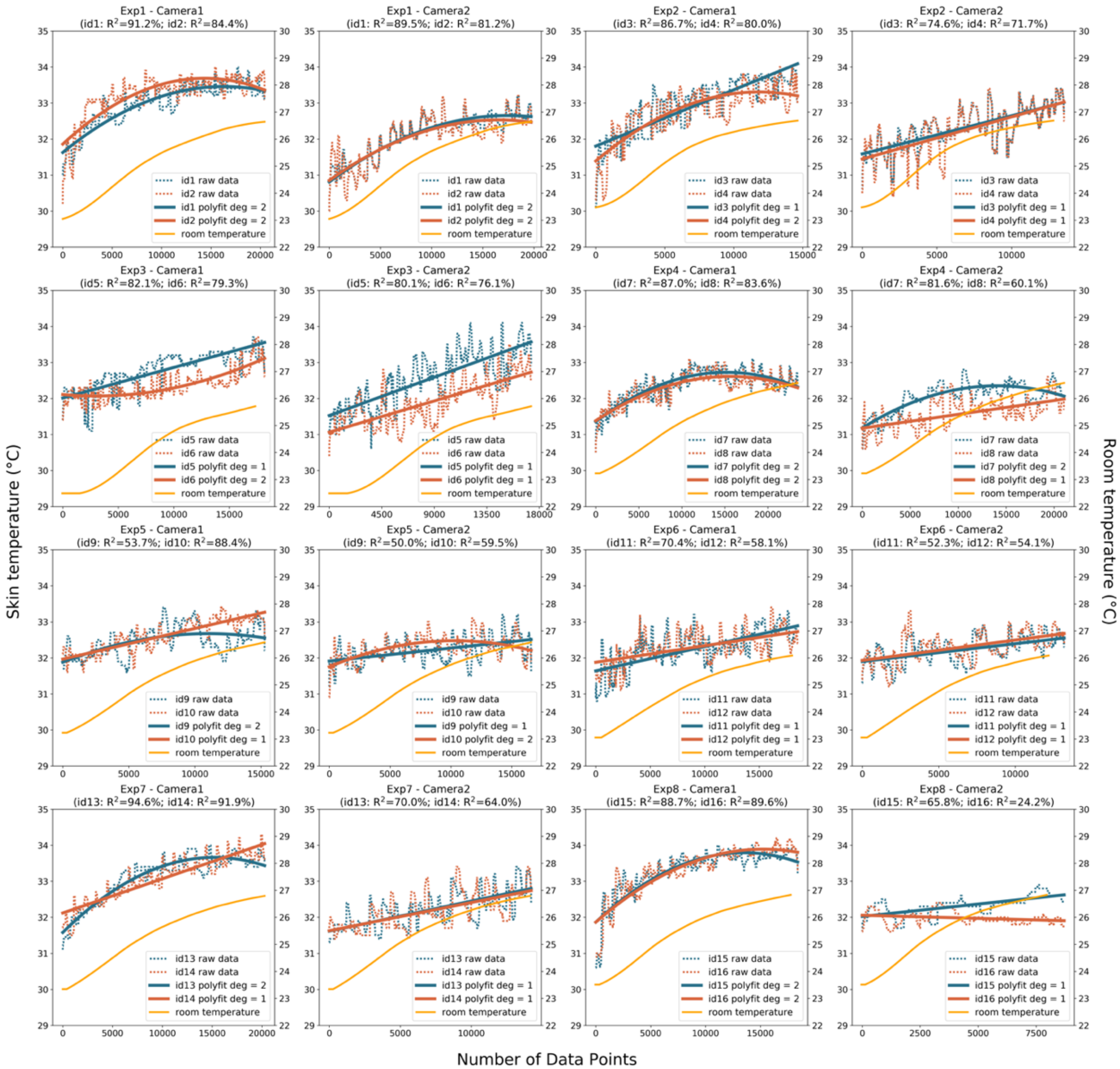

Figure 4-13 Polynomial Fit of the Facial Mean Skin Temperature of Each Subject

To map the thermoregulatory process to thermal comfort state, facial mean skin temperature of the first five minutes (denoted as $\overline{T}_{start}$) and the last five minutes (denoted as $\overline{T}_{end}$) in the heating experiment (from 23 °C to 27 °C) are calculated to represent a subject's starting and ending physiological states, respectively. As shown in Table 4-10, a two-tailed *t*-test shows that all 16 subjects have a statistically higher facial skin temperature ($p < .001$) as the room temperature increases in the experiment. In addition, all subjects reported distinct thermal comfort states (i.e., thermal sensation and preference) at these two stages, which are denoted as TCS_{start} and TCS_{end} in Table 4-10. As an example, Figure 4-14 presents a subject's thermal sensation votes and his/her corresponding facial mean skin temperature. Results of the analysis of variance (ANOVA) show that the means of different votes are significantly different, which suggests that facial skin temperature collected by the proposed camera network can serve as an indicator of subjects' thermal comfort state.

Table 4-10 *t*-tests between the Starting and Ending Facial Mean Temperature in the Experiment

Subject		Camera node	$\bar{T}_{start}$ (°C)	$\bar{T}_{end}$ (°C)	*p-value*	TCS_{start}	TCS_{end}
Exp. 1	Id1	1	31.6	33.4	<0.001	Cold	Warm
		2	31.2	32.9	<0.001	(warmer)	(no change)
	Id2	1	31.5	33.6	<0.001	Cold	Hot
		2	31.4	32.8	<0.001	(warmer)	(cooler)
Exp. 2	Id3	1	31.8	33.6	<0.001	Cold	Warm
		2	31.6	32.6	<0.001	(warmer)	(no change)
	Id4	1	31.4	33.5	<0.001	Cold	Neutral
		2	31.7	32.6	<0.001	(warmer)	(no change)
Exp. 3	Id5	1	32.1	33.4	<0.001	Cool	Warm
		2	31.5	33.5	<0.001	(warmer)	(cooler)
	Id6	1	32.1	33.2	<0.001	Cool	Neutral
		2	31.3	32.9	<0.001	(warmer)	(no change)
Exp. 4	Id7	1	31.3	32.5	<0.001	Cool	Warm
		2	31.3	32.3	<0.001	(no change)	(cooler)
	Id8	1	31.4	32.5	<0.001	Cold	Neutral
		2	31.1	32.0	<0.001	(warmer)	(no change)
Exp. 5	Id9	1	32.1	33.0	<0.001	Cool	Neutral
		2	32.0	32.4	<0.001	(warmer)	(no change)
	Id10	1	32.1	33.1	<0.001	Neutral	Warm
		2	31.9	32.2	<0.001	(no change)	(no change)
Exp. 6	Id11	1	31.4	32.8	<0.001	Cool	Neutral
		2	32.0	32.6	<0.001	(warmer)	(no change)
	Id12	1	31.6	32.7	<0.001	Neutral	Warm
		2	32.0	32.6	<0.001	(no change)	(no change)
Exp. 7	Id13	1	31.7	33.6	<0.001	Cold	Warm
		2	31.7	33.0	<0.001	(warmer)	(no change)
	Id14	1	31.9	33.7	<0.001	Neutral	Neutral

		2	31.7	32.8	<0.001	(no change)	(cooler)
Exp. 8	Id15	1	31.7	33.8	<0.001	Cool	Warm
		2	32.2	32.6	<0.001	(no change)	(cooler)
	Id16	1	32.1	33.9	<0.001	Neutral	Hot
		2	32.1	31.9	<0.001	(no change)	(cooler)

Note: Subjects' thermal preferences are shown in the parentheses in the TCS columns.

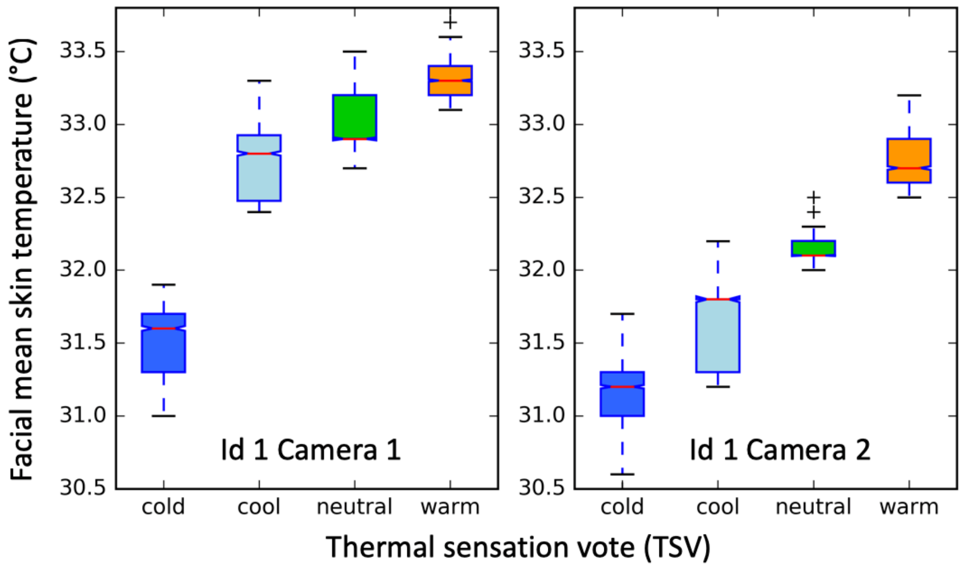

Figure 4-14 Thermal Sensation Vote and the Corresponding Facial Mean Skin Temperature of an Example Subject

4.4.5 Post-experiment Evaluations of User Experience

A survey is distributed to all subjects to understand their experience with the camera network regarding user acceptance, privacy concerns, and level of intrusiveness caused by the system (see Figure 4-15). The feedback suggests that the proposed approach has a high user acceptance regarding its application in the built environment (mean: 4.31, see Table 4-11), relatively low privacy concern caused by the use of cameras (mean: 3.94), and strong agreement in the non-intrusiveness of the approach (Q1 mean: 4.50, Q2 mean: 4.81).

Please rate the degree to which you agree or disagree with each of the following statements related to the camera network (5 - Strongly agree, 4 - Agree, 3 - Neutral, 2 - Disagree, 1 - Strongly disagree):

User Acceptance – I would recommend such camera network systems to be applied in multi-occupancy spaces to assess occupants' thermal comfort (e.g., classroom, rest lounge).

Privacy Concern – I do NOT have any privacy concern about such camera network systems if they are applied in the built environment.

Level of Intrusiveness Q1 – Based on my experience in the experiment, I think the camera network is not intrusive at all.

Level of Intrusiveness Q2 – Compared to wristband sensors, I prefer using the camera network to collect my skin temperature data as it is less interruptive and does not cause any pain or strain that may arise from wearables.

Figure 4-15 Post-Experiment Survey Questions

Table 4-11 Subjects' Post-Experiment Evaluation

Subject ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Mean
User Acceptance	4	4	4	5	4	5	5	4	4	3	4	5	5	4	4	5	4.31
Privacy Concern	4	4	4	3	4	3	5	4	4	4	4	4	4	4	4	4	3.94
Intrusiveness Q1	4	4	4	3	5	5	5	4	5	4	5	5	5	5	4	5	4.50
Intrusiveness Q2	5	5	5	4	5	5	5	4	5	5	5	5	5	5	4	5	4.81

However, limitations of this study should be acknowledged. First, the skin temperature collected from the frontal and profile faces is not differentiated in the current approach, which can be a reason for the fluctuations in the measurements. As a result, future studies can keep the frontal and profile faces (or possibly different facing directions) as separate datasets when evaluating subjects' thermal comfort. Second, the proposed camera network is tested in a simplified multi-occupancy environment with two subjects. Several challenges may arise from a larger space with more subjects, such as occlusions, increased viewing distance, and occupant registration. Thus, future research can fully explore the scalability potential of the proposed approach.

4.5 Conclusions

This chapter introduced the main characteristics of the non-intrusive detection of thermal comfort and proposed a low-cost networked camera system to non-intrusively measure occupants' facial skin temperature for real-time thermal comfort assessment in multi-occupancy environments. Each camera node in the network fuses the RGB-D and thermal images collected from a Kinect and a low-cost thermal camera. The experimental results from 16 subjects suggest that the variations in low temperature facial regions are more significant than high temperature regions under heat stress, as well as moderate to strong positive correlations between the skin temperature collected by the camera network and wearables (ranged from 0.45 to 0.92). Moreover, subjects' facial skin temperature has observed statistically significant increases when the room temperature changes from 23 °C to 27 °C. Results of ANOVA support our assumption that facial skin temperature can serve as an indicator of one's thermal comfort state. Finally, subjects have expressed positive evaluation regarding the usefulness, privacy issues, and the non-intrusiveness of the proposed approach.

Knowledge gained from this chapter has the potential to transition the current human physiological sensing from an intrusive and wearable device-based approach to a truly non-intrusive and scalable approach such that skin temperature can be automatically measured without any constraints on occupants' activities or participation. The proposed camera network can be incorporated into the building HVAC systems for energy control and thermal comfort management. For example, a real-time interpretation of thermal comfort allows the HVAC systems to dynamically adjust its setpoint and airflow and also select the optimum settings to maximize the overall comfort. If the indoor environment is equipped with personal heating/cooling devices or HVAC zoning systems, personalized conditioning can be delivered to the corresponding location if conflicts of thermal preference exist in the shared space. The proposed approach is particularly promising in multi-occupancy environments, such as offices, conference rooms, rest lounges as personal and wearable devices may not be available for everyone. This approach can also be applied to other critical built environments, including the transportation systems, health facilities, and extreme working environments where occupants' thermal comfort and satisfaction are much needed.

CHAPTER 5

Optimization of Temperature Setpoint through Personal Comfort Models and Physiological Sensing

5.1 Introduction

The preceding Chapters 2, 3 and 4 present novel thermal comfort sensing approaches using human physiological data including wrist skin temperature, facial skin temperature, heart rate, etc. These approaches can be applied in both single and multi-occupancy spaces to achieve real-time prediction of thermal comfort of occupant(s) using personal comfort models. Once the overall thermal comfort in a built environment is evaluated, a closely related question can be raised, i.e., how to adjust the HVAC settings to improve the overall thermal comfort and satisfaction? This is a particularly interesting question in multi-occupancy environments where the thermal preference of each occupant not only can change over time but also may vary from one person to another (Li et al. 2017a). Therefore, a static setpoint according to industry guidelines (e.g., ASHRAE) can hardly provide an optimum thermal environment, i.e., an environment that keeps as many occupants comfortable as possible, if not all, in a multi-occupancy space. In fact, the ASHRAE standard 55 - *Thermal Environmental Conditions for Human Occupancy* specifies that thermal environments should be maintained to make at least 80% of the occupants comfortable, which suggests the challenges in achieving an unanimously satisfied condition.

To adjust and improve the thermal environment, existing literature has proposed various comfort modeling and HVAC control strategies (e.g., Daum et al. 2011, Erickson and Cerpa 2012, Feldmeier and Paradiso, Jazizadeh et al. 2013, Jung and Jazizadeh 2019b, Li et al. 2017c, Purdon et al. 2013). The main approach adopted in these studies is adjusting the thermostat setpoint to increase or decrease the room temperature. This is because the room temperature directly and significantly affects the perceived thermal comfort, and can be easily controlled compared to other environmental factors such as the relative humidity (Ghahramani et al. 2015). Also, studies observed that variations in relative humidity are a byproduct when adjusting the thermostat setpoint in real operational environments where relative humidity shows a negative correlation with the room temperature (Jung et al. 2019, Li et al. 2019a). As a result, only the temperature setpoint is considered as an independent variable in the comfort analysis.

In general, existing studies which aim to adjust the setpoint for improved thermal comfort can be divided into two categories: (1) a passive and iterative control process which implements a corrective temperature in each step, and (2) a closed-form adjustment that attempts to achieve the optimum setpoint in one step.

Studies in the former category typically leverage the feedback (or thermal vote) from occupants over time. For example, Erickson and Cerpa (2012) calculated the corrective temperature using the PMV model to offset discomfort votes received in each decision cycle, which is set at 10 minutes. This corrective temperature then updates the current setpoint to provide additional heating or cooling to restore a thermally neutral state. Purdon et al. (2013) also leveraged this voting mechanism (e.g., -1 for cooler, 1 for warmer) where the net vote, i.e., the sum of votes from all occupants, was calculated in each cycle. The room temperature will decrease by a fixed step of 1 °C for a negative net vote, which means a lower temperature is preferred, and vice versa.

In Li et al. (2017c), occupants' personal comfort models were applied in the HVAC control loop to update the setpoint. If a negative or positive net thermal vote was collected in a decision cycle (i.e., every 30 minutes), the control algorithm will evaluate the new setpoint (i.e., the previous setpoint ±1 °C) using each occupant's comfort model. A corrective temperature will be implemented if more occupants were predicted comfortable under the new setpoint. As discussed in these three example studies, this HVAC control schema is an iterative process as continuous corrective steps are needed when occupants provide new thermal votes; and this is also a passive process as it is unable to proactively determine the optimum setpoint for the future decision cycle. As a result, this schema may lead to longer discomfort time due to its trial-and-error adjustments and also make the setpoints oscillate over time, which may damage the HVAC systems.

Another category of the HVAC control strategy uses personal comfort models to find a closed-form solution for the optimum setpoint. In this schema, thermal comfort is generally modeled as a function of environmental parameters (e.g., room temperature). For example, Feldmeier and Paradiso (2010) built a linear model using room temperature and humidity to classify uncomfortably hot and cold events. Daum et al. (2011) developed occupants' comfort models using logistic regression, which represents the probability of different thermal preferences at different room temperature. This study also suggested the template comfort model can quickly converge to the actual personalized model using around fifty thermal votes. Similarly, Jazizadeh et al. (2013) developed fuzzy models that predict an occupant's probability of different thermal sensations at given room temperature. As personal comfort models adopted in these studies directly associate the room temperature with thermal comfort, a closed-form solution, which outputs the optimum setpoint that maximizes an objective function (e.g., the number of comfortable occupants), can be directly calculated. For example, Jung and Jazizadeh (2019b) compared three HVAC control strategies in determining the optimum setpoint. In this study, personal comfort models, which measure the probability of being comfortable (i.e., comfort probability) as a function of room temperature (see Figure 5-1), are developed using the Gaussian distribution. Specifically, this study introduced the concept of thermal sensitivity, i.e., the increased or decreased comfort probability caused by the variations in room temperature. Using this metric, the optimum setpoint can be selected to maximize the sum of the comfort probability of all occupants. This study provides useful insights into the HVAC control by addressing the optimization question in a probabilistic view and considering occupants' different responses to hot and cold stimuli (i.e., thermal sensitivity).

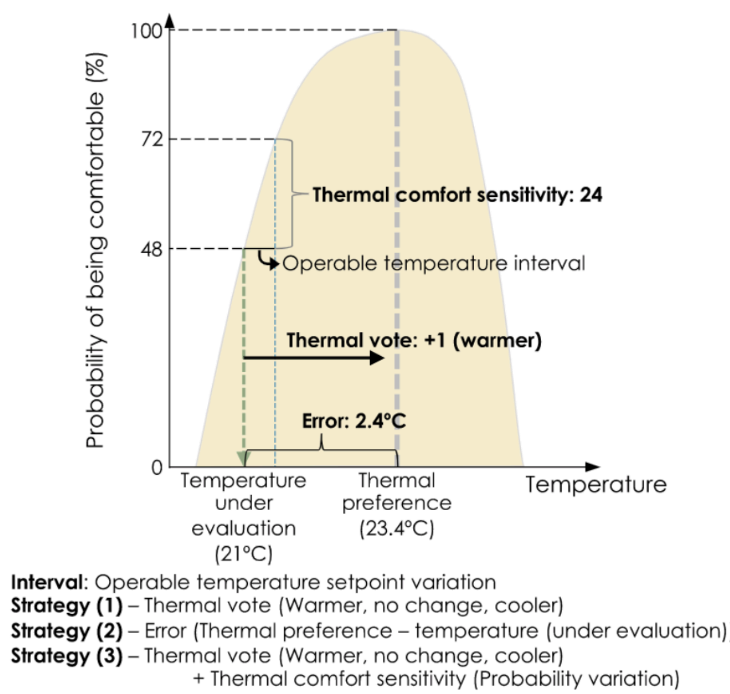

Figure 5-1 Thermal Profile and HVAC Control Strategies in Jung and Jazizadeh (2019b) (adapted from Jung and Jazizadeh 2019b)

However, the one-step HVAC optimization strategies proposed in Jung and Jazizadeh (2019b) cannot directly integrate with human physiological sensing-based comfort models. This type of model maps real-time human physiological data, such as skin temperature, heat flux, and heart rate collected from human body, into a prediction of thermal comfort and has gained a lot of attention in recent years (e.g., Chaudhuri et al. 2018, Jung et al. 2019, Jung and Jazizadeh 2018, Li et al. 2018 and 2019a, Liu et al. 2019). Studies such as Jung and Jazizadeh (2019a), Li et al. (2017c) and (2019a) suggested that physiological sensing-based comfort models can achieve better prediction accuracy than models which only consider the environmental data; and have the potential to reduce the intrusiveness caused by thermal vote. However, a major challenge should be addressed before this model can be integrated into the HVAC control, that is, the uncertainties in occupants' thermal comfort under the new setpoint, which result from the unknown effect of updated thermal environments on human physiological parameters. For example, in a scenario where skin temperature is used for comfort prediction, the model can continuously predict one's thermal preference or its probability as long as a new measurement is collected. If the model predicts "prefer warmer" and the setpoint is increased accordingly, it is unknown how much people's skin temperature will be affected by the new setpoint, and thus it is still in question whether this occupant will feel more comfortable. In other words, the physiological sensing-based models only predict the current thermal comfort state but cannot make predictions into the future. Therefore, it only works with the iterative and passive HVAC control process introduced above.

Figure 5-2 illustrates this problem and the potential outcomes in a built environment due to uncertainties in predicting future thermal comfort using physiological data. In this example, the setpoint is initially set at 24 °C at time t in a room occup ied by three occupants (denoted as id1, id2, and id3). Occupants' physiological data at time t are collected (denoted as $T_{id1}^{t}, T_{id2}^{t}, T_{id3}^{t}$), and predictions show that two of them prefer a warmer environment and one prefers a cooler environment. As a result, the control increases the setpoint by 1 °C, which will be implemented at time $t + 1$. However, as the impact of this adjustment on the physiological parameter is unknown at time t, this control has no knowledge about occupants' future physiological conditions at time $t + 1$ (denoted as T_{id1}^{t+1}, T_{id2}^{t+1}, T_{id3}^{t+1}), and thus fails to predict the future thermal comfort states. Therefore, three possible outcomes of this control (i.e., increase the setpoint by 1 °C) can be encountered at time $t + 1$ including an insignificant control (the majority still prefer warmer), a promising control (the majority now feel comfortable), and an overshoot control (the majority start to prefer cooler). If either the insignificant or overshoot control occurs, then a new adjustment should be implemented and its corresponding impact is unclear until time $t + 2$.

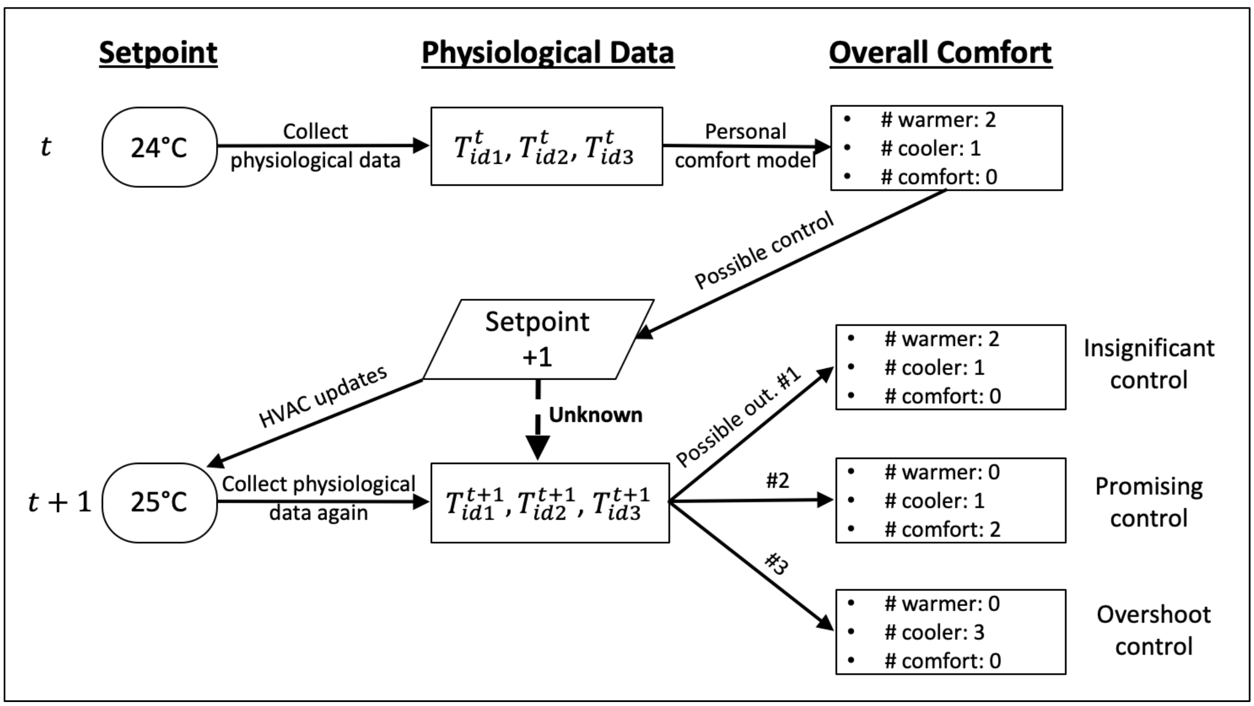

Figure 5-2 The HVAC Control Steps When Using Physiological Sensing Approaches

Therefore, to address this limitation and achieve a proactive HVAC control, it is important to understand the impact of room temperature variations (or other environmental variables if applicable) on the physiological parameters considered in the comfort model. To this end, this chapter presents an approach to predict occupants' physiological parameters and demonstrates how to integrate it with personal comfort models to determine the optimum setpoint. The contributions of this research and the methodology are presented as follows.

5.2 Contributions

This chapter leverages the merits of physiological comfort sensing approaches in preceding chapters and fills an important gap that prevents its integration in the HVAC control strategies. The resulting knowledge closes the loop of occupancy-focused HVAC control systems which evaluate each occupant's comfort through physiological sensing and proactively determine the optimum setpoint of a group of occupants. The specific contributions of this chapter include:

- Demonstrate how to integrate the physiological predictive model and personal comfort model to evaluate an occupant's comfort (i.e., thermal comfort zone or comfort probability) under a new setpoint, particularly when the physiological sensing is adopted.
- Develop a modeling approach to interpret human physiological states (e.g., skin temperature) under different environmental conditions (e.g., room temperature).
- Demonstrate how HVAC control strategies can optimize thermal comfort and energy consumption in a multi-occupancy environment using each occupant's thermal comfort zone and comfort probability.

5.3 Methodology

This chapter will use the facial skin temperature and room temperature as the human physiological and environmental parameters respectively to demonstrate the integration of physiological sensing into the HVAC control process. This process can be decomposed into two steps including (1) occupants' thermal comfort prediction using facial skin temperature (i.e., the "sensing" step); and (2) determination of the optimum setpoint based on the overall comfort prediction (i.e., the "control" step). The former sensing step can be represented by a model f

which maps an occupant's skin temperature T_{skin} into his/her thermal comfort state TC (Eq. 5.1), which can be a regression (e.g., thermal sensation with numerical scales), classification (e.g., thermal preference with categorical scales), or a probability distribution (e.g., probability of being comfortable). The model g, on the other hand, is the missing physiological predictive component that bridges the new setpoint T_{room} which is a possible control strategy and the projected skin temperature T_{skin} under this new setpoint (Eq. 5.2). By chaining these two models f and g, an occupant's thermal comfort under a new setpoint can be predicted with the physiological sensing as an intermediate step (Eq. 5.3). The approaches to develop each model are presented in the following subsections.

$$f\colon\ T_{skin} \rightarrow TC \tag{5.1}$$

$$g\colon\ T_{room} \rightarrow\ T_{skin} \tag{5.2}$$

$$f(g)\colon\ T_{room} \rightarrow TC \tag{5.3}$$

5.3.1 Personal Thermal Comfort Models

Thermal comfort prediction is generally considered as a classification problem, which predicts an occupant's thermal sensation or preference at different conditions. As a result, personal comfort models (i.e., model f) can be trained using various classification algorithms including the Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Classification Tree (Ctree) (e.g., Chaudhuri et al. 2018, Daum 2011, Jung et al. 2019, Kim et al. 2018a, Li et al. 2017c, Li et al. 2019d). Among these approaches, studies such as Li et al. (2019d) and Kim et al. (2018a) suggested that the RF algorithm generally produces better comfort prediction accuracy than others. RF trains a collected of bagged decision trees using a random subset of features on each split and is robust to outliers and high dimensional datasets. However, one major drawback of RF is the low interpretability (Breiman 2001). On the other hand, thermal comfort can also be represented in a probabilistic distribution using LR, Fuzzy Logic models, or Bayesian Networks when the number of features is small (Daum et al. 2011, Ghahramani et al. 2015, Jazizadeh et al. 2013, Jung and Jazizadeh 2019b). This approach offers significant model interpretability as changes in thermal comfort probability, which is a useful metric to determine the optimum setpoint, can be easily associated with the variations in features (typically room temperature). As a result, this chapter adopts LR to develop personal comfort models. However, other modeling approaches can also be adopted without impairing the implications of this work.

LR uses a logistic function to predict the probability (p) that an event happens. The basic form of LR is shown in Eq. 5.4 where the log-odds of an event, $\log\left(\frac{p}{1-p}\right)$, is modeled as a linear combination of input variables x, and the coefficients βs are estimated from the input data. LR is typically used to predict a binary class (e.g., an event happens or not) and an event is classified as 1 (an event happens) if the probability p is greater than 0.5 (James et al. 2013).

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n \tag{5.4}$$

LR can also be generalized to predict events that have multiple classes, which is also known as the multinomial logistic regression. In this chapter, the input variable is occupants' facial skin temperature, and the output variable is the corresponding thermal comfort which has three categorical values including uncomfortably hot, comfortable, and uncomfortably cold.

To develop personal comfort models, we used the data collected from an experiment introduced in Chapter 3 in which a thermal camera continuously measures an occupant's facial skin temperature from six regions including forehead, cheeks, nose, mouth, ears, and neck, under heating, cooling, and steady-state scenarios. During the experiment, occupant's thermal votes (e.g., prefer warmer, cooler, or neutral) are recorded. In this chapter, cheek skin temperature is selected in the personal comfort model as Chapter 3 suggests the cheek temperature is indicative of one's thermal comfort. However, other skin temperature features can also be used without losing the implications of this approach.

Figure 5-3 shows the thermal votes from ten participants while their cheek temperature is collected. In this figure, "+1" denotes uncomfortably cold (or prefer warmer), "0" denotes being comfortable, and "-1" denotes uncomfortably hot. It can be observed that subjects generally feel cold when their cheek temperature is low, and vice versa. However, a few exceptions exist in subjects 6, 7 and 8 where the cheek temperature has some "vacuum regions". For example, for subject 6, the cheek temperature between 31 and 32 °C is not observed. This is because the dataset of each occupant consists of three scenarios (i.e., heating, cooling, and steady-state). Despite similar skin temperature and thermal vote patterns exist in each scenario; when the data from three scenarios are combined, the skin temperature might not be continuous in its full range. This observation can be caused by breaks between two experimental scenarios (heating to cooling) when subjects' skin temperature changes significantly. This phenomenon can cause a problem when using LR for comfort profiling, which will be discussed later in this section.

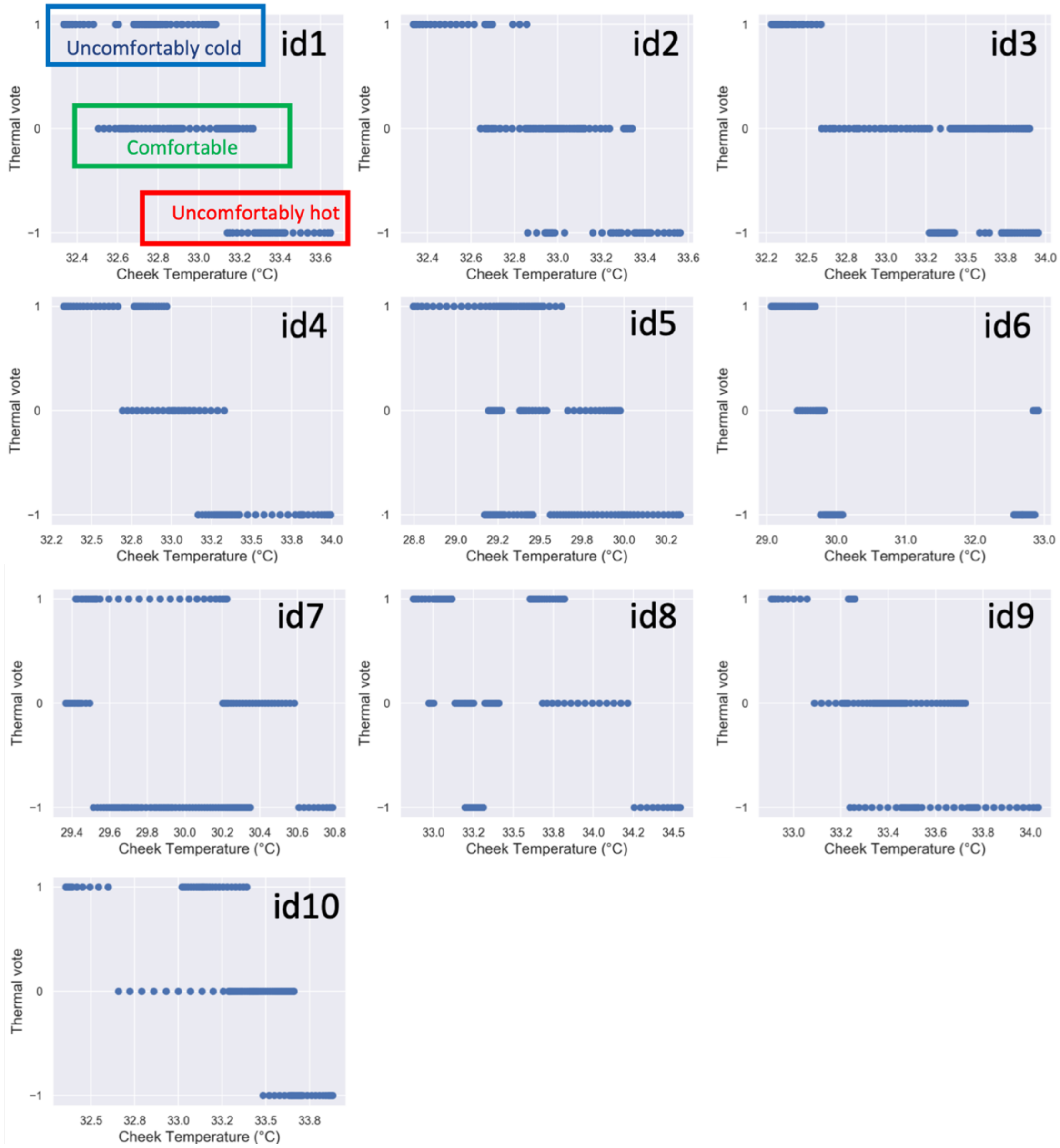

Figure 5-3 Thermal Votes of Each Subject and the Corresponding Cheek Temperature

Using the data presented in Figure 5-3, thermal comfort models can be developed using LR, which are shown in Figure 5-4. In this figure, the green, blue, and red curves represent an occupant's probability of being comfortable, uncomfortably cold, and uncomfortably hot at different cheek temperature. In this probabilistic representation, an occupant is predicted as being comfortable if the corresponding comfort probability is greater than the other two conditions.

Accordingly, the range of skin temperature that is associated with the comfortable state can be obtained, which is highlighted in a yellow region in Figure 5-4. In this figure, subjects have different comfort ranges in cheek temperature. For example, subjects 3 and 8 have a much wider range than the subject 4, which indicate they have a higher tolerance over the variations in room temperature.

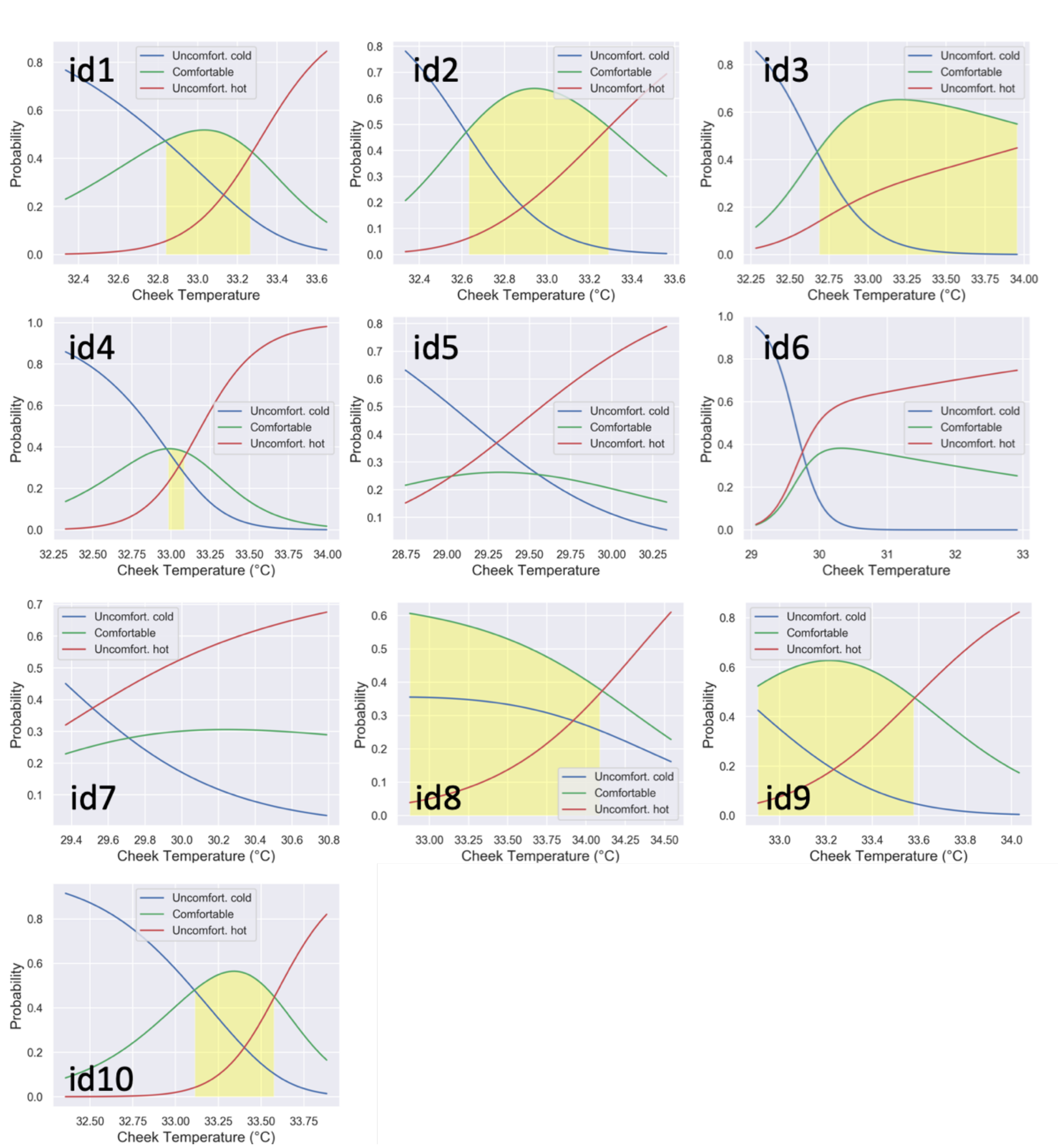

Figure 5-4 Thermal Comfort Model for Each Subject (yellow region denotes the range of cheek temperature when a subject feels comfortable)

As shown in Figure 5-4, comfort models for subjects 6 and 7 do not indicate a comfort range while that of subject 8 does not have a lower bound. This results from the discontinuous cheek temperature data as discussed above. A possible solution to this problem is to use the skin temperature of other facial regions in comfort profiling. For example, Figure 5-5 shows subject 8's comfort models using six different regions. It can be seen that models of both ear and neck regions indicate a comfort range, which can be used to substitute the cheek region. For subject 5, due to the imbalanced feedback that fewer comfort votes are received than discomfort votes, as well as the significant overlap between the cheek temperature in different comfort conditions, the probability of being comfortable is always lower than the other two conditions. In other words, the LR model using a single feature is not suitable for this subject, and more complex models like ensemble models (e.g., RF, XGBoost) should be considered instead.

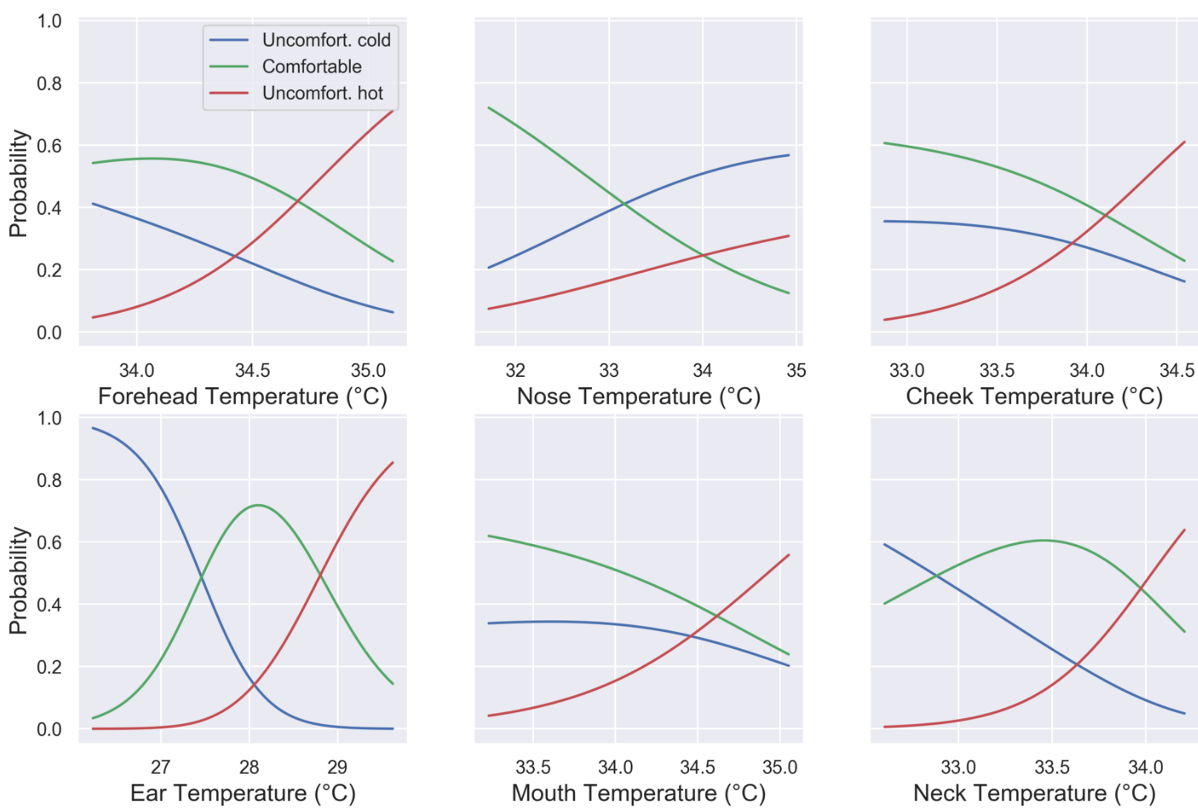

Figure 5-5 Thermal Comfort Models of Six Facial Regions for Subject 8

5.3.2 Physiological Predictive Models

The physiological predictive model (i.e., model g) predicts the resulting skin temperature (or other physiological parameters) under different room temperature, which enables comfort models to evaluate the impact of a new setpoint. In this model, the output variable skin temperature is affected by multiple factors, such as the room temperature (the direct input variable of interest), personal variations (skin temperature variations across different subjects), and the conditioning mode (i.e., under heating or cooling states) due to subjects' different thermal sensitivities to the hot and cold stress.

The linear mixed model (LMM), also known as the hierarchical model, is adopted to develop physiological predictive models. Unlike ordinary linear regression, LMM not only considers variations that are explained by the input variables of interest, i.e., fixed effects, but also variations resulting from the random samples from the population, which are called random effects. A matrix form of the LMM is shown in Eq. 5.5.

$$y = X\beta + Zu + \epsilon \tag{5.5}$$

$$u \sim \mathcal{N}(0, G)$$

Where y is a vector of responses, β is the unknown vector of fixed effects, u is the unknown vector of random effects which is assumed to follow a Gaussian distribution, X and Z are the design matrices corresponding to β and u, ϵ is a vector of error terms, G is the variance-covariance matrix of random effects.

In statistical studies, "human subject" is often used as a random effect as responses from the same subject cannot be considered as independent; and introducing this random effect accounts for the individual differences between subjects (Winter 2013). In this study, LMM lies between the ordinary linear regression, which uses the aggregated sample data to train a single model (i.e., assuming each data point is independent and develop one model using all subjects' data) and the fully personalized model, which develops a model for each subject using only the personal data. In the former case, the assumption of sample independence is violated as multiple samples from the same subject share similarities. For the latter, however, one's personalized model does not use the information from other subjects, which can result in less robust models if the sample size of each subject is small. LMM addresses these two problems by acknowledging the dependence between data within each subject as well as the commonality between subjects (Winter 2013). As a result, for physiological predictive models, LMM is adopted considering that subjects share similarities in skin temperature variations under heating or cooling scenarios; while for the thermal comfort prediction, personal models are developed as thermal votes are subjective which may vary significantly across subjects.

The form of LMM for skin temperature is shown in Eq. 5.6 in which the human subject is considered as a random effect.

$$T_{skin} = \beta_0 + \beta_1 \cdot R_t + \beta_2 \cdot S_t + \beta_3 \cdot R_t S_t + b_0 + b_1 \cdot R_t + b_2 \cdot R_t S_t \tag{5.6}$$

Where T_{skin} is a subject's corresponding skin temperature under a new setpoint R_t, S_t is the conditioning mode which is a binary variable (1 for cooling, 0 for heating), β_0 to β_3 represent the coefficients of fixed effects, and b_0 to b_2 represent the coefficients of random effects, which include both random slopes and a random intercept.

The LMM models are developed using the *R* package (version 1.2.1335). Subjects' cheek temperature from the heating and cooling scenarios is used for model training as the skin temperature in these two scenarios varies with respect to the room temperature. The results are shown in Figure 5-6 and Figure 5-7, representing the cooling and heating scenarios respectively. The model summary is presented in Table 5-1 to Table 5-3. As subjects 5 to 8's comfort models are less indicative (Section 5.3.1), physiological models of the rest six subjects are retained in Figure 5-6 and Figure 5-7. It can be observed that subjects have different skin temperature responses to the setpoint changes. For example, subject 3 is most susceptible to cold stress and will decrease cheek temperature by 0.35 °C for every 1 °C drop in room temperature; while subjects 1 and 9 have a smaller temperature gradient of 0.19 °C. As indicated by the slopes, the skin temperature sensitivity is different in cooling and heating scenarios even for the same subject. The skin temperature in this experiment changes more rapidly when the room is cooling down as larger gradients are observed. This finding has also been discussed in Chapter 3 that the skin temperature varies in a smaller range in the heating scenario, which might be caused by the slower response time of the HVAC system in the testbed. However, it should be noted that physiological models are only defined when the room temperature is between 22 and 28 °C (which is the range of the data collection experiment). These models may not be accurate when extrapolated to room temperature which is outside of this range.

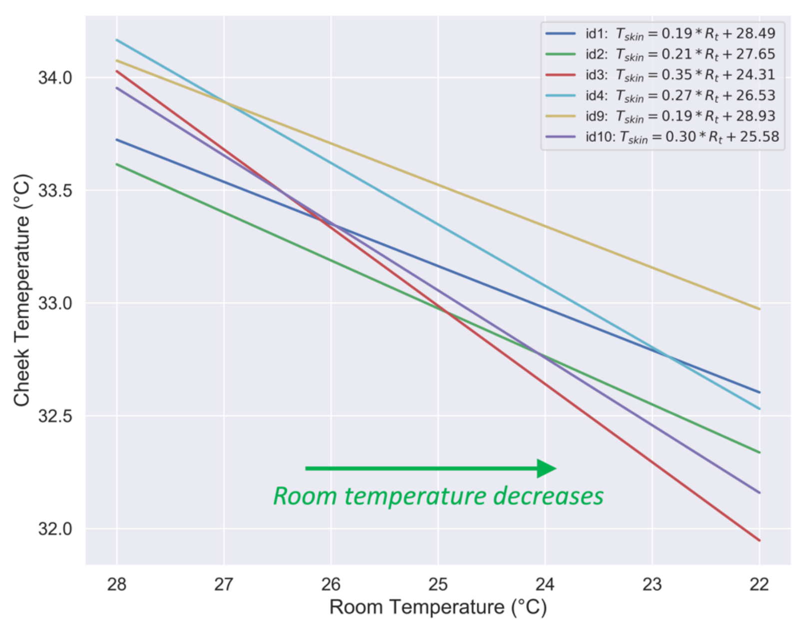

Figure 5-6 Linear Mixed Model for Cheek Temperature in the Cooling Scenario (the x-axis is reversed to represent the decreasing room temperature)

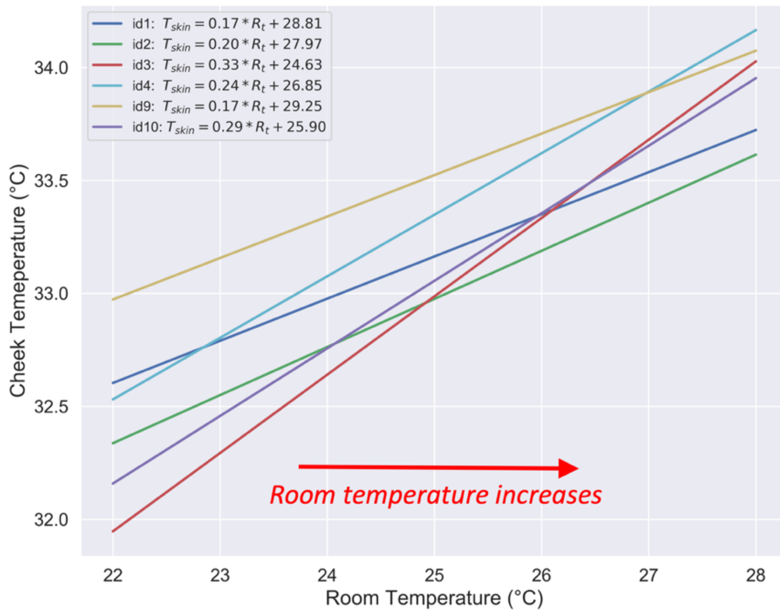

Figure 5-7 Linear Mixed Model for Cheek Temperature in the Heating Scenario

Table 5-1 Estimates of the Fixed Effects

Fixed effects	Estimate	Std. Error	*t* value
Intercept	26.62	0.64	41.31
R_t	0.21	0.02	11.52
S_t	- 0.32	0.16	-2.0
$R_t \cdot S_t$	0.03	0.02	1.70

Table 5-2 Correlations of the Fixed Effects

Correlation of fixed effects	Intercept	R_t	S_t
R_t	-0.690		
S_t	-0.115	0.162	
$R_t \cdot S_t$	0.051	-0.311	-0.368

Table 5-3 Statistics of the Random Effects

Groups	Name	Std. Dev.
Subject	Intercept	2.11
	R_t	0.06
	$R_t \cdot S_t$	0.05
Residual		0.16

5.4 Thermal Comfort Optimization Strategies

As subjects' personal comfort models and physiological predictive models are developed in the previous sections. Chaining these two models enables the prediction of a particular subject's thermal comfort at different setpoints including (1) thermal comfort zone, i.e., the range of setpoints that a particular subject is predicted as being comfortable; and (2) thermal comfort probability, i.e., the probability distribution that a particular subject is comfortable across the feasible setpoints. Based on these two metrics, three comfort optimization strategies are proposed:

Strategy 1: The optimum setpoint should maximize the number of comfortable occupants in the environment, as shown in Eq. 5.7:

$$Setpoint^* = \underset{R_t}{\operatorname{argmax}} \sum_i Comfort_i(R_t) \tag{5.7}$$

Where $Setpoint^*$ is the optimum setpoint, R_t is the feasible setpoints of a particular room, $Comfort_i(R_t)$ is a binary comfort state of subject i, which is 1 if subject i is comfortable at R_t, and 0 otherwise.

Strategy 2: If there is a tie in the results of strategy 1, the optimum setpoint should also maximize the overall thermal comfort probability in the environment, as shown in Eq. 5.8:

$$Setpoint^* = \underset{R_t^*}{\operatorname{argmax}} \sum_i Prob_i(R_t^*) \tag{5.8}$$

Where R_t^* is the selections of strategy 1, i.e., the range of setpoints that can make most subjects comfortable in the shared environment, $Prob_i(R_t^*)$ is the thermal comfort probability of subject i at room temperature R_t^*.

Strategy 3: The optimum setpoint should maximize the overall thermal comfort probability in strategy 2 with constraints in the HVAC energy consumption, as shown in Eq. 5.9:

$$Setpoint^* = \underset{R_t^*}{\operatorname{argmax}} \ \{\alpha \cdot Comfort\_score - (1-\alpha) \cdot Energy\_score\} \tag{5.9}$$

$$Comfort\_score = \frac{\sum_i Prob_i(R_t^*)}{\max_{R_t \in R_t^*} \sum_i Prob_i(R_t)}$$

$$Energy\_score = \left| \frac{R_{base} - R_t^*}{R_u - R_l} \right|$$

Where α is the weight of thermal comfort, which ranges from 0 to 1. A larger α implies more importance is given to the thermal comfort than energy consumption. If α = 1, strategy 3 only focuses on maximizing the overall comfort probability, which will yield the same result as strategy 2; on the contrary, if α = 0, strategy 3 focuses on making most subjects comfortable with the least energy use, which will choose the setpoint in R_t^* that is close to the baseline setpoints R_{base}. In this chapter, we used 22 °C as the baseline for heating seasons and 28 °C for cooling seasons to represent the lowest energy consumption situations. By tuning α, a trade-off can be found between the thermal comfort and energy consumption. R_u and R_l are the upper and lower bound of the feasible setpoints, which are 28 °C and 22 °C, respectively, $|\cdot|$ is the absolute value.

5.4.1 Thermal Comfort Optimization using Strategy 1

To determine the optimum setpoint, we first assume the room temperature is originally set at 25 °C according to conventional settings (which is the median of our experimental temperature between 22 °C and 28 °C) in a multi-occupancy environment. All feasible setpoints are then searched from 25 °C to 28 °C (i.e., heating scenario) and from 25 °C to 22 °C (i.e., cooling scenario) at a step size of 0.1 °C. Despite the actual HVAC systems may not allow a 0.1 °C adjustment, this implementation does not lose implications in real situations as thermal comfort conditions at two adjacent integer setpoints can be compared to choose the optimum and feasible setpoint.

When applying strategy 1, the thermal comfort zone of each subject is calculated, which is shown in the horizontal bar in Figure 5-8. Each subject's comfort zone is determined by first finding the corresponding skin temperature at a given setpoint using the physiological predictive models; and then evaluating the categorical thermal comfort states (i.e., uncomfortably hot, comfortable, and uncomfortably cold) through personal comfort models. If the probability of being comfortable is the highest, then the corresponding setpoint is added into this subject's comfort zone. Therefore, the optimum setpoint should pass as many subjects' comfort zones as possible if they share the same environment. As shown in Figure 5-8, for the six subjects in our experiment, 25.3 °C and 25.4 °C are selected as all subjects are comfortable at these two setpoints.

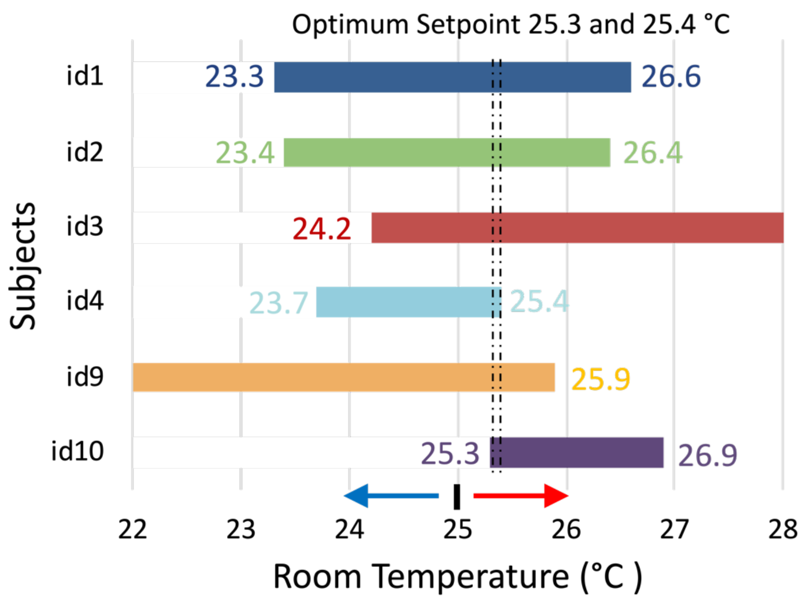

Figure 5-8 Optimum Setpoint Selection Using Strategy 1 (maximize the number of comfortable occupants)

5.4.2 Thermal Comfort Optimization using Strategy 2

When applying strategy 2, besides thermal comfort zones, comfort probability distributions (i.e., the probability of being comfortable) are also calculated, which are shown as the bell curves in Figure 5-9. The average comfort probability can then be obtained by averaging the probability distributions of all subjects (denoted in the black dash-dotted line). As strategy 1 suggests both 25.3 °C and 25.4 °C (i.e., R_t^*) yield the same number of comfortable subjects, the overall comfort probability at these two setpoints are then compared. As 25.4 °C yields a higher overall comfort probability than 25.3°C, it is chosen as the optimum setpoint for these six subjects.

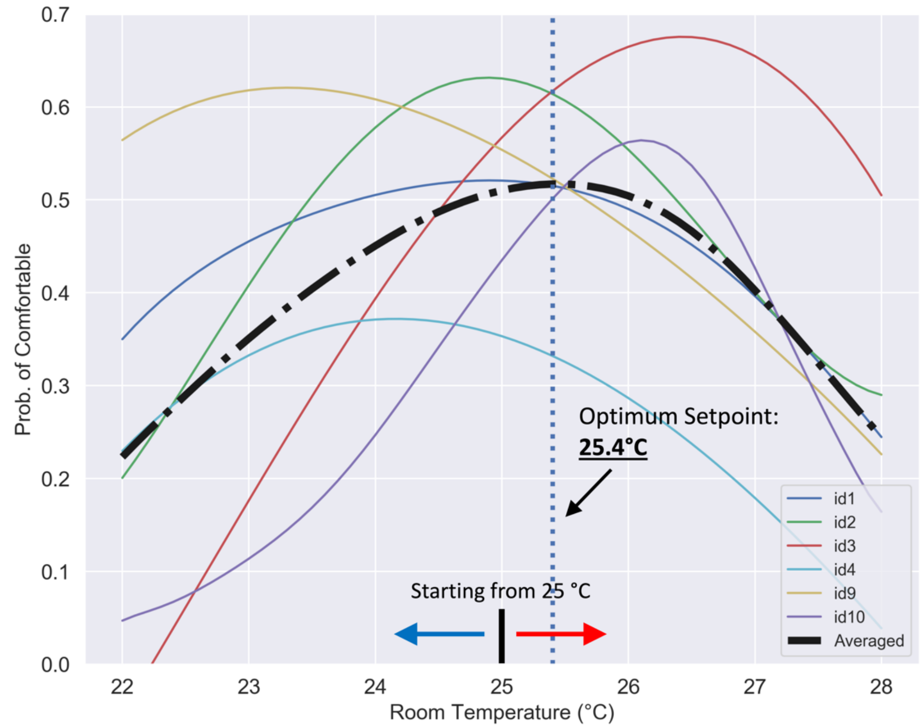

Figure 5-9 Optimum Setpoint Selection Using Strategy 2 (maximize the overall comfort probability when multiple setpoints yield the same number of comfortable occupants)

5.4.3 Thermal Comfort Optimization using Strategy 3

When applying strategy 3, two components should be calculated including a comfort score and an energy score. The comfort score ($Comfort\_score$), which ranges from 0 to 1, is the overall comfort probability at the current setpoint over the highest comfort probability that can be achieved in the range R_t^*. The energy score ($Energy\_score$), which also ranges from 0 to 1, is the absolute value of the setpoint deviation from the baseline over the range of setpoint options.

As R_t^* for all six subjects only includes two possible setpoints, i.e., 25.3 °C and 25.4 °C, a subset consisting of three subjects (id 1, 2, and 3) is chosen as an example to demonstrate strategy 3 as a wider common comfort zone can be obtained. Figure 5-10 shows the overall comfort zone (i.e., $R_t^* \in [24.2, 26.4]$, denoted in yellow) and comfort probability of these three example subjects. Using strategy 1, any setpoint within the comfort zone can be selected as the three subjects are all comfortable in this range. More specifically, the lower bound 24.2 °C is optimum in heating seasons due to its lower HVAC energy consumption, and vice versa for cooling seasons. When using strategy 2, 25.5 °C is the optimum setpoint as it achieves the highest comfort probability without considering the energy consumption.

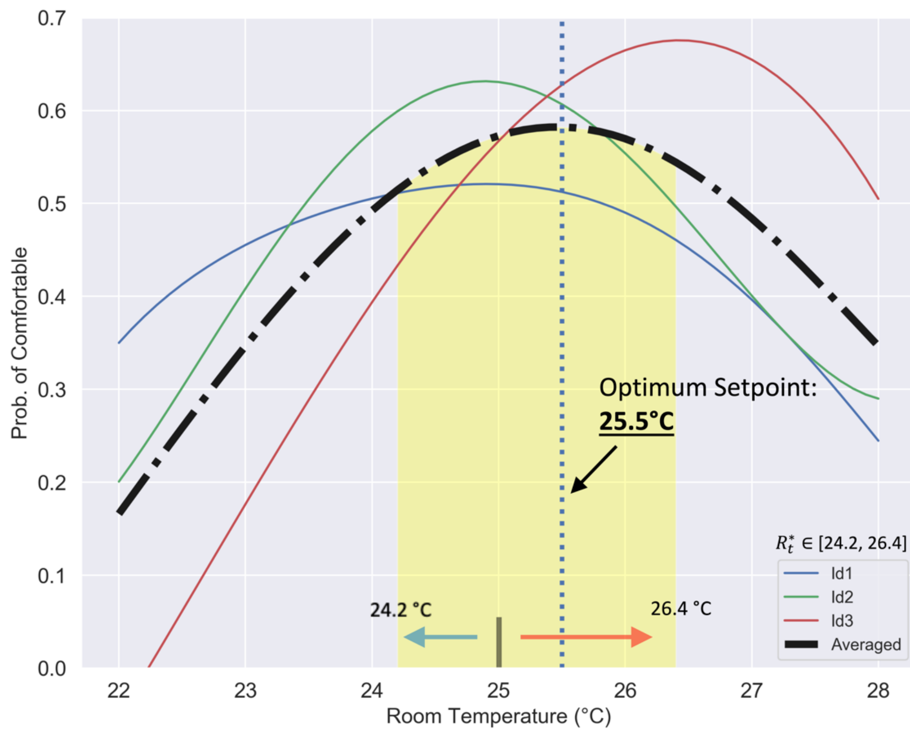

Figure 5-10 The Comfort Zone and Probability for a Shared Room with Subjects 1, 2, and 3

Assuming it is in heating seasons, for strategy 3, the comfort score and energy score of different setpoints in R_t^* are calculated, which are shown in Table 5-4. Only setpoints between 24.2 °C and 25.5 °C are presented as setpoints higher than 25.5 °C will lead to a reduced comfort probability yet increase the energy use. The weighted comfort and energy score S (Eq. 5.9) with three example α values (i.e., 0.3, 0.5, and 0.7) are presented in Table 5-5. As the result suggests, 24.2 °C, 24.2 °C and 24.7 °C are chosen as the optimum setpoints for α = 0.3, 0.5 and 0.7, respectively.

Table 5-4 The Comfort Score and Energy Score at Different Setpoints with Subjects 1, 2, and 3

$\boldsymbol{R_t^*}$	**24.2**	**24.3**	**24.4**	**24.5**	**24.6**	**24.7**	**24.8**
$\sum_i Prob_i(R_t^*)/n$	0.51	0.52	0.53	0.54	0.55	0.56	0.56
$Comfort\_score$ (1)	0.88	0.90	0.92	0.93	0.94	0.96	0.97
$R_{base} - R_t^*$	-2.2	-2.3	-2.4	-2.5	-2.6	-2.7	-2.8
$Energy\_score$ (2)	0.37	0.38	0.40	0.42	0.43	0.45	0.47
$\boldsymbol{R_t^*}$	**24.9**	**25.0**	**25.1**	**25.2**	**25.3**	**25.4**	**25.5**
$\sum_i Prob_i(R_t^*)/n$	0.57	0.57	0.57	0.58	0.58	0.58	0.58
$Comfort\_score$ (1)	0.98	0.98	0.98	0.99	0.99	1.00	1.00
$R_{base} - R_t^*$	-2.9	-3	-3.1	-3.2	-3.3	-3.4	-3.5
$Energy\_score$ (2)	0.48	0.50	0.52	0.53	0.55	0.57	0.58

Table 5-5 Optimum Setpoint Selection Using Strategy 3 (for α = 0.3, 0.5, and 0.7)

R_t^*	24.2	24.3	24.4	24.5	24.6	24.7	24.8	24.9	25.0	25.1	25.2	25.3	25.4	25.5
S (α = 0.3)	**.01**	.00	.00	-.01	-.02	-.03	-.04	-.04	-.06	-.07	-.08	-.09	-.10	-.11
S (α = 0.5)	**.26**	.26	.26	.26	.25	.26	.25	.25	.24	.23	.23	.22	.22	.21
S (α = 0.7)	.51	.52	.52	.53	.53	**.54**	.54	.54	.54	.53	.53	.53	.53	.53

Note: The bold number is the highest score for each α value, the corresponding R_t^* is the optimum setpoint.

5.5 Discussion

In Section 5.3, personal comfort models and physiological predictive models are developed using multinomial logistic regression and linear mixed model, respectively. However, as explained earlier, the main contribution of this chapter is the integration of these two models to address the limitations in physiological sensing-based HVAC control methods. These two components, which form a subject's thermal profile, can be substituted by other modeling approaches. For example, personal comfort models can also be developed using multinomial mixed-effects logistic regression or Random Forest.

Section 5.4 demonstrates the optimum setpoint selection using three different strategies considering occupants' thermal comfort and energy consumption. Specifically, optimum setpoints in strategies 2 and 3 come from the candidate range R_t^* determined by strategy 1. In other words, optimum setpoints in all strategies will always be selected on the premise that most subjects will feel comfortable. However, if the domain of strategy 2 is the operational range of 22 °C to 28 °C instead of the narrowed range R_t^*, setpoints with the highest overall comfort probability may not yield the largest possible number of comfortable subjects. This scenario is illustrated in Figure 5-11 where two subjects share the same environment. The overlap of two subjects' comfort zones, i.e., the common comfort zone (denoted in yellow), represents R_t^*. The result shows that setpoints corresponding to the highest overall comfort probability, in these two scenarios, are outside of R_t^*. In this case, subject 4 no longer feels comfortable even though the overall comfort probability is maximized.

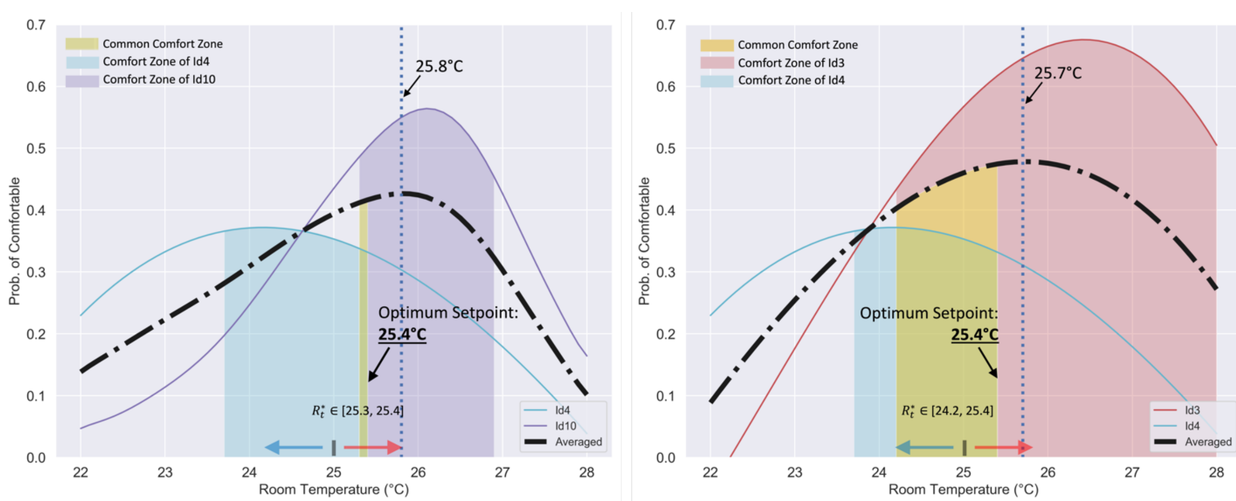

Figure 5-11 The Comfort Zone and Probability for a Shared Room with Two Subjects (left: subjects 4 and 10; right: subjects 3 and 4)

The optimum setpoints can be updated based on the presence of subjects. For example, as shown in Figure 5-11, the optimum setpoint for subjects 1 and 2 is 24.9 °C. If subject 3 joins, the setpoint should increase to 25.5 °C to accommodate the newcomer's preference for warm environments while not reducing the overall comfort. This approach has implications in shared environments, such as conference rooms and offices where an optimum solution can be found given different combinations of thermal profiles (personal comfort models and physiological predictive models). Thermal profiles can be carried by occupants as they move around places using approaches introduced in this dissertation. For example, thermal profiles saved in the smartphones can be retrieved when occupants scan a QRcode when entering a room or connect to a nearby Wifi router (Li et al. 2017c). Motion sensors or thermal cameras can also determine the presence of occupants if they have dedicated working areas (Li et al. 2019a). For occupants who are outside of the common comfort zones, adaptive behaviors (e.g., putting on a jacket) or personal devices (e.g., portable heater) can be adopted to restore personal comfort without affecting others.

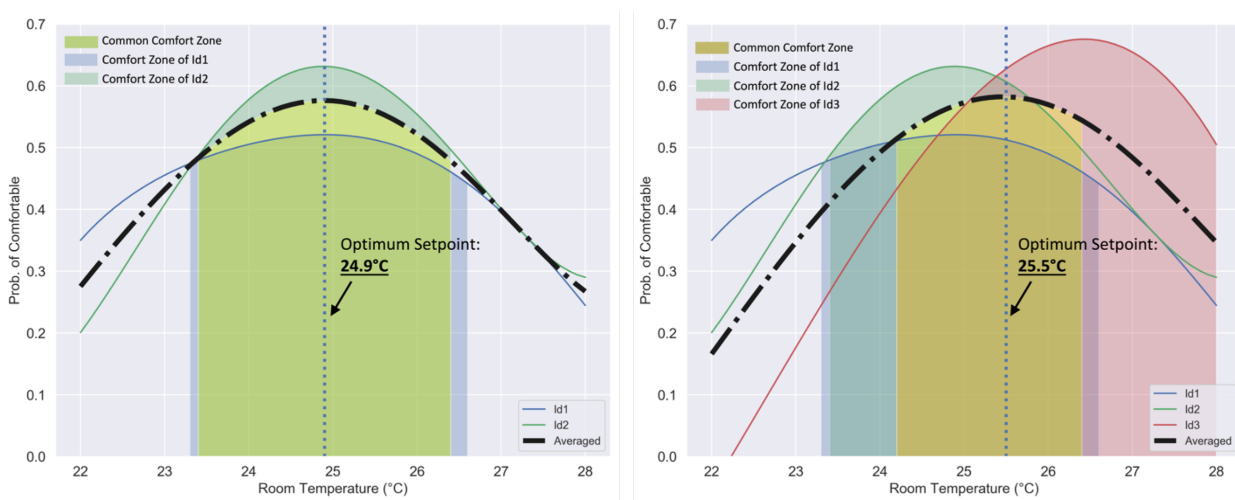

Figure 5-12 The Comfort Zone and Probability for a Shared Room When a New Subject Joins (left: subjects 1 and 2; right: subject 3 joins)

As subjects' skin temperature has different sensitivities in heating and cooling scenarios as shown in Figure 5-6 and Figure 5-7, thermal comfort zones and comfort probabilities can be slightly different when the room is preset at a low temperature versus a high temperature (subjects reached the steady-state conditions). This scenario is demonstrated in Figure 5-13 and Figure 5-14, which show the differences in thermal comfort zones and probabilities when room temperature starts from the high and low baseline setpoints, especially for subjects 1 and 4 whose comfort zones and probabilities can shift by over 1 °C. These differences are mainly caused by the psychological process in which the reference points that people compare with in the transient environment have changed. Subjects' evaluation of thermal sensation is relative to their initial thermal states at the high or low setpoints instead of the absolute air temperature.

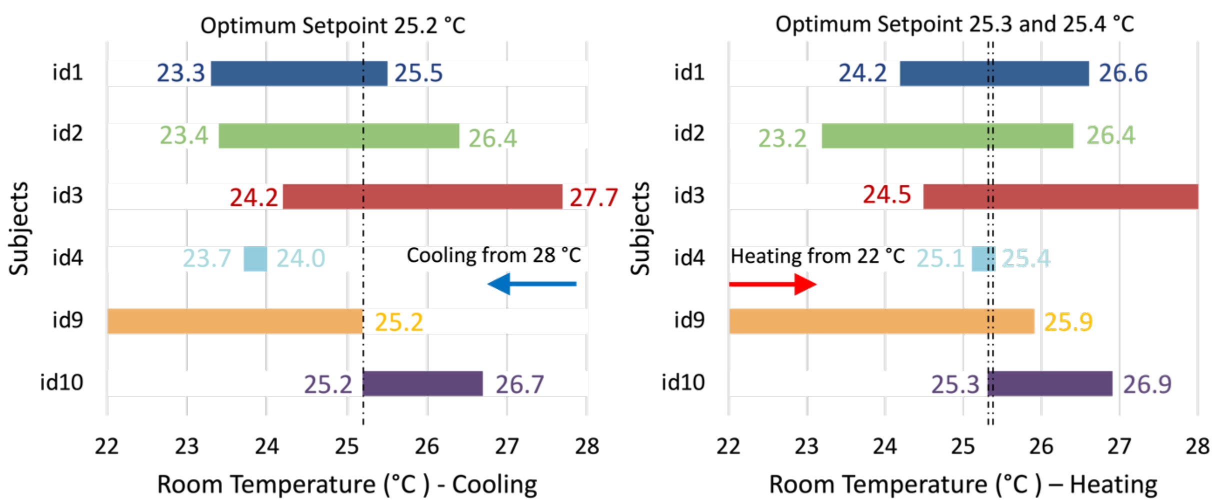

Figure 5-13 Optimum Setpoint Selection Using Strategy 1 When Room Temperature Starts from the Baseline (Left: starting from a high setpoint; Right: starting from a low setpoint)

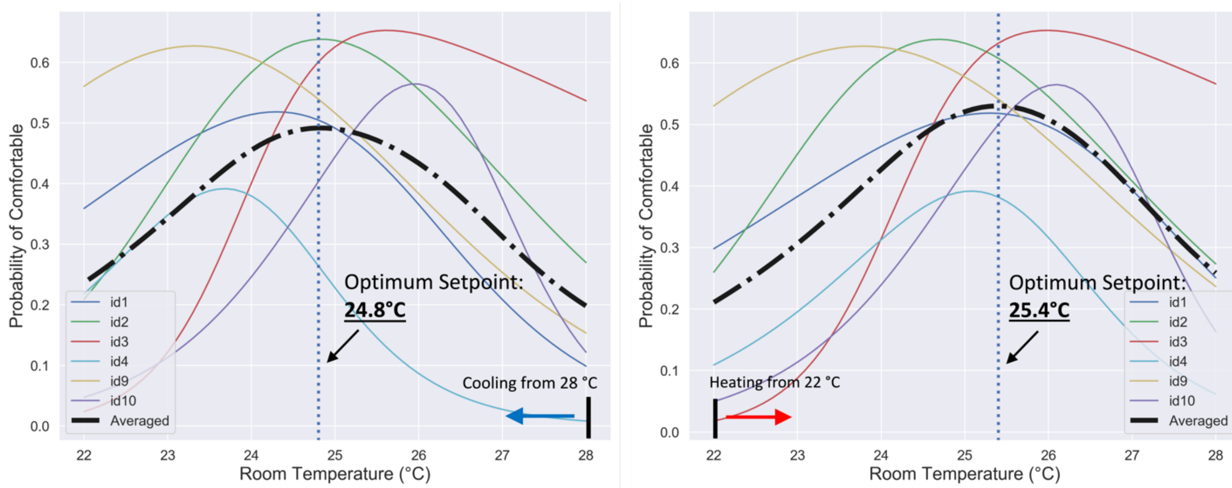

Figure 5-14 Optimum Setpoint Selection Using Strategy 2 When Room Temperature Starts from the Baseline (Left: starting from a high setpoint; Right: starting from a low setpoint)

The main contribution of this chapter is to propose an approach for proactive HVAC control using human physiological sensing. The proposed methodology, as opposed to the iterative and trial-and-error process, can directly determine the optimum setpoint for a given group of subjects which maximizes thermal comfort with constraints in energy consumption. This chapter is not meant to suggest a specific setpoint for buildings as industry standards as the optimum setpoints can be different for other human subjects, built environments and HVAC systems, seasons, locations, etc. However, the proposed methodology can be adopted by researchers and HVAC engineers to develop their own thermal profiles and determine the optimum setpoint in a specific setting accordingly.

However, one limitation should be acknowledged. In the experiment, the skin temperature data are collected from sedentary subjects with a low workload level. As a result, the physiological predictive model may not be valid when extrapolated to subjects in high workload or metabolic rate situations. In future studies, if subjects' skin temperature data at different workload conditions are collected, the proposed approach can not only select the optimum setpoint for a given group of subjects but also dynamically determine the setpoint over time according to subjects' workload.

5.6 Conclusions

This chapter proposes a temperature setpoint optimization approach which aims to overcome the limitations in existing HVAC control schema, and directly determine the optimum setpoint of a given multi-occupancy environment using the thermal profiles. To this end, the proposed approach integrates personal comfort models and physiological predictive models to predict the overall thermal comfort at different setpoints. The thermal comfort can be represented in two forms, i.e., thermal comfort zone and comfort probability distribution. Based on these two metrics, three HVAC control strategies are introduced to demonstrate the selection of setpoints for improved overall thermal satisfaction or reduced energy use while maintaining comfort.

This chapter provides insights into proactively determining the optimum setpoint in the physiological sensing-based HVAC control and has the merits of reducing the discomfort time and oscillation of setpoints. After the initial setpoint is optimized using the proposed approach, if physiological sensing or thermal votes from occupants indicate that further adjustments are needed, the setpoint can be updated following the human-in-the-loop schema introduced in Section 5.1 to fine-tune the thermal environment. The proposed setpoint optimization approach, when coupling with the sensing approaches introduced in Chapters 2 to 4, can serve as a basis for automated environment control to improve the human experience, well-being, and building energy efficiency.

CHAPTER 6

An Integrated Framework to Understand Energy Use behaviors in Buildings

6.1 Introduction

In Chapter 1, we introduced the significant role that occupants play in affecting building energy consumption, and also identified two major knowledge gaps in existing studies – the lack of (1) fundamental research to understand behavioral determinants of energy-saving behaviors, and (2) methods to describe and quantitively measure occupants' energy use characteristics, which can affect their behaviors in buildings. To fill these two gaps, in this chapter, we propose an integrated framework to understand occupants' energy use behaviors in buildings.

The rest of this chapter is organized to first provide a detailed review of existing human behavior models and their relations to energy use behaviors in the building context. Then, we present the Motivation-Opportunity-Ability (MOA) framework, the measures of each factor, and our research hypotheses. The new framework and hypotheses are tested through a Structural Equation Model (SEM) using the survey data. Finally, the results and findings are discussed at the end of this chapter.

6.2 Related Work

Existing studies have proposed several behavior models to understand the influential factors of human behavior and behavior change (Ajzen 2005, Fishbein et al. 2000, Fogg 2009, Hong et al. 2015, Michie et al. 2011). For example, Fishbein et al. (2000) identified three factors:

strong intention, absence of environmental constraints, and necessary skills as the prerequisites to generate behavior. Michie et al. (2011) reviewed existing literature of behavior change interventions and proposed the Behavior Change Wheel (BCW) framework to guide the design of interventions. The BCW aims to strengthen the identified weak components in motivation, opportunity, and capability to enhance the effectiveness of interventions. In Fogg's behavior model (Fogg 2009), an effective persuasive intervention should possess three necessary driving factors - sufficient motivation, required ability, and appropriate trigger in order to elicit a targeted behavior. In relation to energy-saving behaviors, some of the aforementioned models and principles have been introduced in the building domain to design and implement intervention strategies (Bang et al. 2006, Geelen et al 2013, Petkov et al. 2012, Staddon et al. 2016, Wilson and Marselle 2016). For example, to assess the comprehensiveness of the BCW framework in explaining energy behaviors, Wilson and Marselle (2016) mapped the BCW framework to four energy behavior change guidance documents. The result indicates that energy-relevant behavioral determinants can be generalized into motivation, opportunity and ability (MOA) categories and the most frequently occurring determinants in the documents are reflective motivation, psychological capability, physical and social opportunities. Other studies like Petkov et al. (2012) and Bang et al. (2006) incorporated the persuasive techniques introduced in Fogg's model and developed applications which aim to raise the awareness of energy-related issues and encourage efficient lifestyle.

On the other hand, researchers also applied social psychology approaches for understanding and promoting pro-environmental behaviors (Abraham and Michie 2008, DEFRA 2008, Stephenson et al. 2010, ThØgersen 1995, Vlek 2000), such as Defra 4Es framework, i.e., enable, encourage, engage, and exemplify, which aimed at promoting sustainable behaviors in accordance with social marketing principles (DEFRA 2008), the needs-opportunities-abilities

(NOAs) framework for analyzing the determinants of consumer's environmental behaviors (Vlek 2000), taxonomy of behavior change techniques in intervention (Abraham and Michie 2008).

However, the aforementioned models and frameworks are generic behavioral models developed in the field of psychology. None of them demonstrates a way to measure occupants' characteristics in the energy use domain and analyze their impact on occupant behaviors. To fill this gap, we adapt the motivation, opportunity, and ability (MOA) model which is widely applied to study consumers' purchasing behaviors (e.g., buying products from one brand vs. another) to analyze occupants' energy-saving behaviors. The MOA model has traditionally been used to understand consumers' attention and comprehension processes to brand information, and other significant factors motivating consumers to purchase certain products on a regular basis (Buurma 2001, Celsi and Olson 1988, Machleit et al. 1990, MacInnis et al. 1991, Moorman 1990, Polonsky et al. 2004, Rothschild 1999).

Several studies emphasized that customers' MOA characteristics play a significant role in their purchasing behaviors. For example, Hastak et al. (2001) highlighted the importance of the MOA model to determine the communication effectiveness of advertisements. This study found that consumers with loyalty to a particular product have higher MOA levels which facilitate the adoption of the product. MacInnis et al. (1991) used the MOA model to investigate the influential factors such as the extent of brand information processing from advertisements. This model proposed that consumers' MOA levels have major impacts on the brand information processing stage during and/or after exposure to advertisements. Bigné et al. (2010) implemented the MOA model for online airline ticket purchases reported that the MOA model accounts for 55 percent of the variations in predicting consumers' ticket purchasing intentions.

6.3 Contributions

This chapter presents a theoretical framework, i.e., the Motivation-Opportunity-Ability (MOA) framework, to identify the determinants of energy-saving/use behaviors. The three factors, i.e., M, O, and A are also used to describe an occupant's characteristics. The proposed model aims to help decision-makers design occupancy-focused interventions to achieve building sustainability. The specific contributions of this chapter include:

- Identify the influential factors of human behavior in existing studies and adapt them into the context of energy savings (e.g., what are the definitions and measures of each factor).
- Develop an integrated framework that establishes the relationship between the identified factors (e.g., mediation effect, direct effect).
- Validate the proposed model using survey data.
- Demonstrate the use case of the proposed framework for energy intervention and occupants' characterization.

6.4 Methodology

In this chapter, we draw on the analogy between the MOA characteristics of customers to process brand information and pick up certain products in marketing and the MOA levels of building occupants to interpret energy reduction interventions and adopt energy-saving behaviors (e.g., adjusting the thermostat to save energy). The definition of each factor (i.e., M, O, and A) in psychology, consumer science, and its adapted interpretation in energy efficiency are detailed in Table 6-1 and additionally described in subsequent paragraphs.

6.4.1 The Motivation, Opportunity and Ability Characteristics

6.4.1.1 Motivation (M)

The psychological definition of motivation is the brain processes that energize and direct human behavior toward goals (Gruen et al. 2005, Hoyer and MacInnis 1997, Michie et al. 2011). More specifically, in consumer science, motivation is defined as the goal-directed arousal to engage consumers in a desired behavior to process brand information in the advertisement and perform the corresponding purchasing behavior (Celsi and Olson 1988, MacInnis et al. 1991, Moorman and Matulich 1993, Rothschild 1999, Steg and Vlek 2009, Zaichkowsky 1985) (See Table 6-1). Motivation measures the perceived personal relevance of people and their level of involvement/interest with particular information (Richins and Bloch 1986, Steg and Vlek 2009, Zaichkowsky 1985). For example, Parra-Lopez et al. (2012) analyzed key factors in human intentions to use social media to organize holiday travels. This study highlighted that consumers' motivation is based on the functional, social, and hedonic benefits of social media. Moorman and Matulich (1993) highlighted that motivation independently influences consumers' preventive health behaviors and moderates the impact of ability and opportunity on adopting desired behaviors through encouraging consumers to put their knowledge, skills, or resources into practice.

In this chapter, we define the motivation as an occupant's readiness, willingness, interest, and desire to process energy-saving information provided through intervention strategies and subsequently adopt the stipulated saving behaviors. Thus, the motivation (M) of occupants measures their perceived personal relevance and the level of involvements with the information presented in the energy reduction strategies (see Table 6-2). For example, occupants with a high motivation level can volunteer to attend workshops or receive emails about energy saving tips. As shown in Table 6-2, motivation metrics are divided into internal and external stimuli that interventions should improve to achieve efficiency. For example, improving the awareness of energy use and desire to receive information on energy reduction approaches.

Table 6-1 Application of the MOA Model in Energy Use Characteristics

Psychological definitions (Blumberg and Pringle 1982, Gruen et al. 2005, Hoyer and MacInnis 1997, Michie et al. 2011)	Definitions in consumer science (Celsi and Olson 1988, MacInnis et al. 1991, Moorman and Matulich 1993, Rothschild 1999)	Proposed framework with adapted MOA factors in energy efficiency
Motivation is defined as the brain processes that energize and direct human behavior toward goals	Motivation is defined as consumers' interest, desire, and readiness to engage in processing the brand information in an ad and the willingness to perform purchasing behaviors. E.g., high motivation consumer is willing to pay attention to the advertised message	Motivation measures an occupant's needs, goals, and values (self-related knowledge), and the level of involvement with energy use information, whether an occupant is concerned about the personal energy consumption and looking for ways to save energy from various sources
Opportunity is defined as the external factors (i.e., lie outside of the individual) that make the behavior possible or prompt it	Opportunity is defined as the environmental factors (e.g., distraction, lack of conditions, limited exposure time) which affect consumer's attention to brand information in an ad. E.g., Consumers who are unfamiliar with a brand may choose other competitive products	Opportunity measures an occupant's availability and accessibility to the energy-saving information and energy control system, as well as some environmental and interpersonal factors that may affect occupants processing the information in the environment (both physical and social opportunities)
Ability is defined as the necessary psychological and physical capabilities to make an outcome happen	Ability is defined as consumers' resources, skills, or proficiencies in interpreting brand information and performing the purchasing behavior. E.g., high ability consumer is able to search desired items online and compared with different brands	Ability is a knowledge-based measure which affects how an occupant interprets and processes the energy-saving information. Ability implicates an occupant's prior knowledge about energy use, its impact, and consequences, as well as knowledge about possible saving strategies

Table 6-2 Metrics for Occupants' MOA Level

Metrics of Construct	Measures
Motivation (M) Self-related Knowledge (Internal Stimuli) • Needs • Goals • Values Energy Use Knowledge (External Stimuli) • Level of Energy Use • Impact and Consequences	Assess **self-awareness** about the importance of Energy Use Knowledge Measure the **desire to receive** Energy Use Knowledge Detect **norms of avoiding** Energy Use Knowledge (e.g., not interested in attending workshops or receiving emails)
Opportunity (O) Ease of implementation Amount of Information Information Format Modality Rate of Exposure to Information	**Determine the number of times**: Accessible and easy to use controls (e.g., thermostat, lighting, shading) Attend awareness seminars Read information on general advertisement boards (self-reported) Read emails (ask for responses with a blank email) Discuss with peers (self-reported)
Ability (A) Energy Use Prior Knowledge • Impact • Consequences • Conservation Strategies	Measure the **extent** conservation strategies are used (e.g., estimate number of times someone consciously turns off lights when leaving) Measure the **subjective knowledge** of energy use relative to the average person Measure **actual knowledge** (i.e., factual information): • Terminology • Possible impacts/consequences • Criteria to evaluate impacts/consequences • Perceived effectiveness of intervention strategy to reduce impacts/consequences

6.4.1.2 Opportunity (O)

The psychological definition of opportunity is the external factors that make the behavior possible or prompt it (Gruen et al. 2005, Michie et al. 2011). Similarly, in consumer science, it is defined as the environmental factors (e.g., exposure time to ads) that are not in the control of consumers to enable desired actions (Bigné et al. 2010, Hallahan 2001, MacInnis et al. 1991, Rothschild 1999) (See Table 6-1). Opportunity level is directly related to the immediate environment of the people and how that affects the availability, accessibility, and time allocated for the comprehension of the brand information (Celsi and Olson 1988, Maclnnis et al. 1991, Rothschild 1999). Other studies described opportunity level as the extent to which circumstances evidenced during advertisement exposure are favorable for brand processing (Govindaraju et al. 2013, MacInnis et al. 1991, Rothschild 1999). For example, Govindaraju et al. (2013) studied key drivers for physicians to adopt electronic medical records (EMR), and defined "opportunity" as the "access to EMR system" and "access to information" which refer to physicians' opportunity to get in contact with any information media and other sources.

In this research, opportunity (O) refers to the surrounding environmental factors influencing occupants' attention and comprehension processes in adopting energy-saving behaviors. As shown in Table 6-2, when occupants have easily accessible building controls, opportunity metrics can be improved during an intervention by focusing on the amount, format, modality, and rate of exposure to the information. Thus, opportunity measures how favorable conditions and limited time of exposure affect an occupant's attention to the information presented in interventions.

6.4.1.3 Ability (A)

The psychological definition of ability is the necessary psychological and physical capabilities to engage in a targeted behavior or make an outcome happen (Blumberg and Pringle 1982, Gruen et al. 2005, Michie et al. 2011). In consumer science, the definition of ability is modified to focus more on the psychological aspect and it is defined as consumers' self-perceived knowledge capacity of the brand information, and how they interpret this information to create new knowledge structures (Bigné et al. 2010, Celsi and Olson 1988, MacInnis et al. 1991, Parra-Lopez et al. 2012) (See Table 6-1). As Wilson and Marselle (2016) suggested that physical capability is the least frequently occurring determinant in behavior change guidance documents. They argue that the need for physical capability might be more common in the health field compared to the building domain. Therefore, the physical capability is excluded in the ability factor (E.g., light switches are set too high for a wheelchair user to reach it).

Ability level is largely dependent on a consumer's prior knowledge about brand information typically acquired through experience, as well as a consumer's skills in interpreting brand information in an advertisement (Celsi and Olson 1988, Rothschild 1999). For example, Bigné et al. (2010) defined the ability level as individuals' perception of their capacity to search for information about flights on the Internet and to carry out online purchases of airline tickets. Results show that customers' Internet ability positively influences their intentions for online purchasing.

In this research, ability (A) level measures a given occupant's proficiencies in interpreting energy use knowledge. The ability (A) is largely dependent on an occupant's prior knowledge about energy use, its impact and consequences, as well as knowledge about possible conservation strategies (see Table 6-2). The type and quality of this pre-existing knowledge will in turn determine if energy use information can be cognitively and immediately retrieved in a given situation (e.g., occupants turn off lights before leaving their offices).

6.4.2 Framework for Measuring MOA Levels of Building Occupants

Previous studies (e.g., medical field, ticket purchasing website) found that motivation is directly associated with most behaviors (Bigné et al. 2010, Moorman 1990). However, opportunity and ability affect behaviors only when motivation is present, which means these two factors moderate the impact of motivation on behaviors. Therefore, we propose the motivation as a precondition of successful implementation of energy-saving behaviors with opportunity and ability as moderating factors and design the framework described in the following section accordingly. The proposed framework is developed by stating a set of research hypotheses and their relevant measures to investigate occupants' energy use characteristics through assessing their MOA levels on adopting energy-saving behaviors. These hypotheses are designed based on the extended context of the MOA levels of occupants and incorporated with a set of measures that are identified based on a comprehensive literature review, as shown in Figure 6-1. These measures are utilized to demonstrate the link among each motivation, opportunity, and ability levels of occupants, their related research hypotheses, and their intended energy use behaviors.

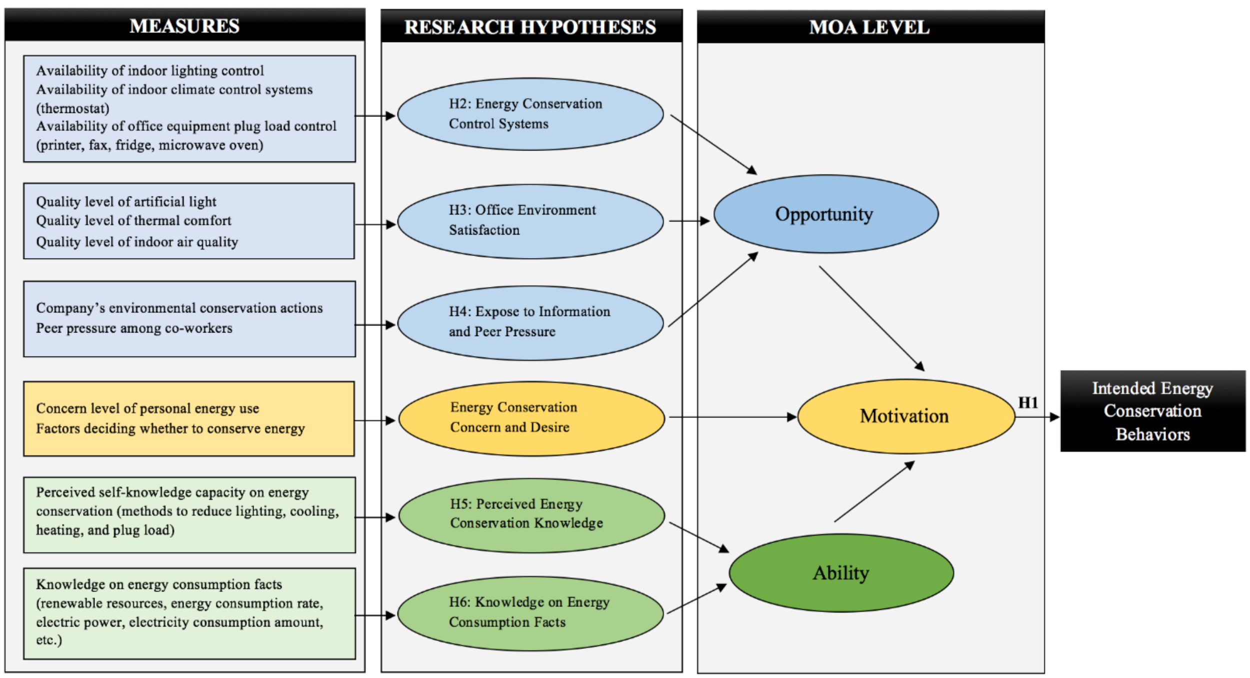

Figure 6-1 Measures of Occupants' MOA Levels in Energy-Use Behaviors

6.4.2.1 Identifying Measures for Occupants' Motivation Characteristic

As mentioned earlier, motivation level (M) refers to a particular occupant's perceived personal relevance in terms of needs, goals and values, and the level of involvement with the information (e.g., external stimuli) presented in the energy intervention. Therefore, occupants' concern and desire for energy conservation are investigated as the measure of their motivation. Motivation level independently affects occupants' energy use behaviors, how often they look for ways to conserve energy, and which factors are important for them to conserve energy, as shown in Figure 6-1. Accordingly, the related hypothesis is stated as follows:

H1: Occupants with higher energy conservation motivation levels will perform more energy conservation behaviors than occupants with lower motivation levels.

6.4.2.2 Identifying Measures for Occupants' Opportunity Characteristic

In this research, occupants' opportunity (O) level is directly related to their immediate environment and how that affects the availability and accessibility for comprehension of the energy use knowledge. Adopting Moorman and Matulich's (1993) approach, we assume that occupants' opportunity level moderates the effect of motivation on energy-saving behaviors. For example, highly motivated occupants are not able to present energy-saving behaviors in their offices such as adjusting temperature setpoint, if they do not have any control over the thermostat. Studies have shown that people have more tendency to make permanent changes in their energy use behaviors when they have available resources and if the new behaviors are easy and convenient to perform (McMakin et al. 2002). Therefore, opportunity level of occupants is measured by investigating: (1) the availability of energy conservation control systems (e.g., if the occupant has any individual control over the climate control system); (2) the satisfaction level of the indoor environment (e.g., overall quality of artificial lighting in the office); and (3) exposure to information and peer-pressure about environmental concerns through interventions (e.g., having energy conservation information available for occupants on bulletin boards and often discuss environmental conservation strategies with colleagues). (see Figure 6-1) Accordingly, the corresponding hypotheses are stated as follows:

H2: When energy conservation motivation is high, occupants with higher control over their indoor environment will perform more energy conservation behaviors.

H3: When energy conservation motivation is high, occupants who are satisfied with their indoor environment will perform more energy conservation behaviors.

H4: When energy conservation motivation is high, occupants with more exposure to information about the environmental impacts of their behaviors will perform more energy conservation behaviors.

6.4.2.3 Identifying Measures for Occupants' Ability Characteristic

Ability (A) level measures each occupant's proficiency in interpreting energy use knowledge. Ability is largely dependent on two major factors – an occupant's perception of the energy consumption level, and prior knowledge about energy use facts. A set of studies has shown that people need to have sufficient ability (e.g., self-efficacy) before they can actively take environmentally responsible actions that benefit others (Eccles et al. 2005, Geller 1981, Southwell and Torres 2006, Wilson and Dowlatabadi 2007). These studies highlighted that occupants' ability level also moderates the effect of motivation on adopting certain behaviors. Abrahamse and Steg (2009) concluded that occupants with higher perceived energy conservation knowledge (e.g., "I know how to reduce the cooling load in summer") and knowledge on energy consumption facts (e.g., what a kWh unit means) are more likely to save energy than occupants with lower energy use knowledge. On the other hand, previous studies also show that higher ability levels may reduce consumers' acquisition of information if they feel less need for more information (Moorman 1990). Therefore, it is also important to ensure that knowledgeable occupants are also highly motivated to maintain their saving behaviors. Based on Abrahamse and Steg (2009), occupants' knowledge-based ability level is measured by (1) the perceived energy conservation knowledge (we assume their self-claimed knowledge is correct), and (2) level of knowledge on energy consumption facts, as shown in Figure 6-1. Accordingly, related hypotheses are stated as follows:

H5: When energy conservation motivation is high, occupants with higher perceived energy conservation knowledge will perform more energy conservation behaviors.

H6: When energy conservation motivation is high, occupants with better knowledge of energy consumption facts will perform more energy conservation behaviors.

6.4.3 Framework Implementation

The proposed framework is implemented in four phases as shown in Figure 6-2: (1) survey phase that involves designing an online survey to test the stated hypotheses, (2) reliability analysis phase that evaluates the validity of each measure using the survey data, (3) structural equation modeling (SEM) phase that investigates the relations among motivation, opportunity, ability, and intentional energy use behaviors of occupants, and (4) data output phase that proposes energy interventions for the occupants given their characteristics and predicts the expected energy savings. The following paragraphs provide detailed explanations of each phase of the research.

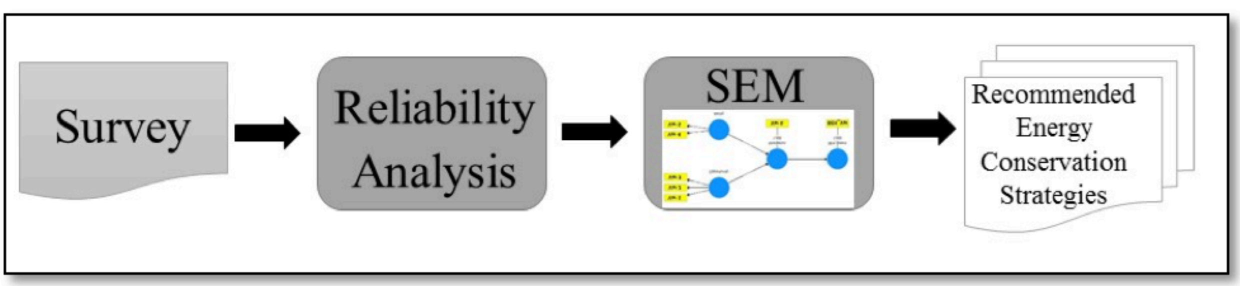

Figure 6-2 Framework Implementation

6.4.3.1 Survey Design Phase

An online survey is developed to collect data for testing the stated hypotheses and identify occupants' MOA level and their corresponding behaviors. The survey is designed to be flexible for both residential and commercial settings. To test and validate Hypothesis 1 (i.e., H1), two measures are identified as: (1) occupants' concern level on their personal energy consumption (e.g., how often are you concerned about your personal energy consumption at your office?), and (2) factors deciding whether to conserve energy (e.g., how important are the following factors to you in deciding whether to conserve energy?).

Hypothesis 2 - 4 (H2, H3, and H4) are tested through measures presented in Figure 6-1. H2 measures if occupants' energy use control levels have an impact on their behaviors when they have motivation to conserve energy. In the survey, measures of H2 are identified as the availability of lighting control, thermostat control, and office equipment (e.g., printer) plug load control. H3 predicts that office (or residence) environment satisfaction levels have an effect on occupant behaviors in the presence of energy conservation motivation. The measures of H3 are designed as occupants' satisfaction with the lighting quality (e.g., how would you describe the quality of artificial lighting in your typical work area?), thermal comfort, and indoor air quality in their offices. H4 studies whether occupants exposed to environmental conservation information changes their behaviors when they have motivations. This hypothesis is tested using the measures of occupants' exposure level to environmental concern through a company's (or landlord) actions (e.g., my company provides all employers with strategies to help us save energy), and peer-pressure among co-workers (or neighbors) (e.g., my close friends in the company always use strategies to save energy).

Finally, the last two hypotheses about the ability level, Hypothesis 5 and 6 (H5 and H6), are tested through measures presented in Figure 6-1. H5 studies if the occupants' perceived energy conservation knowledge level would affect their behaviors when they are motivated. H5 is tested using the measure of occupants' self-assessed knowledge level (e.g., I know methods to reduce the heating load in my office). On the other hand, H6 determines if occupants' knowledge level of energy consumption facts would have an impact on behaviors with high motivation. The measures for H6 are designed as six test questions asking occupants about their knowledge on energy consumption facts (e.g., which lighting choice saves the most energy assuming the same amount of light delivered?).

6.4.3.2 Reliability Analysis Phase

Reliability analysis is conducted to check the internal consistency of multiple measures. Through reliability analysis, highly correlated constructs are combined as one composite construct to reduce the multicollinearity and make the multi-item integration intensity scale to be unidimensional (Ray et al. 2005, Rosenzweig et al. 2003). In this research, the reliability analysis is evaluated based on the recommended threshold of Cronbach α with a value of $\alpha = 0.70$ (Nunnally 1978) and inter-item correlation with a value of 0.30 (Hair 2010). Questions with Cronbach α greater than 0.70 and inter-item correlation greater than 0.30 are combined into a single construct. For example, plug load control, as a construct of opportunity, can encompass four correlated equipment questions (i.e., printer, fax, fridge, and microwave oven).

6.4.3.3 Structural Equation Modeling Phase

Structural equation modeling (SEM) phase is implemented to test the stated hypotheses. SEM is a confirmatory multivariate analysis methodology for hypotheses testing, which has the capability of constructing variables that explain the major part of the unobserved heterogeneity in the model (Bollen and Long 1993). In social science and marketing field, several research studies implemented SEM models to investigate the influential factors on consumers' characteristics and their behaviors (Al-Maghrabi et al. 2011, Bigné et al. 2010, Bruner and Kumar 2005, Childers et al. 2002, Govindaraju et al. 2013, Van der Heijden et al. 2003). Childers et al. (2002) studied the dominant factors in customers' online retail shopping behavior using SEM. Results indicated that hedonic aspects of the new media play at least an equal role as instrumental aspects in predicting online attitudes. Van der Heijden et al. (2003) used SEM to explore factors that influence consumer's purchasing behavior on an electronic commerce website and found a strong positive relationship exists between attitude towards online purchasing and the corresponding purchasing intention. This study also suggested that the perceived risk and ease of use are antecedents of attitude towards online purchasing.

In this research, SEM is implemented using the Stata (2015) where exogenous variables (e.g., quality of artificial lighting in the working zone) are computed as factors affecting the endogenous outcome (i.e., turning off the monitor when not in use). A detailed description of the model structure and interpretation is presented in the case study section.

6.4.3.4 Results and Energy Implication Phase

This phase helps decision-makers analyze the identified influential factors on occupants' characteristics and their behaviors to design effective occupancy-focused interventions. The proposed MOA model can not only help decision-makers monitor the effectiveness of interventions (e.g., the effect of peer pressure, resulted energy savings) but also identify the weak components in occupants' MOA characteristics and modify their interventions accordingly over time.

To this end, the K-means clustering analysis is conducted using the Matlab to cluster occupants with similar MOA characteristics into the same groups (MacQueen 1967). According to the individual MOA level and the MOA distribution within the building clusters, an occupant can be categorized as prone, mildly unable, unable, mildly resistant, or resistant to change their behavior (Karatas et al. 2016). The resulted clusters are then integrated with the Agent-Based Model (ABM) which studies how occupants interact and respond to interventions. The resulting knowledge will provide an initial prediction of the effectiveness of the chosen intervention. Details about ABM and its functionalities can be found in Azar and Menassa (2011b, 2014b, 2015).

At the agent initialization phase, each agent (i.e., an occupant in our context) is associated with two variables: (1) energy intensity (EI) in kWh/person, which defines the energy use intensity of an agent, and (2) energy variability (Var), which refers to an agent's openness to adopt new energy use characteristics (Azar and Menassa 2015). In the implementation, EI can be obtained from the actual building energy consumption or from databases such as the Commercial Building Energy Consumption Survey (CBECS) published by the Energy Information Administration (EIA 2003). Occupants' MOA characteristics (i.e., prone, mildly unable, unable, mildly resistant, resistant) can be mapped by the Var parameter, where occupants who are prone to change behaviors tend to have a high Var (i.e., flexible habits) while those with resistant MOA characteristics tend to have a low Var (i.e., rigid habits). As a result, agents which are initialized by the MOA levels can reflect the real occupancy characteristics in a building.

6.5 Case Study

A total of 177 occupants from a 32-story building in Chicago, IL, responded to the online. The case study building is a multifunctional university building which contains classrooms, student dorms, administrative offices. Participants are mainly from offices located on floors 6 to 10 representing administrative staff in a typical office environment. In total, 205 people routinely occupy the surveyed floors (survey response rate is 86%). The case study building is equipped with a building automation system (BAS) with centralized monitoring and control of building environment to maintain the operational performance of the facility and the comfort of building occupants. This BAS system provides occupants with different levels of control over the built environment. For example, some occupants, especially those in single occupancy rooms, are able to change the thermostat settings, shading, and lighting. But occupants in multi-occupancy rooms do not have much control, which may lead to different energy use behaviors in the same building.

The demographic information of the respondents are as follows: (1) 65% are female and 35% are male, (2) 9% are between the age of 20-30 years, 43% are between the age of 30-49, and 48% are older than 49 years, and (3) 8% have high school degree, 26% have college degree, 66% have a graduate level degree of Master's and/or PhD. The survey results are reviewed for completeness and result in a total of 130 completed surveys which were subsequently used for the reliability and SEM analysis.

Through reliability analysis, some highly correlated constructs in the survey are combined into simple constructs (see Table 6-3). As shown in Table 6-3, the Cronbach α for some listed constructs is greater than the recommended cut-off value of 0.7 and thus can be combined into a single construct. Other constructs with low Cronbach α (e.g., availability of the lighting control) are used directly in the SEM model. Some measures are reported as "not applicable" by all the respondents (e.g., availability of the space heater) and thus are removed.

Table 6-3 Constructs for Occupants' MOA Levels through the Reliability Analysis

Constructs that can be combined into a single construct			
Construct	**Highly Correlated Constructs**	**Cronbach α**	**Single Construct**
Opportunity (Control systems)	Availability of the office equipment as follows: (1) printer (2) fax (3) fridge (4) microwave oven	0.812	Plug load
Opportunity (Expose to information)	My company performs the actions as follows: (1) taking energy conservation very seriously (2) encouraging all staff to conserve energy (3) providing all staff with strategies to conserve energy	0.868	Company's actions

<table>
<tr><td>Opportunity
(Expose to peer pressure)</td><td>I would feel comfortable explaining to (1) my close friends; (2) other colleagues in the company how they can conserve energy.
My (3) close friends; (4) other colleagues in the company always use strategies to conserve energy.</td><td>0.839</td><td>Peer pressure</td></tr>
<tr><td>Motivation</td><td>(1) How concerned are you about your personal energy consumption at your office?
(2) How often do you look for ways to conserve energy at your office?
(3) How important are the following factors to you in deciding whether to conserve energy? (e.g., it is morally the right thing to do)</td><td>0.760</td><td>Motivation</td></tr>
<tr><td>Ability
(Perceived energy conservation knowledge)</td><td>I know methods to reduce the power load as follows:
(1) lighting
(2) cooling
(3) heating
(4) plug load</td><td>0.861</td><td>Perceived energy conservation knowledge</td></tr>
<tr><td colspan="4">Constructs that exist individually</td></tr>
<tr><td>MOA Category</td><td>Construct Description</td><td colspan="2">Single Construct</td></tr>
<tr><td rowspan="2">Opportunity
(Control systems)</td><td>Availability of the lighting control</td><td colspan="2">Lighting control</td></tr>
<tr><td>Availability of the thermostat control</td><td colspan="2">Thermostat control</td></tr>
<tr><td rowspan="3">Opportunity
(Environment satisfaction)</td><td>How do you describe the quality of artificial light in your work area?</td><td colspan="2">Lighting quality</td></tr>
<tr><td>How do you describe the quality of thermal comfort in your work area?</td><td colspan="2">Thermal comfort</td></tr>
<tr><td>How do you describe the indoor air quality in your work area?</td><td colspan="2">Indoor air quality</td></tr>
<tr><td>Ability
(Knowledge of energy consumption facts)</td><td>Questions aiming to test occupants' knowledge about energy consumption facts (e.g., Which of the following energy resources is not renewable?)</td><td colspan="2">Knowledge of energy consumption facts</td></tr>
<tr><td colspan="4">Constructs that are removed due to non-applicability</td></tr>
<tr><td>MOA Category</td><td>Construct Description</td><td colspan="2">Removed Construct</td></tr>
<tr><td rowspan="3">Opportunity
(Control systems)</td><td>Availability of the task lighting</td><td colspan="2">Control of task lighting</td></tr>
<tr><td>Availability of the space heater</td><td colspan="2">Control of space heater</td></tr>
<tr><td>Availability of the coffee machine</td><td colspan="2">Control of coffee machine</td></tr>
<tr><td rowspan="2">Opportunity
(Environment satisfaction)</td><td>How do you describe the quality of natural lighting in your work area?</td><td colspan="2">Quality level of natural lighting</td></tr>
<tr><td>How do you describe the glare comfort in your work area?</td><td colspan="2">Quality of glare comfort</td></tr>
</table>

The distribution of occupants' MOA level and behaviors are shown in Figure 6-3 and Figure 6-4, respectively. Figure 6-3 shows that around 30% of occupants (36 out of 130) are highly motivated, and around 14% (18 out of 130) possess high ability level. However, the opportunity level is relatively low (77 out of 130 possess low or medium-low opportunity level) compared to the other two characteristics, with only 5 occupants having a high opportunity. This might be a direct result of the limited ability placed on the occupants by the existing BAS, which reduces occupants' potential to contribute to energy saving.

Figure 6-4 shows the number of occupants who performs well for different behaviors. Occupants report several poor energy use behaviors, such as Behavior 4 (i.e., B4: turn off the monitor when not in use), Behavior 5 (i.e., B5: turn off the computer when not in use), Behavior 6 (i.e., B6: adjust shades to reduce glare), Behavior 7 (i.e., B7: adjust shades to increase daylighting), Behavior 8 (i.e., B8: adjust shades to reduce heat gain from the sun), and Behavior 9 (i.e., B9: turn off the light when there is enough daylight). For B4, B5, and B9, occupants fail to show better behaviors even though most of them have control to the equipment (lighting and computer), that is they have a high opportunity to perform these actions. The low action rate of B6, B7, and B8 is because many occupants (52 out of 130) reported that they have no control to the shading system, which indicates a strong correlation between opportunity and the behavior.

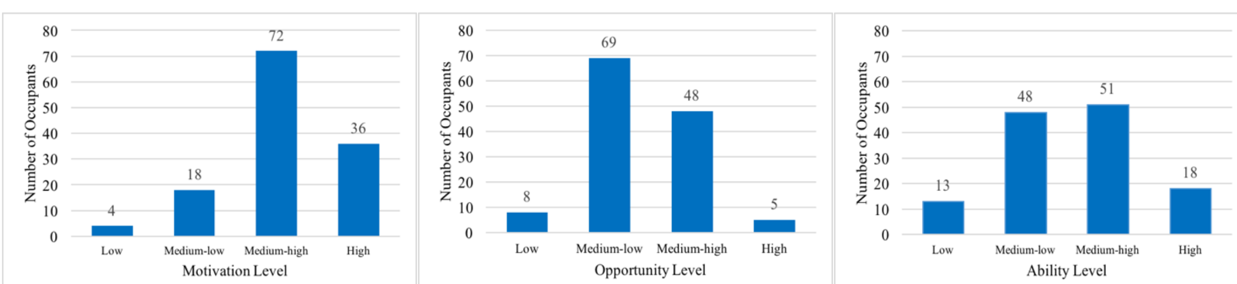

Figure 6-3 Occupants' MOA Level: (left) Motivation, (middle) Opportunity, (right) Ability

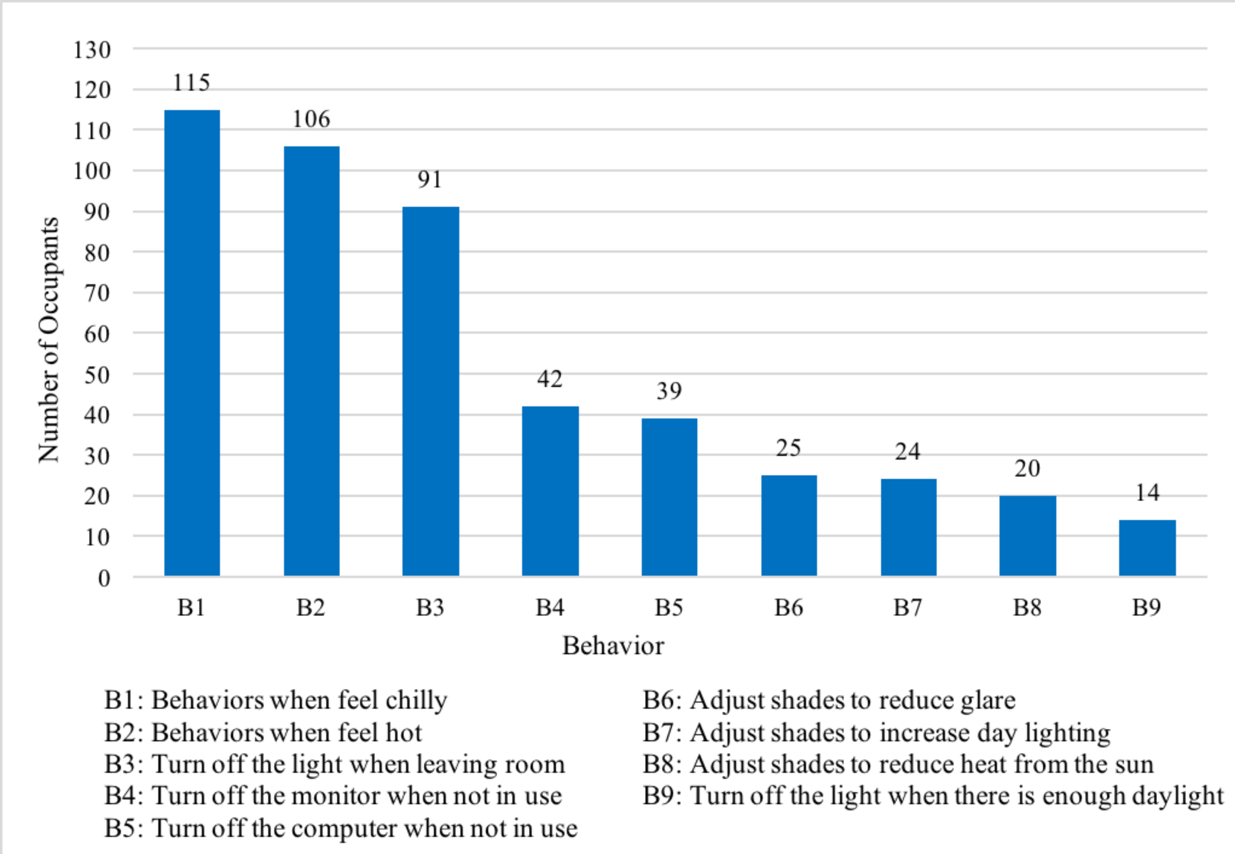

Figure 6-4 Number of Occupants who Perform Better Energy Use Behaviors

In SEM, models are illustrated in a path diagram. The rectangles represent observed variables (or indicators) that are observed from the data. These variables are measured directly from the survey (e.g., lighting quality). The ellipses are unobserved latent variables that are measured by a number of observed variables (e.g., occupant's exposure to information is measured by the company's action and peer pressure). Single head arrows, called paths, connect variables in the path diagram. When a path points from one variable to another, it means that the first variable affects the second (e.g., the arrow between motivation and behaviors represents that motivation is a predictor of behaviors). According to the measures for the MOA level discussed in Figure 6-1, an SEM model is developed to test the hypotheses (see Figure 6-5). For example, to test H2 "occupants with higher control over their indoor environment will perform more energy conservation behaviors when motivation is high". Latent variable "Control level" is indicated by three observed variables: lighting, thermostat, and plug load control. Then the "Control level", Motivation, and Behaviors are connected using paths to represent their proposed relationship. The best four behaviors shown in Figure 6-4 (i.e., Behavior 1 - 4) are selected to represent occupants' intentional energy use behaviors. However, the above-mentioned structure of the SEM model depends on the data. Several structures are evaluated in Stata and the best fit model is shown in Figure 6-5. It should be noted that the SEM model might look different in other buildings (e.g., M, O, and A are distinct precursors of behaviors and are parallel to each other) but the framework presented here can be adopted to achieve the best fit model.

The model fit statistics obtained from the survey show an R^2 of 0.174. However, it can be insufficient to evaluate the model fit only using R^2, especially considering that people are fairly unpredictable (Minitab 2014). Therefore, we also adopt the root mean squared error of approximation (RMSEA) to evaluate the model fit. The RMSEA of the developed model is 0.05, which is equal to the ideal standard of "less than or equal to 0.05" (Acock 2013, MacCallum et al. 1996). Also, the Normalized Chi-Squared value X^2/df is 0.80, which also suggests a good model fit (Kline and Santor 1999). Therefore, the model shown in Figure 6-5 is retained for further analysis.

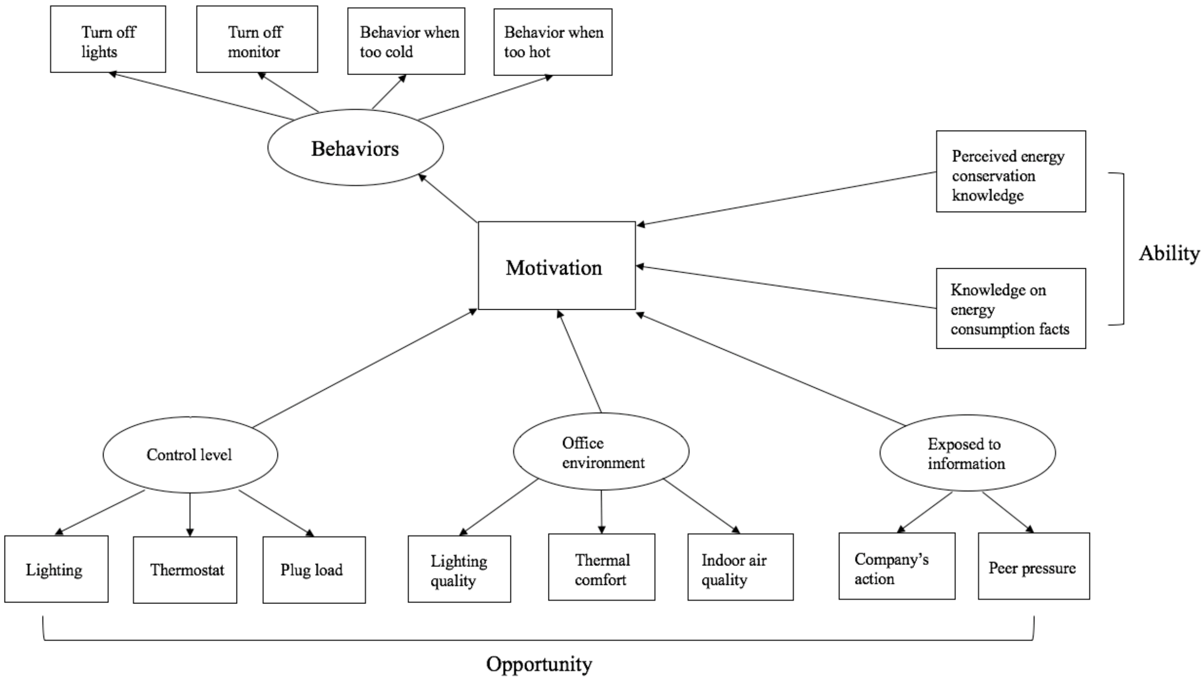

Figure 6-5 SEM Model for the Case Study Building

The SEM results are presented in Table 6-4. β is the coefficient of the observed variable and the latent variable. For each unit of change in the observed variable, the latent variable will change by β units while holding all other observed variables constant (Stata 2013). Statistically significant coefficient is highlighted with a label ("*" for $p < 0.1$, "**" for $p < 0.05$). The following subsections present the implication of these results.

5.5.1 Test of the Hypothesized Relationships

H1 predicts that energy conservation motivation will positively affect all the intended energy-saving behaviors. The results show that motivation level has a positive effect on some behaviors like turning off the office lights ($\beta = 0.34, p < 0.05$), and computer monitors when not in use ($\beta = 0.24, p < 0.05$). However, there is no significant relationship (abbreviated as "ns") between occupants' motivation and behaviors when the office is: (1) too chilly/cold (e.g., wearing a jacket, using space heater) ($\beta = -0.02, ns$), and (2) too warm/hot (e.g., wearing a thin layer of clothing, using an electric fan) ($\beta = -0.03, ns$). These findings indicate mixed support for H1.

Table 6-4 Results from the Structural Equation Model

Outcome		Coeff. (β)
Behavior		
	Motivation → Behavior (H1)	
	Motivation Level → Turning off the office room lights when not in use	0.34 **
	Motivation Level → Turning off the office monitor when not in use	0.24 **
	Motivation Level → Energy conservation behavior when the office is too chilly/cold	- 0.02
	Motivation Level → Energy conservation behavior when the office is too warm/hot	- 0.03
Motivation		
	Opportunity → Motivation	
	H2 → H1	
	Control on Lighting → Motivation Level	- 0.11
	Control on Thermostat Settings → Motivation Level	- 0.32 *
	Control on Office Equipment Plug Load → Motivation Level	0.13
	H3 → H1	
	Indoor Lighting Comfort Level → Motivation Level	- 0.06
	Thermal Comfort Level → Motivation Level	0.16 *
	Indoor Air Quality Level → Motivation Level	- 0.09
	H4 → H1	
	Exposed to Information → Motivation Level	- 0.01
	Peer Pressure → Motivation Level	0.19 *
	Ability → Motivation	
	H5 → H1	
	Perceived Self-Knowledge on Energy Conservation → Motivation Level	0.23 **
	H6 → H1	
	Knowledge on Energy Use Facts → Motivation Level	0.16

*$p < 0.1$, **$p < 0.05$

H2 focuses on whether energy use control levels affect behaviors in the presence of motivation. The results indicate that having thermostat control to adjust the indoor climate conditions is negatively and significantly correlated with occupants' motivation ($\beta = -0.32, p < 0.1$). This result indicates that for the case study building, even some occupants do not have control over the thermostat, they still have high motivations to conserve energy. Moreover, there is no significant impact of the control level over office plug load (e.g., printer, microwave oven) ($\beta = 0.13, ns$) and lighting ($\beta = -0.11, ns$) on the motivation. These results do not support H2.

H3 studies if higher office environment satisfaction levels will affect behaviors in the presence of motivation. For example, occupants with higher thermal comfort tend to perform more energy-saving behaviors than uncomfortable occupants when their motivation is high. The results indicate that there is no significant correlation between occupants' motivation and their lighting comfort ($\beta = -0.06, ns$), and indoor air quality ($\beta = -0.09, ns$). However, occupants' thermal comfort is positively and significantly correlated with the motivation to save energy ($\beta = 0.16, p < 0.1$). This finding can be interpreted as providing higher thermal comfort in the office will increase the motivation for energy savings. Accordingly, these results present mixed support for H3.

H4 studies if higher exposure to ambient conservation information will positively affect behaviors in the presence of motivation. This hypothesis is tested under two conditions, occupants' exposure to information through (1) company's energy-saving actions, and (2) peer-pressure from co-workers. The results show that peer-pressure is positively and significantly correlated with the motivation ($\beta = 0.19, p < 0.1$), which indicates if an occupant observes his/her co-workers always use strategies to conserve energy, he/she will also be highly motivated to do so. The direct exposure to energy conservation-related information, however, does not have any effect on the motivation ($\beta = -0.01, ns$). These results also indicate mixed support for H4.

H5 evaluates if the perceived energy conservation knowledge has a positive impact on behaviors in the presence of motivation. The results indicate that there is a positive and significant correlation between the perceived knowledge of energy conservation and the motivation to conserve energy ($\beta = 0.23, p < 0.05$). This result indicates that higher perceived energy conservation knowledge results in higher motivation. These findings indicate support for H5.

H6 determines if a higher knowledge level of energy consumption facts would lead to more energy-saving behaviors, such that more knowledgeable occupants would perform better than less knowledgeable occupants when motivation is high. The results indicate that there is no significant correlation between the knowledge level on energy consumption facts and motivation ($\beta = 0.16, ns$). Therefore, these results do not support H6.

6.5.2 Discussion of SEM Analysis Results

Based on the results obtained from the previous section, higher occupants' motivation level (e.g., looking for ways to save energy in the office) can lead to some energy-saving behaviors. Therefore, occupancy interventions aiming at better behaviors can focus on improving the motivation level. Moreover, we identified two factors of the opportunity characteristic and one factor of the ability characteristic which demonstrate strong correlations with occupants' motivation. These three factors are the major influential factors of occupants' behavior in this particular building. Therefore, to promote energy-saving behaviors, occupancy interventions can be designed to: (1) provide occupants with thermal comfort conditions, (2) increase the peer-pressure among the co-workers, and (3) enhance occupants' self-assessed knowledge on energy conservation to promote their motivation level. For example, facility managers of can install a thermostat in each office room to improve the indoor thermal comfort, and also send regular emails to occupants presenting their personal energy usage with a comparison of the energy consumption among colleagues, as well as some tips on energy savings.

Findings from the case study also support existing studies conducted by Agha-Hossein et al. 2014, Dolan and Metcalfe 2013, Hayes and Cone 1977, He et al. 2010, Klein et al. 2012, Marans and Edelstein 2010, Peschiera and Taylor 2012, Peschiera et al. 2010, Pieters et al. 1998. Agha-Hossein et al. (2014), Dolan and Metcalfe (2013), and Hayes and Cone (1977) suggested that information distribution of energy consumption facts and reduction guidelines do not appear to effectively influence occupants. Moreover, He et al. (2010) and Marans and Edelstein (2010) demonstrated that feedback and peer-comparison are the most effective education methods to influence occupants' energy-saving behaviors. Klein et al. (2012) highlighted that occupant engagement in building energy reduction strategies is critical and can be achieved through informed feedback and suggestions. Peschiera and Taylor (2012) and Peschiera et al. (2010) argued that feedback which monitors and reports the energy use of peers is very effective in promoting energy reduction. Additionally, the finding of thermal comfort as an influential factor of energy-saving behaviors also conforms to Maslow's hierarchy of needs (Maslow 1987). Occupants are willing to take energy-saving actions and make contributions to the environment (self-actualization) only when their fundamental needs (e.g., physiological needs of thermal comfort) have been satisfied.

However, it should be noted that these findings depend on the data collected from the case study building. The major influential factors identified here may not remain the same for other buildings. For the non-influential factors, further investigations in the workplace can be conducted to identify the reason why these factors fail to show a strong impact on behaviors. Also, it might seem counterintuitive that people with control of lighting and office plug loads fail to perform better. However, there can be several reasons leading to such situations. For example, some office equipment is public appliances (e.g., printer, microwave oven) which are not managed by a single person. It is also likely that occupants may not turn off the light in a multi-occupancy room even if there is enough daylight, because the switch is next to an overbearing colleague. Moreover, company's eco-promotion efforts may fail if the posters are not noticeable to the employees, or the proposal is difficult to perform.

6.5.3 Energy-saving Implications

This section explains how the results obtained from the MOA and SEM analyses can be used to predict potential energy savings from a chosen intervention strategy. First, K-means clustering is conducted to group the occupants in five categories (as shown in Figure 6-6) based on each occupant's MOA level measured in a scale of 0 to 100. The centroid of each cluster is calculated (see Table 6-5) and then mapped to the five MOA characteristics. For example, occupants in the prone category have the highest motivation (80) and relatively high opportunity (51) and ability level (61), while occupants in the resistant category can have the lowest motivation (20), opportunity (30) and ability level (21). More details about the occupants clustering can be found in Aslihan et al. (2016). For the case study building, the number of occupants in each category (from prone to resistant) is 29, 30, 29, 37, and 5, correspondingly.

As shown in Figure 6-5, peer pressure is one of the factors that affect the opportunity level, which thus has a positive influence on motivation. Therefore, peer pressure in the ABM is selected to study the potential impact of this intervention on reducing energy. The occupants are assumed to form a single small-world network, and their energy intensity (EI) is initialized using log-normal distribution (μ=1.626, σ=0.875, min=0.272), emulating the energy consumption of a typical office building in the U.S. based on the CBECS data. However, the energy variability (Var) and the corresponding number of people are decided based on the MOA characteristics of this study. Occupants in the prone category have the largest Var, followed by mildly unable category, unable category, and so on. During the simulation, occupant's EI and Var will evolve due to the presence of peer pressure. When the model converges, results show that 95 out of 130 occupants have reduced their EI. The average EI decreases from 6.93 to 4.19 kWh/m2/person/year. Figure 6-7 shows the number of occupants in each category before the intervention and also the number of occupants who have reduced the energy consumption after the intervention. These results support the conclusions from the SEM analysis that peer pressure can enhance the opportunity level, which then improves motivation and behaviors. However, if the building has a large number of people in each cluster (or in a multi-tenanted building), different interventions can be considered for each cluster. The choice of multi-intervention is beyond the scope of this chapter and is part of our future research efforts to map building occupancy clusters obtained from the MOA model to different interventions.

Table 6-5 Centroid of Each Category for the Case Study Building

Number of Occupants	Occupancy Characteristics	M	O	A
29	Prone	80	51	61
30	Mildly Unable	56	43	32
29	Unable	53	40	66
37	Mildly Resistant	52	61	53
5	Resistant	20	30	21

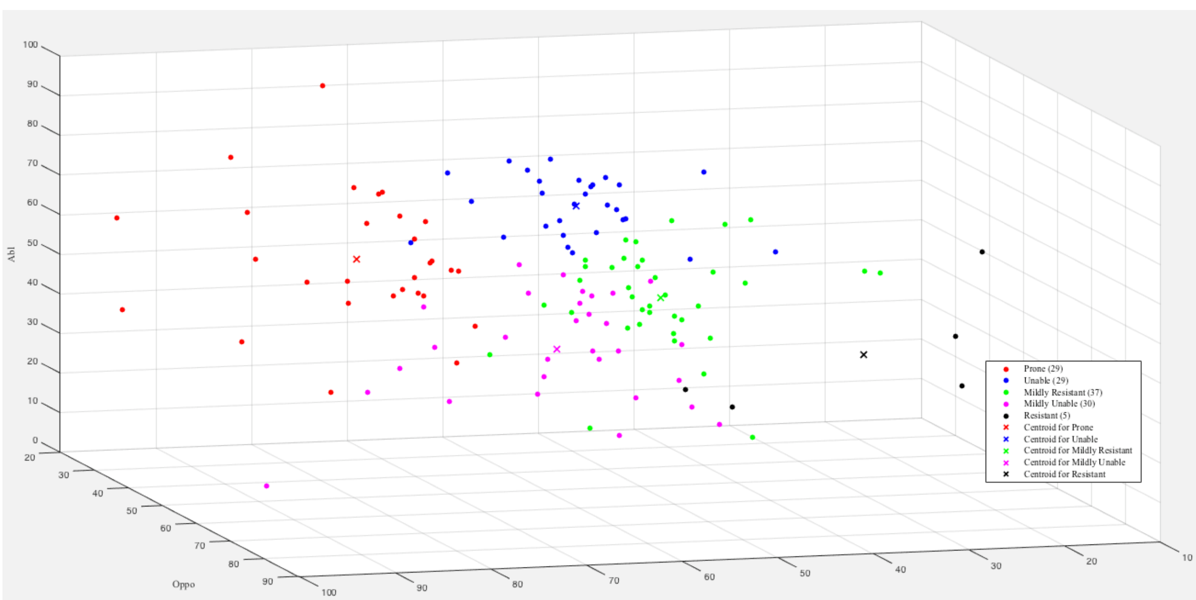

Figure 6-6 K-means Clustering Analysis for Occupants in the Case Study Building

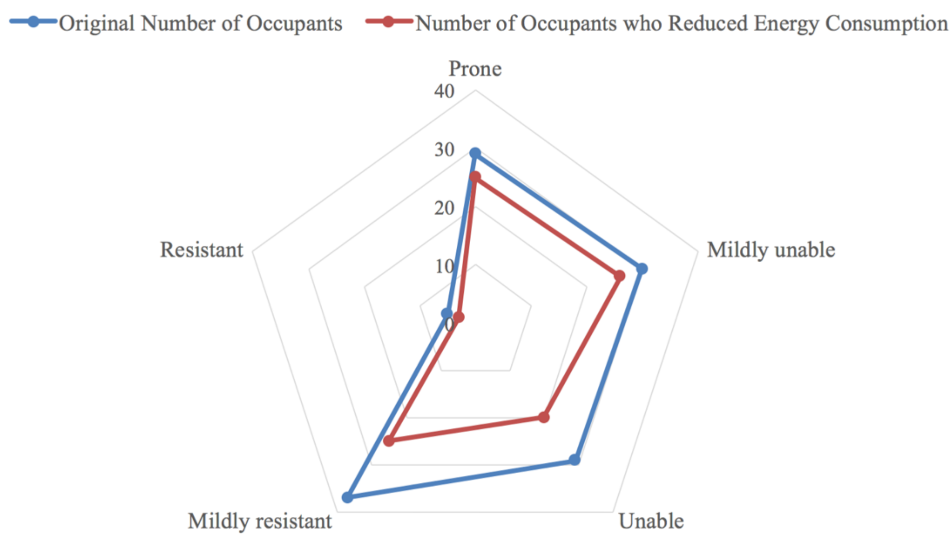

Figure 6-7 Distribution of Occupants who Reduced Energy Consumption

6.6 Limitations

A few limitations of this study should be acknowledged. First, when evaluating the ability level, occupants' perceived knowledge is assumed correct, which might not always be true. Occupants' wrong assumption about energy-saving actions might turn out to be counterproductive. Second, the proposed framework mainly focuses on individual's MOA level to determine energy use characteristics. However, other social factors (e.g., education, religion, economic status, lifestyle) may also collectively affect an occupant's behavior. Third, the motivation level is treated as an overall measure of an occupant's concern and desire for energy conservation. However, in reality, people may have a mixed level of motivation for different behaviors. For example, people may be more motivated to turn off the light than to adjust the thermostat. Fourth, the proposed framework is only tested in commercial buildings. In residential settings, utility bill can become a key factor of energy use. Future studies will take it into consideration when investigating the influential factors in residential buildings.

6.7 Conclusion and Policy Implications

This chapter presents an integrated MOA framework which draws an analogy between consumers' purchasing behaviors and occupants' energy use behaviors. Based on this analogy, a set of research hypotheses are tested using the survey data to identify the determinants of energy use behaviors and occupant characteristics. The results suggest a direct impact of motivation and moderating effect of opportunity and ability on energy use behaviors. ABM is then conducted to estimate the impact of a chosen intervention on energy reduction.

The contribution of this chapter is the flexible MOA framework to identify behavioral determinants and occupant characteristics. This framework can be modified according to the actual situation of a given building, including different building types, weather zones, occupancy states (multi-tenanted vs single company) to name a few. Decision-makers can first identify the behavioral determinants and occupant characteristics of a particular building, and then use the resulting information to design occupancy-focused energy reduction interventions. For example, if a building has a high percentage of occupants who are identified as "prone" to change behaviors, the intervention can focus on knowledge-based approaches such as education (see Figure 6-8). For buildings which show diverse occupant characteristics, multi-level interventions can be adopted to account for different groups. Given the results from the ABM, great saving potentials can be expected from the proposed framework. In particular, policy makers can implement this framework to obtain an understanding of the population perspective in city blocks, urban environments, or residential neighborhoods. They can then use the results to determine which of the M, O or A factors needs to be supplemented or addressed by the intervention to achieve large scale and effective energy reductions.

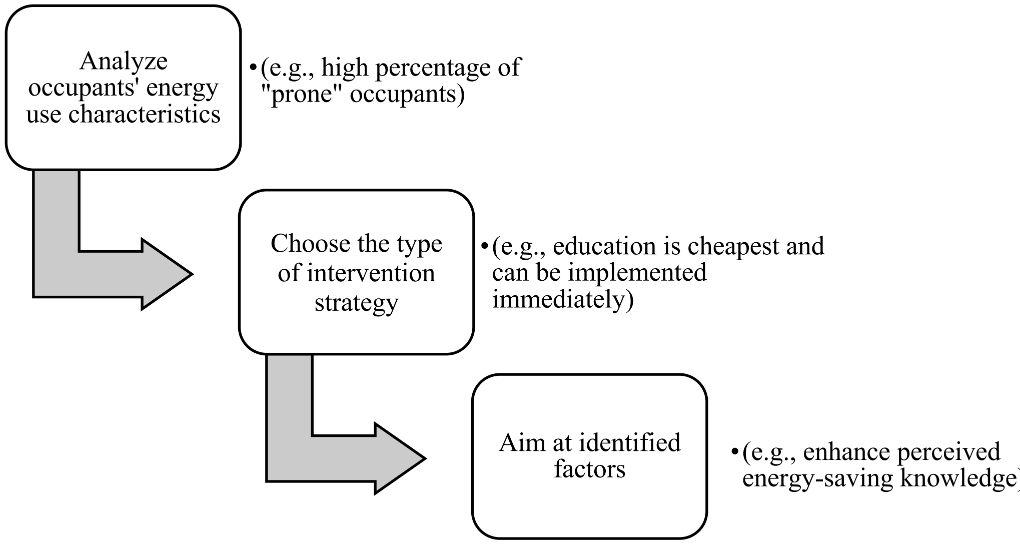

Figure 6-8 Steps for Designing Occupancy-focused Intervention Strategies

CHAPTER 7

A Unified Theory of the Motivation-Opportunity-Ability Framework with Social-Psychology Models

7.1 Introduction

Chapter 6 presents the MOA framework to understand occupants' energy use characteristics and behaviors. However, several limitations of this framework should be acknowledged: First, the rather vague measures failed to capture additional dimensions of motivation, such as values and cognitive processes underlying the decision making. For example, the motivation was a direct measure of the concern and desire about energy conservation (e.g., how concerned are you about your personal energy consumption in your office?) without catching broader dimensions of motivation in the energy context such as perceived consequence and responsibility. Second, for the measures of opportunity, peer pressure was used as a mixed measure of descriptive norms (e.g., other colleagues always use strategies to save energy) and perceived ease of interaction with co-workers (e.g., I would feel comfortable explaining to others how they can save energy) to describe the interpersonal factors influencing energy behaviors. The subjective norms from the Theory of Planned Behavior (TPB), however, were overlooked. Subjective norms can affect an individual's behaviors as he/she tends to perform a particular behavior in the workplace if it is approved by the colleagues. In this case, one's perception of what behavior is approved or disapproved by others becomes the external factor influencing behavioral intention which falls in the category of opportunity). Third, as for the measure of ability, it was considered only as a knowledge-based factor measuring one's interpretation, comprehension, and reasoning about energy use information. This is mainly due to the fact that physical difficulties are uncommon in the built environment (Wilson and Marselle 2016). However, certain behaviors do require occupants to possess physical abilities (e.g., the vinyl window is hard to open and close). Thus, an additional measure is needed to broaden the concept of ability. Fourth, the previous MOA framework was only tested on a small dataset consisting of 177 responses from a single office building. A large-scale dataset involving additional contextual measures from social science theories to capture diverse energy behaviors is much needed in evaluating the applicability of the MOA framework in various office settings. Importantly, clear definitions and valid measurements for the latent components in the MOA framework require further investigation.

Therefore, the main objective of this chapter is to enhance the previous MOA framework through the integration of social-psychology models. Specifically, variables from the Norm Activation Model (NAM) and the Theory of Planned Behavior (TPB) are adopted. These proposed variables are not only proven predictors of energy-saving behaviors but also inherently supplement the motivation, opportunity, and ability factors by definition. In sum, the NAM is adopted to strengthen the broader implications of energy behaviors, while the TPB can be used to reflect the cognitive deliberation process of certain energy behaviors.

7.2 Interdisciplinary Approach and Integrated Framework

There is great potential in using interdisciplinary research approaches to understand the interactions of human occupants and building energy systems (Pellegrino and Musy 2017). As Sovacool (2014) suggested that "*a broader pool of expertise is needed to understand how human behavior affects energy demand and the uptake of technologies.*" (*p.529*). Knowledge gained from this field can provide insights into the drivers of energy-saving behaviors, especially in the office environment where workplace norms and social interactions exist. The office environment is an interesting research setting as employees may lack interest in saving energy because they are not responsible for utility bills. To fill these gaps, researchers have investigated energy behaviors from social-psychological and interdisciplinary perspectives in the context of office workers. For example, Chen and Knight (2014) found that injunctive norms and perceived behavioral control (PBC) fully mediated the effect of energy concerns on workplace energy-saving intentions and that injunctive norms had the strongest direct effect on energy-saving intentions. Greaves et al. (2013) investigated the intentions of pro-environmental behaviors in the workplace and suggested TPB can explain between 46% and 61% variance in behavioral intentions. Li et al. (2017b) proposed an adapted MOA framework to reason the factors influencing energy-saving behaviors. In this study, building occupants were categorized into five categories (i.e., prone, mildly unable, unable, mildly resistant, resistant to behavioral change) based on their MOA characteristics; which provided useful information for decision-makers to design interventions for energy reduction in office buildings. However, since the MOA framework requires more detailed components and measurements to explain the occupant behaviors, it needs to incorporate clear operationalization of concepts and enriched dimensions suitable for the organization or group setting. One approach to achieve this is to investigate the integration of the MOA framework with constructs from well-established theories in human behavior and decision-making.

To address the complexity of human behaviors, researchers have recently stressed the importance of integrating different theories to perform synergistic studies (Bamberg and Moser 2007, Chan and Bishop 2013, D'Oca et al. 2017, Han 2015, Shi et al. 2017, Wolske et al. 2017). In general, model integration can address the inherent limitations of each theory by integrating meaningful measures from various social-psychological perspectives and empirical evidence. The resulting new framework can broaden and deepen the understanding of behaviors and achieve an enhanced predictive power over a single theory. For example, D'Oca et al. (2017) developed an interdisciplinary framework by integrating building physics and multiple theories from social psychology including social cognitive theory and the TPB to investigate building-user interaction in offices, which improved the understanding of the impact of social and contextual factors on occupant behavioral control of building technology in office settings. Chan and Bishop (2013) used both the TPB model and the value-belief-norm (VBN) framework to explain recycling behavioral intention and found that moral norms, subjective norms, and PBC were the most influential predictors. Shi et al. (2017) integrated the norm activation model (NAM) with the TPB in explaining behavioral intention to reduce particulate matter (PM) 2.5 and reported that environmental concerns and moral norms contributed to the behavioral intention to address severe haze pollution beyond the TPB variables. Furthermore, PBC moderated the effect of moral norms on the intention to reduce PM 2.5. Han (2015) proposed a theoretical model comprising VBN and TPB to predict travelers' intention of staying in "green" hotels and suggested that awareness of consequences and normative variables significantly affected the behavioral intention.

7.3 Contributions

In order to promote energy-saving behaviors in office buildings, the following research question should be carefully examined: *what are the determinants of energy-saving behaviors in the organizational context?* Answering this question can help supplement the existing body of literature with a more systematic approach to identify the influential factors of behavioral change, as well as the capability to quantitatively measure their impacts. Implications of this research question can improve the effectiveness of energy interventions as decision-makers can tailor strategies in accordance with the characteristics of occupants in a particular setting. In summary, the specific contributions of this chapter include:

- Present an integrated framework to strengthen the current MOA framework by incorporating constructs from the TPB and the NAM.
- Conduct a large-scale survey in office buildings and test the improved framework to identify the important factors influencing energy-saving behaviors in the workplace.

7.4 Theoretical Framework and Hypotheses

This section presents a review of relevant theoretical frameworks and their applications leading to the integrated framework, including the MOA, the NAM, and the TPB models. The model integration and research hypotheses are discussed at the end of this section.

7.4.1 The Motivation-Opportunity-Ability Framework

The MOA framework was originally developed and applied to understand consumer engagement in processing brand information and corresponding purchasing behaviors (Bigné et al. 2010, Gruen et al. 2005, Hastak et al. 2001, MacInnis et al. 1991, Moorman and Matulich 1993, ThØgersen 1995). The MOA framework posits that consumers' processing of information from advertisements and purchasing behaviors are affected by three factors: motivation (i.e., one's interest and desire to process the advertisements), opportunity (i.e., favorable conditions or time availability that affect one's attention), and ability (i.e., one's skills and proficiencies to interpret brand information) (Hoyer and MacInnis 1997, MacInnis et al. 1991). Similarly, Fishbein suggested the three necessary factors for any volitional behavior to occur as "*the strong positive intention to perform the behavior*", "*the skills necessary to carry out the behavior*", and "*the context of opportunity provided by the environment, or be free of constraints*" (*p.5*) (Fishbein et al. 2000).

The MOA framework has been successfully adopted in existing studies to explain various types of behaviors. For example, Moorman and Matulich's study (1993) suggested that consumers' health motivation directly affected the health-related behaviors (e.g., improving dietary intake) while the effect of health ability was moderated by health motivation. Bigné et al.'s study (2010) indicated that consumers' online purchasing intentions of airline tickets were affected by the convenience and financial advantages of online purchases (motivation factors), and consumers' Internet proficiency and capabilities to search flight information (ability factors). Opportunity, however, did not show a strong influence on the purchasing intention due to the perceived ease of use of the online ticketing website (e.g., do not request excess information for the transaction).

Recently, the MOA framework has also been applied to investigate energy behaviors. For example, Li et al. (2017b) adapted the MOA framework to analyze factors influencing energy-saving behaviors in office buildings (see Figure 7-1). In Li et al. (2017b), the MOA factors were defined as follows: motivation measures an individual's concern and involvement in energy conservation, which directly affects his/her energy-saving behaviors and moderates the effect of opportunity and ability; opportunity defines the surrounding environmental (e.g., organizational support) and interpersonal (e.g., peer pressure) factors facilitating one's energy-saving intention; ability measures one's prior knowledge in energy-savings and proficiencies in interpreting information received from behavioral interventions. Through the SEM analysis, Li et al.'s study confirmed the proposed effects of the MOA factors on an individual's energy-saving behaviors and identified three influential factors in promoting occupants' motivation, namely satisfaction about the thermal environment, peer-pressure from co-workers, and perceived knowledge on energy conservation.

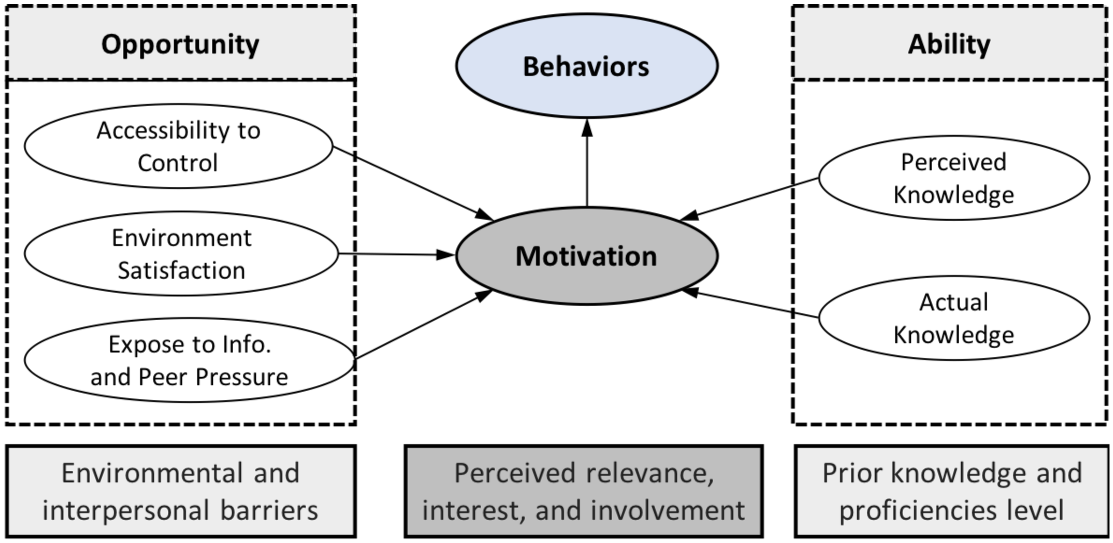

Figure 7-1 The MOA Framework Applied in Energy-Saving Behaviors

7.4.2 The Norm Activation Model

This chapter adopts the NAM to extend several important psychological measurements to capture the essential aspects of motivation (see Figure 7-2). The NAM was developed by Schwartz (1977) to explain altruistic behaviors such as recycling (Park and Ha 2014), volunteering (Schwartz and Fleishman 1982), and other pro-social behaviors such as driving and traveling style (Onwezen et al. 2013, Ünal et al. 2017), environment protection (van Riper and Kyle 2014), and energy-saving behaviors (Black et al. 1985, van der Werff and Steg 2015, Zhang et al. 2013). The NAM argues that altruistic intention and behaviors are largely driven by one's moral considerations, which are activated by three key components: awareness of consequence, ascription of responsibility, and personal norms. Most closely, behaviors are influenced by "expectations, obligations, and sanctions anchored in the self," termed "personal norms" (Schwartz 1977, *p.223*). Moreover, awareness of consequence, defined as being aware of the consequences of actions, and ascription of responsibility, defined as feeling responsible for taking actions, are two important antecedent variables contributing to personal norms (De Groot and Steg

2009). The NAM is a pro-social theory which argues that people will perform altruistic behaviors for the benefits of the society/environment even though the behaviors can sometimes go against their self-interest (De Groot and Steg 2009). In the context of office buildings in this study, for example, employees may increase the thermostat set point in summer to reduce the cooling load and save energy despite their thermal comfort.

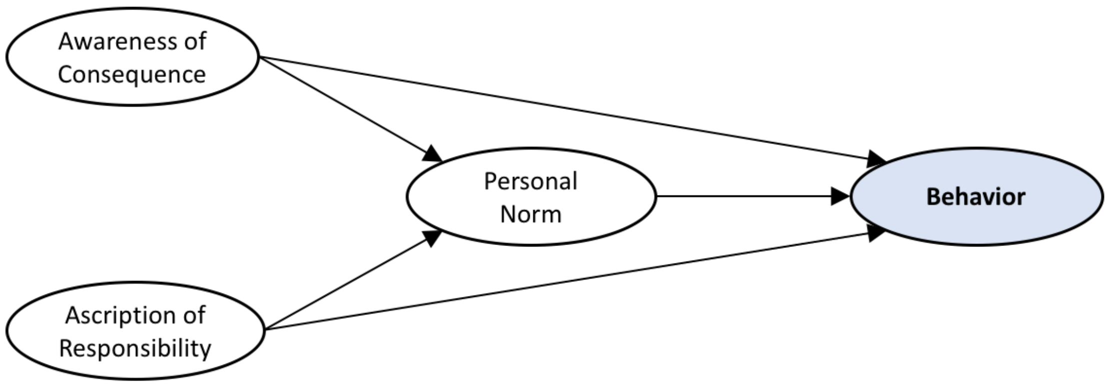

Figure 7-2 Norm Activation Model (Schwartz 1977)

7.4.3 The Theory of Planned Behavior

This chapter adopts the TPB to strengthen the MOA framework by clearly capturing the rational aspects of energy behaviors (see Figure 7-3). The TPB is an extension of the theory of reasoned action (Fishbein and Ajzen 1975). The TPB proposes that behavioral intention is determined by three constructs: attitude towards a behavior, subjective norms (i.e., perceived social pressure to engage or not engage in the behavior) (Ajzen 1991), and perceived behavioral control (PBC, i.e., perceived ease/difficulty to perform the behavior). Recent studies also extended the TPB by adding descriptive norms (i.e., perceptions of important other’s opinions and behaviors) to capture the additional social influence and suggested increased explanatory power of behavioral intention (Ajzen 2002, Forward 2009, Rivis and Sheeran 2003). Particularly, descriptive norms play an influential role in adopting a behavior for low PBC individuals (Rai and Beck 2015). As opposed to the NAM, the TPB is a self-interest theory such that the behavior is a rational choice of individual benefits (Ajzen 1991). The TPB has been demonstrated as an effective framework to predict a variety of behaviors, including opinions toward wind farm development (Read et al. 2013), adoption of residential solar photovoltaic (Rai and Beck 2015), online trade (Gopi and Ramayah 2007), voting choice (Netemeyer and Burton 1990), driving violation (Forward 2009), and energy-saving behaviors (Kaiser and Gutscher 2003, Scherbaum et al. 2008), to name a few.

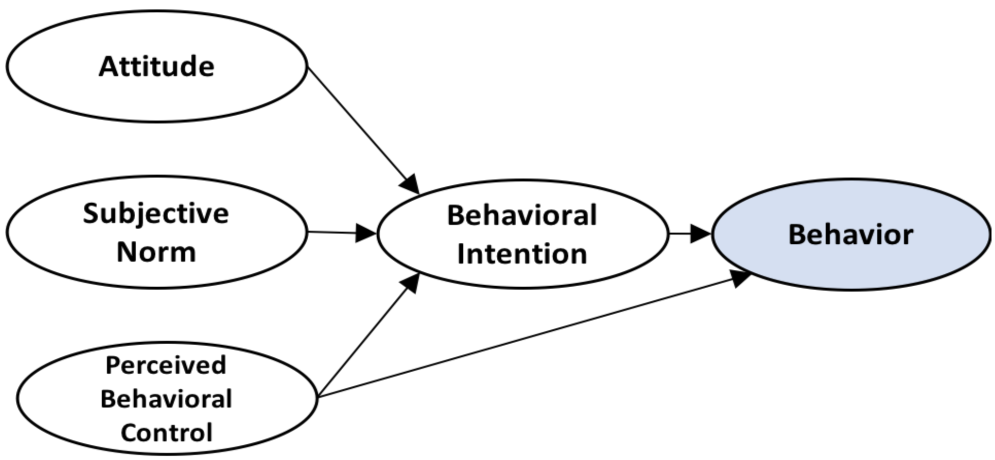

Figure 7-3 Theory of Planned Behavior (Ajzen 1991)

7.4.4 Integrated MOA Framework and Research Hypotheses

This chapter proposes an integrated MOA framework to analyze the determinants of energy-saving behaviors and characteristics in the office environment by considering the disciplines of building science and social psychology. In the MOA framework, the three main factors, i.e., motivation, opportunity, and ability, are high-level abstractions of antecedents of behaviors. In general, the MOA factors are not directly observed from the survey but are rather inferred from other variables. To provide clearly defined and measurable components for each MOA factor, we adopt constructs from the NAM and the TPB models, as well as other constructs which have been identified as the dimensions of the MOA factors in existing models (see Figure 7-4). As each MOA factor encompasses several constructs, it has a broader conceptual scope than individual constructs in the existing models. This hierarchical framework also has the benefits of abstraction of concepts and alleviation of multicollinearity (Koufteros et al. 2009). For example, representing motivation as a high-level factor can address the difficulties of defining and measuring motivation in behavior studies (Ambrose and Kulik 1999, Siemsen et al. 2008). Specific factors in the integrated MOA framework are described as follows.

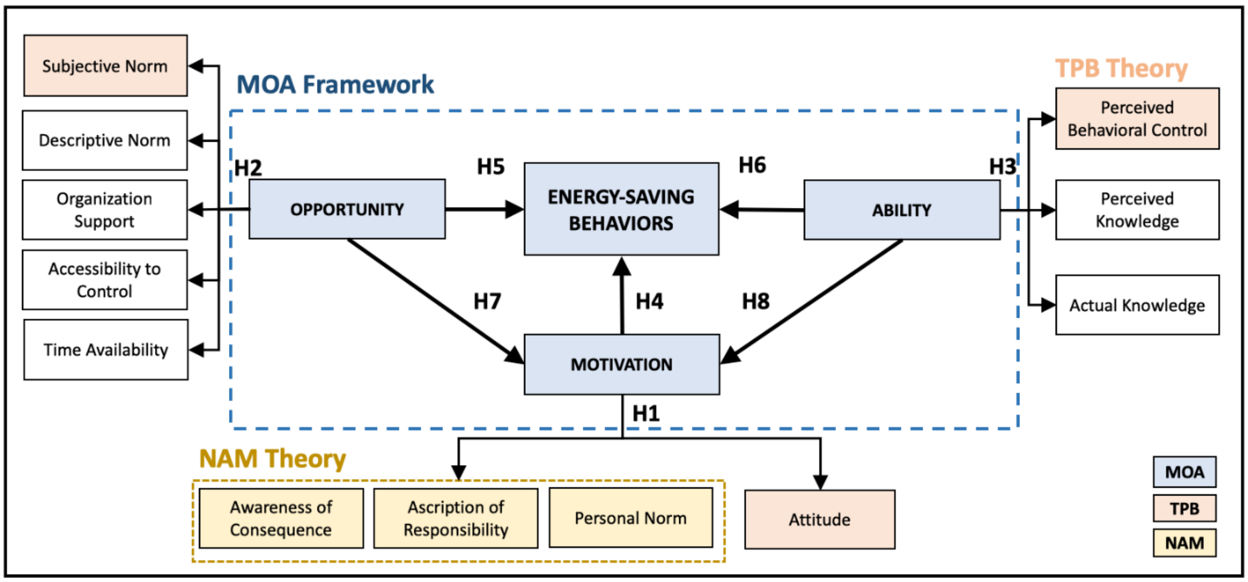

Figure 7-4 Overview of the Integrated MOA Framework

Motivation: Motivation is defined as the goal-directed arousal to engage in desired behaviors (MacInnis et al. 1991, Michie et al. 2011). In the context of energy behaviors, it captures an employee's needs, values, concerns, and involvements in performing a behavior in the workplace (Li et al. 2017b). In order to capture the social-psychological factors in motivation, we adopt the three main NAM constructs - awareness of consequence, ascription of responsibility, and personal norms, as well as a construct from the TPB theory - attitude as the fourth dimension.

In relation to motivation, both awareness of consequence and ascription of responsibility play important roles in cognitive choice-based motivation theories (Kanfer 1990). Those theories emphasize the cognitive processes involved in decision making; people usually undergo a series of cognitive processing before deciding whether to initiate, maintain, or cancel efforts. In particular, awareness of consequence resembles the key construct, expectancy, in the expectancy-value theory, which asserts that expectancy drives behaviors (Wigfield and Eccles 2000). The ascription of responsibility is also an important cognitive component for motivation (Wilson and Marselle 2016). Personal norms, on the other hand, relate to the need-motive-value theories of motivation. Personal norms are usually value-driven and act as an internalized need to commit to pro-social or pro-environmental behaviors. Stronger impact of personal norms on behavior has been observed as the decision process progresses from intention to action (Rai and Beck 2015). In summary, these theories emphasize the impact of stable dispositions on behaviors. Additionally, the cognitive, affective, and behavioral components of attitude (Eagly and Chaiken 1993) align well with the conceptualization of motivation - brain processes that direct and energize behaviors (Michie et al. 2011). In fact, Thøgersen (1995) identified attitudes as one of the motivational factors in determining behavioral intentions.

The four specified dimensions define the formation of motives to engage in energy-savings, i.e., if an employee is aware of the consequences of a behavior (e.g., saving electricity can reduce environmental impact and also reduce the utility cost of my company), he/she may feel responsible to perform this behavior (e.g., it is my responsibility to protect the environment and do something good for my company). The awareness and perceived responsibility are considered as relating to one's personal norms (e.g., I feel guilty if I use a lot of electricity). As an essential psychological aspect, attitude captures one's favorable or unfavorable evaluation of certain behaviors by weighing the associated benefits and costs (Ajzen 1991). Thus, the more an employee's positive attitude towards energy-savings, the more likely he/she is motivated to perform that behavior.

Opportunity: Opportunity is defined as the external factors lying outside of the individual that enable or inhibit a behavior (Michie et al. 2011, Siemsen et al. 2008). In the context of energy behaviors, it includes both environmental and interpersonal factors in the workplace that facilitate or constrain energy behaviors (Li et al. 2017b). Under the construct of opportunity, we measure five factors including subjective norms from the TPB theory, and another four important social-psychological factors identified in existing studies - accessibility to control, time availability, organizational support, and descriptive norms.

First, accessibility to control (Li et al. 2017b) and time availability (Siemsen et al. 2008) capture the physical-temporal constraints in an office environment. Accessibility to control measures one's degree of actual controllability over the building systems (e.g., whether the thermostat is adjustable) which may not be accurately reflected by the PBC. Time availability has been previously used as a proxy of opportunity (Siemsen et al. 2008). It captures the necessary slack time during working hours to enact a behavior. An employee may not be able to save energy if he/she does not have control or is overwhelmed by the work. Organizational support is another construct reflecting the level of commitment or encouragement of a company in promoting energy -saving behaviors (e.g., the company rewards employees for saving energy). Studies have shown that employees' engagement in pro-environmental behaviors is positively associated with the support from their company (Ramus and Steger 2000, Thøgersen 2014, Xu et al. 2017).

On the other hand, normative factors capture the social influences that are prevalent in the office environment. The social influence can prompt or inhibit a behavior; thus it is a situational condition which is beyond the control of an individual. Therefore, they are ascribed as the constructs of opportunity. This study considers two social norms. First, descriptive norms capture the perceptions of others' actual behaviors; for example, the perception of colleagues' actual wasting or saving electricity behaviors. Descriptive norms reflect the impact of social influences. Second, subjective norms (a type of injunctive norms) reflect the expectation of significant others towards a behavior; for example, the majority of colleagues expect an employee to turn off lights when leaving the office. Descriptive and subjective norms are found positively correlated and are both important in influencing individual behaviors (Ajzen 2002, Rivis and Sheeran 2003). Thus, we posit that positive social norms will lead to enhanced perceived opportunity through social interaction with peers. This is particularly the case in a multi-occupancy office where occupants share device controls. For example, an employee may not feel comfortable to adjust the thermostat due to an overbearing colleague who is unwilling to save energy at the price of decreased personal comfort. In this case, one's opportunity to save energy is constrained by negative social norms. It is also worth noting that in the recent iterations of the TPB theory (e.g., integrative model of behavioral prediction), researchers adopted the concept of environmental constraints – "*factors other than those underlying the intention to perform the behavior"* (*p.6*) (Fishbein and Cappella 2006) as a different factor from the subjective and descriptive norms. However, the scope of environmental constraints does not seem to be clearly defined (e.g., Fishbein 2000, Yzer 2012). In this study, the opportunity component broadly involves all the environmental and interpersonal factors that lie outside of an individual and thus we include the subjective and descriptive norms as its constructs. From another perspective, norms can be conceptualized as the belief to accept the common rules, which are "opportunities" leading to social rewards. In this case, if the employees are anticipating social rewards from abiding by the social norms, the social norms should be considered as an opportunity.

Ability: Ability is defined as the necessary psychological and physical capabilities to make an outcome happen (Michie et al. 2011). In the context of energy behaviors, three constructs are adopted to capture one's ability, including the perceived knowledge, actual knowledge, and PBC from the TPB theory.

The two knowledge-based constructs, perceived knowledge and actual knowledge, capture one's mental capabilities to perform a behavior. Perceived knowledge refers to one's perception of his/her knowledge about energy conservation (e.g., whether an individual knows methods to reduce the cooling load). Perceived knowledge reflects the necessary prior knowledge to achieve the desired outcome. Actual knowledge is another factor that has been used in existing studies to measure one's mental capabilities. This factor measures the understanding of energy-related facts, such as "LED light uses less electricity than CFL light assuming the same amount of light delivered." Abrahamse and colleagues described such questions as "energy quizzes" and suggested that a higher level of actual knowledge can contribute to energy-savings (Abrahamse et al. 2007). The two knowledge factors are both constructs of ability because one's perceived knowledge is not always accurate and also is often subject to personal judgment. Thus, a universally correct and consistent measure (i.e., actual knowledge) is included. In addition, PBC complements one's ability by including the components of physical capability and perceived ease to enact a behavior. In an office environment, an employee may be reluctant to save energy if the behavior requires much physical effort (e.g., removing furniture blocking the air return vents) or causes inconvenience (e.g., turning off the printer after use requires future booting when needed).

Based on previous literature and integrated framework, we propose the hypotheses for the constructs of MOA factors (H1, H2, H3) and the effects of MOA factors on energy behaviors (H4, H5, H6) as listed in Table 7-1.

Relationships between the specified constructs in the MOA framework have also been evaluated in previous studies. For example, PBC, an ability component, has been suggested to be positively related to feelings of responsibility and attitude towards energy-savings (which are the dimensions of motivation) (Abrahamse and Steg 2009). Moreover, the effect of descriptive and social norms on behavioral intention is mediated through personal norms (also a specified dimension in motivation) (Thøgersen 2014). Therefore, in addition to the proposed direct effects, we also hypothesize that opportunity and ability are expected to affect energy-saving behaviors through motivation. Opportunity and ability will matter the most if they can internalize into one's motivation, which manifests the mediating effect of motivation on behaviors suggested by literature (e.g., energy-saving behaviors, Li et al. 2017b; preventive health behaviors, Moorman and Matulich 1993; pro-environmental behaviors, Thøgersen 1995; behavior change model, Michie et al. 2011). Therefore, we propose the hypotheses for the mediating effects of motivation (H7 and H8) as listed in Table 7-1.

Table 7-1 Summary of Research Hypotheses

	Hypothesized constructs of MOA factors
H1	Motivation consists of the following constructs: a) attitude, b) awareness of consequence, c) ascription of responsibility, and d) personal norms. Statistically speaking, the four constructs each shares a significant portion of variance with motivation.
H2	Opportunity consists of the following constructs: a) subjective norms, b) descriptive norms, c) organizational support, d) accessibility to control, and e) time availability.
H3	Ability consists of the following constructs: a) PBC, b) perceived knowledge, and c) actual knowledge.
	Hypothesized direct effects of MOA factors
H4	Motivation has a positive and direct effect on energy-saving behaviors.
H5	Opportunity has a positive and direct effect on energy-saving behaviors.
H6	Ability has a positive and direct effect on energy-saving behaviors.
	Hypothesized mediating effects of motivation
H7	The effect of opportunity on energy-saving behaviors will be mediated by motivation.
H8	The effect of ability on energy-saving behaviors will be mediated by motivation.

7.5 Methodology

7.5.1 Participants

The research hypotheses are tested through the SEM analysis using data collected from an Internet-based survey, which targets at full-time office employees (40 hours or over) located in the U.S. Specifically, the data collection was carried out across several office buildings to identify the common drivers of energy behaviors among employees. The survey was distributed in October 2017 through Qualtrics Paid Panel Service - a frequently used online data collection platform by researchers - to collect responses from office workers in organizations that have 200 or more employees. A total of 1161 responses were collected. In the data cleaning process, responses with missing values in energy behaviors were removed. As a result, 612 responses were retained for the SEM analysis.

Among our samples, the age ranged from 18 to 64 years (Mean = 44.3). The majority of the participants were Caucasians (76.6%), followed by Asian and African American comprising 10.2% and 4.9%, respectively. 89.9% of the participants indicated that they had at least some college or university education. Quotas were set so that the distribution of gender was similar to that of the U.S. population and that about half of the participants were sharing the office with others while the other half were not.

7.5.2 Survey Structure and Measures

The survey consisted of three sections. The first section included screening and quota questions (i.e., employment status, organization size, office sharing status, and gender). The second section included socio-demographics (e.g., age, ethnicity, education, and occupation) questions. Lastly, the third section included major measures of this study in the following order: (1) behavioral measures (e.g., turning off office appliances when not in use, see Table 7-2), (2) motivation measures (i.e., awareness of consequence, ascription of responsibility, personal norms, and attitudes, see Table 7-3), (3) opportunities measures (i.e., accessibility to control, subjective norms, descriptive norms, organizational support, and time availability, see Table 7-4), and (4) ability measures (i.e., PBC, perceived knowledge, and actual knowledge, see Table 7-5). The measures were adopted from previous literature such as Abrahamse and Steg (2009), Carrico and Riemer (2011), Jansson et al. (2011), Li et al. (2017b), Ramus and Steger (2000), Siemsen et al. (2008), Steg et al. (2014), Zhang et al. (2013). All variables were measured on 5-point Likert-like scales, with a minimum of 1 and a maximum of 5. Table 7-2 toTable **7-5** show the detailed descriptions of measures, means and standard deviations (SD), factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR).

Table 7-2 Main Variables and Associated Survey Questions for Energy-Saving Behaviors

Construct	Description	M(SD)	Loading	AVE	CR
Energy-saving Behaviors	How often do you turn off the following devices when not in use to save energy: Ceiling light	3.19 (1.63)	.72	.53	.87
	Desk light	3.27 (1.54)	.82		
	Portable space heater or personal fan	3.31 (1.50)	.79		
	Computers (off or sleep mode)	3.44 (1.52)			
	Air conditioner (A/C)	2.70 (1.52)	.73		
	Heating	2.80 (1.49)	.75		
	Set point (adjust)	2.41 (1.41)	.49		

Note: Gray shading indicates the items that were later taken out due to low loadings in the test of the measurement model.

Table 7-3 Main Variables and Associated Survey Questions for Motivation

Construct	Description	M(SD)	Loading	AVE	CR
Attitude (AT)	Reducing electricity use at work: Not good at all – Very good	3.86 (1.04)	.71	.70	.87
	Not important at all – Very important	3.93 (1.00)	.90		
	Not beneficial at all – Very beneficial	4.00 (1.00)	.89		
Awareness of Consequence (AC)	When I reduce electricity use in my workplace, I cut down the cost for my company	3.81 (1.12)	.90	.68	.89
	When I reduce electricity use in my workplace, I do something good for my company	3.85 (1.08)	.94		
	When I reduce electricity use in my workplace, I reduce the carbon emissions	3.78 (1.08)	.71		
	When I reduce electricity use in my workplace, I do something good for the environment	4.00 (1.02)	.72		
Ascription of Responsibility (AR)	I feel jointly responsible for the energy use at work	3.32 (1.24)	.86	.74	.90
	Because my personal contribution would be negligible, I do not feel responsible for the energy use at work	3.09 (1.29)			
	Our company, not me, is responsible for the energy use at work	2.96 (1.29)			
	I feel responsible for reducing energy use at work	3.32 (1.18)	.88		
	Because I use energy during work, at least somewhat, I am responsible for energy use at work	3.54 (1.10)	.84		
Personal Norms (PN)	I feel personally obliged to save energy at work	3.42 (1.18)	.90	.72	.88
	Regardless of what others do, I feel morally obligated to save energy at work	3.53 (1.16)	.90		
	I feel good about myself when I do not use a lot of energy	3.72 (1.04)	.73		
	I feel guilty when I use a lot of energy at work	3.17 (1.17)			

Table 7-4 Main Variables and Associated Survey Questions for Opportunity

Construct	Description	M(SD)	Loading	AVE	CR
Accessibility to Control (CN)	How conveniently can you control the following options: Ceiling light	3.57 (1.46)	.69	.52	.76
	Thermostat (heating and cooling)	3.17 (1.51)	.75		

	Windows (i.e. open and close)	2.77 (1.58)			
	Window blinds and shades	3.66 (1.43)	.72		
Descriptive Norms (DN)	My coworkers are concerned about using too much energy	2.57 (1.18)	.89	.85	.94
	My coworkers pay attention to their energy use	2.61 (1.20)	.92		
	Many of my coworkers are trying to reduce their energy use	2.65 (1.18)	.95		
Subjective Norms (SN)	Most of my coworkers expect me to turn off the computer/monitor when leaving	2.79 (1.36)	.67	.60	.86
	Most of my coworkers expect me to turn off the lights when leaving	2.93 (1.40)	.73		
	Most of my coworkers expect me to shut down or change the A/C and heater thermostat settings	2.42 (1.32)	.78		
	Most of my coworkers expect me to save energy at work in general	2.69 (1.24)	.91		
Organizational Support (OS)	My company encourages employees to save energy	3.06 (1.28)	.81	.80	.92
	My company rewards employees (either financially or socially) for saving energy	2.16 (1.23)			
	My company highly values saving energy	2.90 (1.25)	.93		
	My company is committed to saving energy	2.96 (1.26)	.94		
Time Availability (TA)	I have little time to pay attention to saving energy at work	3.04 (1.19)	.82	.74	.89
	I usually have a lot of work to do during the workday, and cannot make extra efforts to save energy at work	2.99 (1.16)	.88		
	I don't have extra time during the weekday to think about ways to save energy at work	3.05 (1.16)	.87		

Table 7-5 Main Variables and Associated Survey Questions for Ability

Construct	**Description**	**M(SD)**	**Loading**	**AVE**	**CR**
Perceived Behavioral Control (PBC)	Whether or not I save energy at work is completely up to me	3.26 (1.29)	.81	.71	.88
	Adopting energy-saving practices in my workplace is entirely within my control	3.13 (1.32)	.90		
	I am confident that if I want, I can save energy at work	3.55 (1.20)	.81		
Perceived Knowledge (PK)	I know methods to reduce the lighting load in my office space	3.33 (1.33)	.72	.73	.91
	I know methods to reduce the plug load in my office space	3.25 (1.33)	.77		
	I know methods to reduce the cooling load in my office space	3.12 (1.34)	.96		
	I know methods to reduce the heating load in my office space	3.14 (1.37)	.94		
Actual Knowledge (AK)	Please rate the degree to which you think the following statements are true or not true: LED light bulbs save more energy than CFL (compact fluorescent light) bulbs assuming the same amount of light delivered	4.14 (0.96)	.59	.40	.66
	The amount of energy consumed by an electrical appliance is calculated by the voltage of the appliance multiplied by the current	2.37 (0.92)	.64		
	A photocopier left on overnight uses enough energy to produce over 1000 copies	3.37 (0.95)			
	Heating and cooling use the most amount of energy in an office building, compared with lighting, ventilation, and office equipment	3.81 (0.98)	.66		

7.5.3 Analytical Approach

The SEM is adopted to test our hypotheses. Specifically, we use the maximum likelihood estimation method for analysis in the IBM SPSS Amos software. The SEM models are represented in a path diagram in which rectangles represent the indicators (e.g., how often do you turn off the ceiling light) and ellipses represent the latent factors which are inferred from the indicators (e.g., attitudes toward energy-savings). In this study, we adopt the second-order SEM model in which each second-order factor (i.e., motivation, opportunity, and ability) is a composite of several first-order factors (e.g., attitude, awareness of consequences, personal norms; the construct column shown in Table 7-3 toTable **7-5**). Compared to the first-order model, the second-order model is more parsimonious and can capture the unique variance of each first-order factor (Byrne 2005). In this hierarchical structure, first-order factors can be considered as the various dimensions of the second-order factors, and thus help understand which particular facet (i.e., the first-order factor) contributes to the motivation, opportunity, and ability (Koufteros et al. 2009). The behavior is also a latent factor which encompasses several specific behaviors discussed in Table 7-2 to represent a general measure of energy-saving behaviors. Single-headed arrows connecting second-order factors and behaviors (e.g., motivation → behavior) represent the hypothesized direct effects of one factor on another. The two-headed arrows represent the covariance between the second-order factors.

There has been considerable debate over the measures of goodness of fit. Generally, a combination of model fit indices is adopted by researchers as each index reflects some facet of the model (Hooper et al. 2008). If the hypothesized model satisfies all fit indices, it is then retained for interpretation. In this study, the following fit indices are examined: chi-square (χ^2), the root mean square error of approximation (RMSEA) (Steiger 1990), the comparative fit index (CFI)

(Bentler 1990), and the standardized root mean square residual (SRMR) (Hu and Bentler 1999). In general, a good fit of the model has χ^2/df < 3 (Schreiber et al. 2006), RMSEA ≤ 0.05 (with the lower bound of 90% confidence interval ≤ 0.05 and upper bound ≤ 0.10) (Kline 2011), CFI ≥ 0.90 (Hopper et al. 2008), and SRMR ≤ 0.08 (Kline 2011, Schreiber et al. 2006).

7.6 Results

7.6.1 Confirmatory Factor Analysis

Hierarchical confirmatory factor analysis is conducted to evaluate (1) convergent and discriminant validity of each first-order factor, as indicated by AVE and CR, and (2) whether each first-order factor meaningfully contributes to the second-order factor (i.e., motivation, opportunity, or ability), which is supposed to affiliate with, as hypothesized by H1, H2, and H3. Indicators and first-order factors with low factor loadings are considered to be removed from the hypothesized model (Kline 2011).

Results indicate that the measurement model has a decent global fit: χ^2/df = 2.295 (χ^2 = 1308.231, df = 570), RMSEA = 0.046 (90% confidence interval = 0.043 - 0.049), CFI = 0.957, SRMR = 0.050. In the test for convergent validity, the AVEs for almost all first-order factors (range from 0.52 to 0.85, see Table 7-3Table 7-5) are greater than the suggested threshold of 0.5 (Kline 2011), indicating that each first-order factor accounts for a significant portion of the variance in its measures. The only exception is the actual knowledge (AVE = .40, Table 7-5). However, as the questions for actual knowledge cover different aspects of energy use from light bulb efficiency to the mathematical calculation of energy consumption, it is reasonable for one to be well-informed in some aspects but know little about others, resulting in a relatively low AVE score. Therefore, we keep actual knowledge as a first-order factor.

The CRs are satisfactory for all first-order factors (range from 0.66 to 0.94, see Table 7-3Table 7-5), which further support the convergent validity. Moreover, the patterns among first-order factor loadings are as expected: each item loads highly on its corresponding factor and no cross-loadings are significant. The discriminant validity is also supported in that the square roots of AVEs (see the diagonal in Table 7-6) are greater than the correlations between each pair of first-order factors (shown as the lower triangle in Table 7-6), passing the Fornell and Larcker (1981) testing system.

Table 7-6 Means, Standard Deviations, and Correlations of First-Order Factors

	Mean	SD	AT	AC	AR	PN	SN	DN	OS	CN	TA	PBC	PK	AK
AT	3.93	.90	**.84**											
AC	3.86	.95	.61	**.82**										
AR	3.39	1.06	.60	.66	**.86**									
PN	3.46	.97	.64	.64	.82	**.85**								
SN	2.71	1.11	.34	.35	.59	.59	**.78**							
DN	2.61	1.12	.30	.26	.53	.55	.76	**.92**						
OS	2.97	1.17	.37	.42	.56	.57	.68	.73	**.90**					
CN	3.47	1.21	.20	.23	.44	.37	.52	.44	.42	**.72**				
TA	3.03	1.06	-.21	-.21	-.31	-.32	-.13	-.11	-.13	-.07	**.86**			
PBC	3.31	1.14	.40	.32	.63	.57	.56	.51	.52	.51	-.25	**.84**		
PK	3.23	1.21	.32	.29	.50	.47	.44	.44	.42	.45	-.13	.59	**.85**	
AK	3.44	0.47	.43	.44	.42	.46	.14	.20	.27	.22	-.01	.35	.27	**.63**

Note: Numbers on the diagonal (in bold) are the square roots of AVEs.

In the test of the structure between the first-order and the second-order factors, AT, AC, AR, and PN all share a significant portion of variance with their higher-order factors - motivation, exceeding the threshold suggested by Kline (2011) (CR > 0.6, AVE > 0.5, see Table 7-7). Therefore, H1a-d are supported. H2a-d are supported in that SN, DN, OS, and CN share a significant portion of variance with their higher-order factor - opportunity. TA (H2e) does not contribute much to opportunity (loading: 0.11) and thus is removed from the model. Lastly, due to the independence of actual knowledge questions, the AVE for ability is slightly lower than 0.5 while the CR is acceptable. Thus, H3a-c are also supported.

Table 7-7 CR and AVE for Each Second-Order Factor

Second-order factor	First-order factor	Loading	CR (above 0.6)	AVE (above 0.5)
Motivation	AT AC AR PN	.66 .68 .96 .95	0.89	0.68
Opportunity	SN DN OS CN	.85 .86 .82 .58	0.86	0.62
Ability	PBC PK AK	.84 .69 .50	0.72	0.48

7.6.2 Structural Equation Models

Two competing SEM models, including the direct effect model and the mediating effect model, are tested to investigate how motivation, opportunity, and ability affected energy-saving behaviors, particularly if opportunity and ability affect behaviors through motivation.

7.6.2.1 Direct Effect Model on Behaviors

Figure 7-5 presents our first hypothesized MOA model (Model 1) testing the direct effects of motivation, opportunity, and ability on energy-saving behaviors (i.e., H4, H5, and H6); the standardized path coefficients are shown along the hypothesized paths. In this model, all three second-order factors, i.e., motivation, opportunity, and ability, are set to covary with each other and directly affect the behavior. All model fit indices indicate a good global fit of the proposed model: $\chi^2/df = 2.250$ ($\chi^2 = 2076.727$, df = 923), RMSEA = .045 (90% confidence interval = .043 - .048), CFI = .942, SRMR = .066.

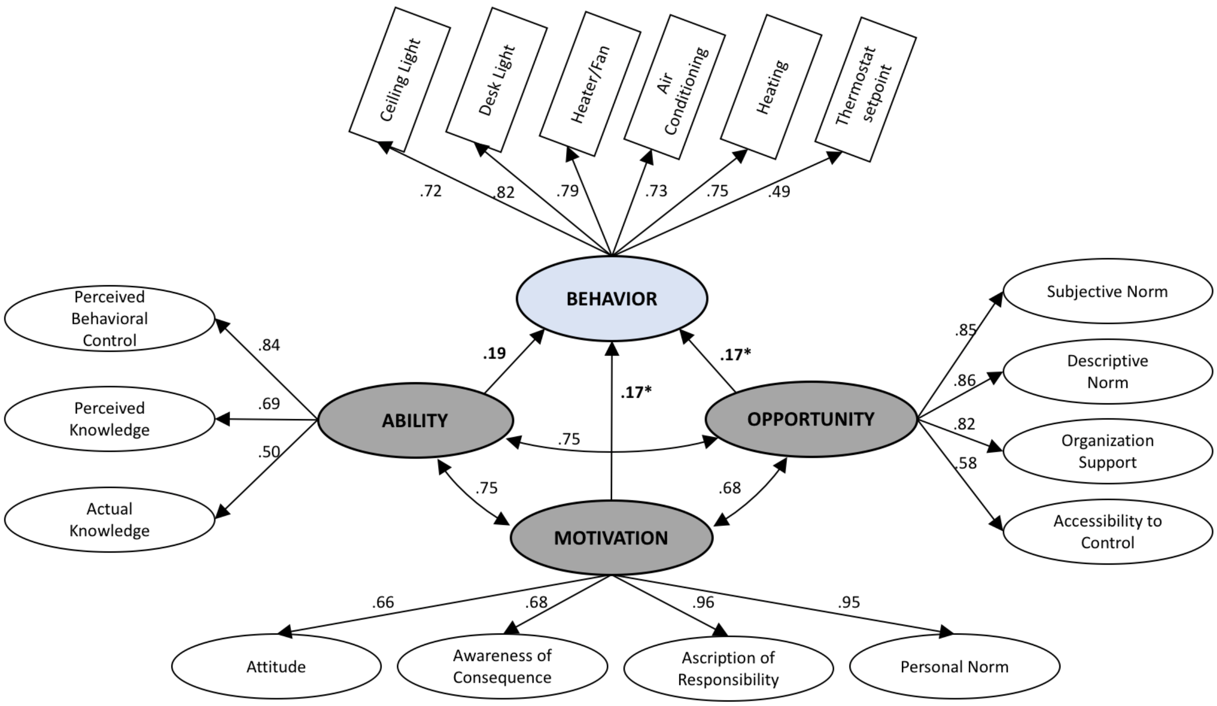

Figure 7-5 Structural Paths of the Direct Effects MOA Model (*p < .05; **p < .001)

The results report the R^2 of behavior as 22.8%; showing that both motivation (β = .17, p = .031) and opportunity (β = .17, p = .042) have statistically significant effects on energy-saving behaviors. Specifically, a one standard deviation (*SD*) increase in motivation is associated with a 0.17 *SD* increase in energy-saving behaviors, holding opportunity and ability constant, supporting H4. Likewise, a one *SD* increase in opportunity is associated with a 0.17 *SD* increase in energy-saving behaviors, controlling for motivation and ability, supporting H5. However, there is no significant direct correlation between ability and behavior (p = .070) with motivation and opportunity hold constant, which fails to support H6. This finding can be interpreted as increasing one's ability level (e.g., educational interventions through emails containing energy-saving tips) will not directly affect an individual's energy-saving behaviors.

7.6.2.2 Mediating Effect Model on Behaviors

To test the mediating effects of the motivation factor (H7 and H8), we develop the competing MOA model (Model 2) based on Model 1. As shown in Figure 7-6, in addition to the direct effects, two indirect paths are added, i.e., opportunity → motivation → behavior, and ability → motivation → behavior. In this model, motivation is affected by the opportunity and ability and mediates their effects on behavior. All model fit indices indicate a good global fit of the mediating effect model: $\chi^2/df = 2.301$ ($\chi^2 = 2126.087$, df = 924), RMSEA = 0.046 (90% CI = .044 - .049), CFI = .939, SRMR = .065.

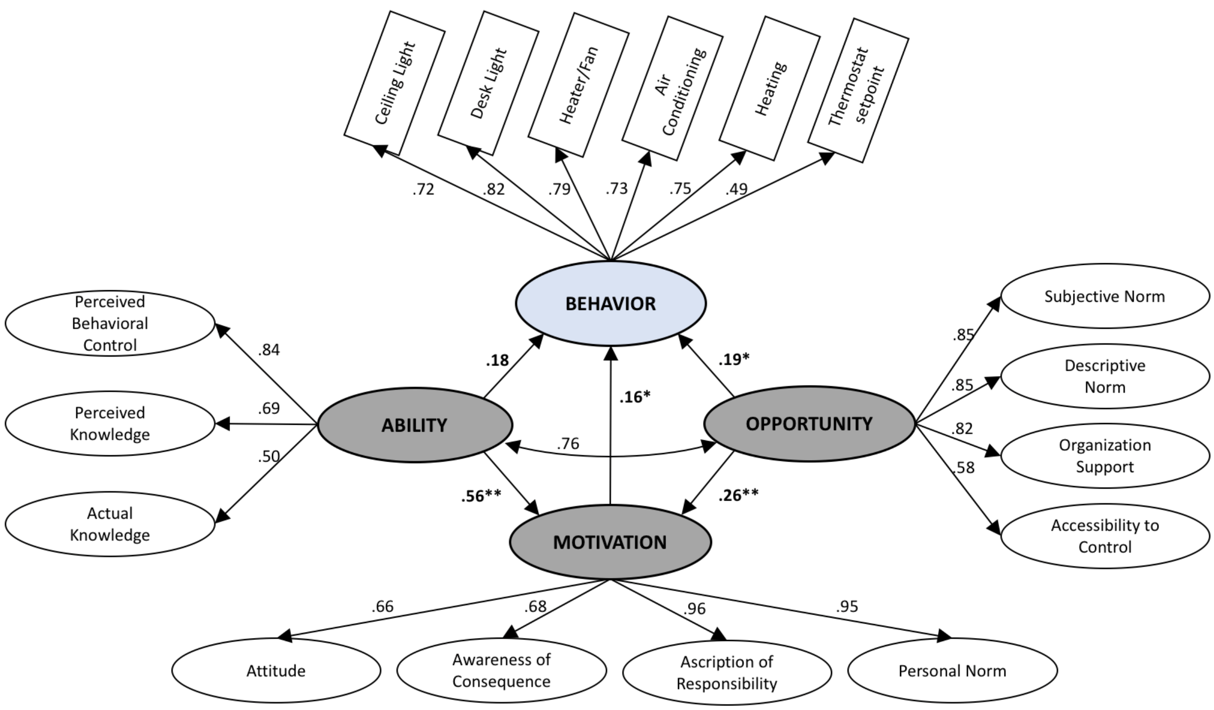

Figure 7-6 Structural Paths of the Mediating Effects MOA Model (*p < .05; **p < .001)

The results report the R^2 of behavior as 23.1%. Table 7-8 presents both the direct and indirect effects of the MOA factors. The results demonstrate a similar direct effect of MOA factors on energy behaviors, suggesting statistically significant effects of motivation ($\beta = .16$, $p = .040$) and opportunity ($\beta = .19$, $p = .023$) on energy-saving behaviors, while there is no significant effect of ability on behaviors (p = .095). Additionally, both of the added paths for mediation - opportunity to motivation (β = .26, p < .001) and ability to motivation (β = .56, p < .001) - are significant, indicating that opportunity and ability both affect behavior through motivation, supporting H7 and H8.

Table 7-8 Path Coefficients of Mediating Effects SEM Model

Exogenous variable (X)	Mediator (M)	Endogenous variable (Y)	Coeff. β ($X \rightarrow M$, a)	Coeff. β ($M \rightarrow Y$, b)	Effect ($a \times b$)
Opportunity	Motivation	Behavior	.26**	.16*	.04* (indirect)
Opportunity		Behavior			.19* (direct)
Ability	Motivation	Behavior	.56**	.16*	.09* (indirect)
Ability		Behavior			.18 (direct)

*p < .05; ** p < .001

7.6.2.3 Comparisons among the theoretical models

The intention of this section is to compare the integrated MOA framework, the NAM, and the TPB model based on their ability to explain energy behaviors in the workplace. For the TPB model, two questions are used as the proxy of behavioral intention - "I always think about ways to save energy at work" and "I am motivated to save energy at work." The model fit indices of both NAM and TPB models indicate a good model fit (NAM model: χ^2/df = 2.814, 90% CI of RMSEA = .047 - .062, CFI = .975, SRMR = .047; TPB model: χ^2/df = 2.865, 90% CI of RMSEA = .050 - .061; CFI = .962; SRMR = .068) The path coefficients are presented in Table 7-9 and Table 7-10.

The NAM and TPB models report the R^2 of behavior as 16.7% and 17.0%, respectively, which are lower than the integrated MOA framework (R^2 = 22.8% and 23.1%) presented above.

Table 7-9 Path Coefficients of the NAM Model[5]

Independent variable (X)	Dependent variable (Y)	Coeff. β
AC	AR	.67**
AR	PN	.92**
PN	Behavior	.41**

*p < .05; ** p < .001

[5] We tested the mediation model in De Groot and Steg (2009)

Table 7-10 Path Coefficients of the TPB model

Exogenous variable (X)	Mediator (M)	Endogenous variable (Y)	Coeff. β ($X \rightarrow M, a$)	Coeff. β ($M \rightarrow Y, b$)	Effect ($a \times b$)
AT	Intention	Behavior	.40**	.29**	.12** (indirect)
SN	Intention	Behavior	.27**	.29**	.08** (indirect)
DN	Intention	Behavior	.16*	.29**	.05* (indirect)
PBC	Intention	Behavior	.12*	.29**	.03* (indirect)
PBC		Behavior			.17** (direct)

*$p < .05$; ** $p < .001$

7.7 Discussion

Promoting energy-saving behaviors has significant potential to reduce energy consumption. This chapter expands the MOA framework to study energy-saving behaviors in office buildings across the U.S. by incorporating important social-psychological concepts from the NAM and the TPB theories. Results indicate that the integrated MOA framework explained significantly more variances than the NAM and TPB models. Although the predictive power of the proposed framework is close to the NAM model reported in van der Werff and Steg (2015), it should be noted that the dependent variable in the referred study is the behavioral intention instead of the actual behavior adopted here. As suggested by Dixon et al. (2015), the variance explained by the model drops from 45% to 6% when replacing behavior intention by actual behavior, indicating that the explanatory power of the model can vary depending on the selection of the dependent variable.

The measurement model confirms that awareness of consequence, ascription of responsibility, personal norms, and attitude all contribute to motivation; subjective norms, descriptive norms, organizational support, and accessibility to control contribute to opportunity; perceived behavioral control, perceived knowledge and actual knowledge contribute to ability. Time availability fails to emerge as a dimension of opportunity to affect energy-saving behaviors. We propose two possible reasons: (1) most energy-saving behaviors (e.g., turning off the light) do not require much time. Thus, employees always have time to perform those behaviors even over heavy workload periods; (2) the effect of time availability might already be accounted for by the PBC because employees may perceive higher behavioral control if they have time to do it. The model fit indices of the two proposed structures, the direct effect model and the mediating effect model, are almost identical; however, the mediating effect model explains slightly more variances in energy behaviors and the hypothesized mediating effects of opportunity and ability to behavior via motivation are also significant. Therefore, the mediating effect model is retained for discussion.

Results of the SEM indicate that motivation and opportunity have a positive direct effect on one's energy-saving behaviors, however, the direct effect of ability is not significant. In addition, motivation partially mediates the effect of opportunity on energy behaviors and fully mediates the effect of ability. Among the three factors in the MOA framework, opportunity shows the strongest effect on behavior with both direct and indirect effects combined, followed by motivation and ability. The demonstrated role of opportunity suggests that interventions for energy conservation in offices can primarily focus on creating a favorable organizational and interpersonal environment which supports energy-saving behaviors. Ability, however, only shows a weak effect on behaviors through motivation. We reason that this is due to the type of behaviors we focused on in this study: saving energy in offices requires no specific or complicated knowledge beyond common sense (e.g., knowing standby equipment still consumes electricity is sufficient for employees to reduce the plug load) and it also requires little effort to perform the behavior (e.g., unplugging the monitor is an easy task). This is in contrast with other behaviors such as body weight control for which people need to have adequate knowledge (e.g., knowing how to pair food) and high PBC (e.g., feeling comfortable to limit food intake) in order to succeed in the desired behaviors (Conner and Norman 1996). However, interestingly, the indirect effect of ability on behaviors suggests that if an individual's ability level is improved, he/she will be more motivated and perform energy-saving behaviors. As a result, the informational campaign towards energy saving can be conducted to solicit knowledge gains to improve (1) one's ability level through the enhanced perceived knowledge (i.e., knows how to save energy), and (2) motivation level through the awareness of consequence (i.e., knows why save energy) and induced positive attitude (Bettinghaus 1986).

The integrated MOA framework also has energy implications which set the basis for future studies on energy-saving interventions. With the clearly defined variables in each MOA factor, this framework can be used as a diagnostic tool to identify the constraining factors of energy behaviors in a particular building, and thus help decision-makers develop efficient and more targeted interventions to promote behavior change. For example, the surveyed buildings observed a relatively strong motivation (attitude, mean: 3.93; personal norms, mean: 3.46) but weak social norms (subjective norms, mean: 2.71; descriptive norms, mean: 2.61), which can be explained as employees believe themselves to be proactive in saving energy; however, they do not observe their colleagues putting efforts or caring about energy-savings. In this case, opportunity becomes a constraining factor in this particular office environment. This could be due to the fact that (1) behavioral intention is weakly correlated with the actual behavior as suggested by several studies (Conner and Norman 1996, Dixon et al. 2015, Sejwacz et al. 1980). Thus, having behavioral intentions does not necessarily lead to actual behaviors; and (2) peer effects among co-workers are not well-manifested leading to perceived lack of organizational norms in energy-savings. To improve the opportunity level, interventions may specifically focus on leveraging the beneficial normative influences in the organization to enhance social norms (e.g., setting a good example).

Similarly, in this survey sample, the level of organizational support is not different from the neutral point, which implies that the majority of respondents do not believe their company/employer has provided adequate support to encourage energy-savings in the workplace. As a result, providing financial and social rewards can be useful strategies to improve employees' perceived opportunities, which in turn boosts motivation and energy-saving behaviors. This supports the original purpose of the MOA framework which is identifying information processing potential. Our main argument in this context is that if we can measure the current MOA levels (pre-intervention), we can design appropriate information delivery approaches to implement interventions targeting the constraining factors in a particular setting (Beck et al. 2017, Siemsen et al. 2008), then use the same approach to measure changes in MOA levels (post-intervention) and thus the effectiveness of the intervention implementation.

The MOA framework is also a flexible and extensible framework which can be adapted to various contexts to understand the characteristics of occupants in a certain department, an office building or a large city district. Although this study was conducted in the U.S., researchers from other countries may also find this framework useful and worth further exploration. In addition, the MOA framework can also be applied to investigate occupants in other settings by updating the most relevant constructs for each MOA factor. For example, in residential housing, utility costs become an important motivational factor for energy savings. Moreover, the federal/state/local incentives (e.g., tax rebates for energy efficient purchases and improvements) can be a substitute for the organizational support, and the access to control can be replaced by the access to energy consumption information (Ueno et al. 2006) as occupants should have better actual control at home.

Three limitations of this study should be acknowledged. First, despite that second-order models have conceptual and methodological advantages (Koufteros et al. 2009), it is only possible to get the path coefficients among the second-order factors (i.e., motivation, opportunity, and ability) and the outcome factor (i.e., behaviors). Therefore, it is unclear which first-order factor has the most significant contribution to the energy-saving behaviors. Second, although the inclusion of AR and PN has been used in many existing studies (e.g., De Groot and Steg 2009, Onwezen et al. 2013), exploratory factor analysis in this study suggests that AR and PN load on the same factor. In future studies, it might be helpful to consider outcome efficacy as a substitute for AR (van der Werff and Steg 2015).

7.8 Conclusions

This chapter presents an integrated MOA framework which incorporates insights from interdisciplinary perspectives including social-psychology and building science. The new framework integrates constructs from the TPB and the NAM theories to define theoretically-sound and measurable dimensions under the three components of the MOA framework. The integrated framework provides researchers with a systematic approach to investigate the determinants of energy-saving behaviors in the office environment. The integrated framework also has policy implications in terms of understanding the barriers and opportunities within office building occupants in varied organizational contexts. As a result, behavioral interventions designed to reduce energy consumption can focus on the constraining factors identified with the integrated MOA framework.

CHAPTER 8

Conclusions

8.1 Significance of Research

This research focuses on two important themes that arise from the daily interactions between buildings and human occupants. Due to the critical health and wellness impacts of thermal environments on their occupants, the first research theme aims to create a robust and scalable non-intrusive HVAC control framework for thermal comfort optimization in various indoor contexts. This goal is achieved by first exploring novel "human-in-the-loop" thermal comfort sensing approaches including (1) personalized thermal comfort prediction through wearable health monitoring devices and smartphone polling applications (Chapter 2), (2) non-intrusive comfort prediction using a low-cost thermal camera (Chapter 3), and (3) robust multi-occupancy comfort sensing via a network of coupled thermal and RGB-D cameras (Chapter 4). These approaches leverage the insights from human thermoregulatory theories, machine learning models, computer vision techniques, and signal processing approaches; and have addressed several limitations in existing studies including (1) the interruption due to continuous human inputs during regular work time, (2) inaccurate thermal comfort prediction without human physiological data, and (3) intrusiveness and lack of scalability caused by personal sensing devices. The novel sensing approaches presented in this research demonstrate an 85% accuracy in predicting thermal preferences without encumbering any proactive occupant feedback or dependency on personal devices. The resulted real-time prediction of thermal comfort is then integrated into the HVAC control loop to determine the optimum temperature setpoint for improved overall satisfaction or energy reduction while maintaining comfort (Chapter 5). This research theme advances knowledge related to the adaptive and personalized thermal comfort and has the potential to transition the building HVAC control from a passive and user-empirical process to an automated, user-centric, and data-driven mechanism that can simultaneously improve occupant satisfaction in indoor environments while reducing energy consumption. Importantly, the resulting new knowledge has a broader impact and a variety of applications, including susceptible communities in hospitals, transportation systems (e.g., cars, buses), and extreme working environments (e.g., construction sites in summer) where a promising approach for improved human thermal comfort is much needed.

The second research theme addresses the knowledge gap in behavior intervention studies which aim to leverage the significant energy-saving potentials of occupant behaviors to achieve building efficiency. Two interrelated research questions are investigated in this research theme including (1) the determinants of occupant behaviors, and (2) methods to quantitively represent occupant characteristics. These are two important questions as answers to the former can help decision-makers identify the constraints of favorable behaviors in a certain context and design targeted intervention strategies to enhance these constraining factors and make a behavioral change happen. However, a single intervention strategy (e.g., education) may not be effective in achieving large-scale energy reduction if occupants face diverse constraints in behavioral change, which can occur in large office buildings or communities where heterogeneity exists in the targeted population. This problem emphasizes the importance to answer the second question – ways to describe occupant characteristics, i.e., their varying energy use intensity and the likelihood of behavioral change, such that customized intervention strategies can be delivered to occupant groups with different characteristics. To address these questions, the second research theme first draws an analogy between consumers' purchasing behavior and occupants' energy-saving behavior and adapts the original Motivation-Opportunity-Ability (MOA) framework in consumer science research to the building energy domain (Chapter 6). In this framework, three factors, i.e., M, O, and A are identified as the behavioral determinants, which can be measured from a set of survey questions in relation to human behaviors in the building. This MOA framework is later integrated with the Norm Activation Model and the Theory of Planned Behavior (Chapter 7) to address the complexities in defining and measuring MOA factors in behavior studies. This leads to the integrated MOA model in which motivation is measured by the *awareness of consequence*, *ascription of responsibility*, *personal norms*, and *attitude*; opportunity is measured by the *subjective norm*, *descriptive norm*, *organization support* and *accessibility to control*; and ability is measured by the *perceived behavioral control*, *perceived knowledge*, and *actual knowledge*. The proposed framework is evaluated using a large-scale online survey which involves multiple office buildings across the U.S. The results suggest that both motivation and opportunity have a direct and positive effect on occupant behavior, as well as the mediating effect of opportunity and ability factors. In terms of the strength of the effect, opportunity shows the strongest effect on occupant behavior, followed by motivation and ability.

To determine occupant characteristics, clustering analysis can be conducted based on the MOA levels of each occupant. Occupants with similar MOA levels are clustered into the same group. In this research, five predefined groups, including prone, mildly unable, unable, mildly resistant, resistant, are chosen to describe occupants in the case study. Based on the characteristics of each group, customized inventions can be delivered to solicit behavioral changes. For example, for the "unable" group, decision-makers may consider removing the environmental barriers or promoting social norms to improve the opportunity level after diagnosing the specific constraints in the environment (e.g., low *accessibility to control* versus unfavorable *subjective norm*).

It is worth noting that the proposed MOA framework is very flexible and can be adapted to different contexts (e.g., type of occupancy, culture, building type) and scales (office, building, community, city). In this research, the office environment is investigated considering that office workers may lack interest in energy savings due to the lack of economic incentives. However, this framework can also be applied in residential settings by updating the constructs that measure the MOA factors. For example, the *organization support* and *accessibility to control* can be removed from the opportunity while the utility cost can be added as a motivation factor in residential settings. Also, the number of occupant characteristics (i.e., number of clusters) can be adjusted based on the actual scenario of the research object without losing the implications in energy intervention.

8.2 Research Contributions

This research contributes to the optimized and sustainable operation of built environments by improving the indoor thermal comfort and building energy efficiency. First, this research develops three novel "human-in-the-loop" comfort sensing approaches for non-intrusive and real-time thermal comfort prediction in both single and multi-occupancy spaces. The comfort sensing techniques enable the HVAC systems to adjust its temperature setpoint and choose optimum conditioning mode to improve occupants' satisfaction, health, and wellness. This research also develops an integrated MOA framework which not only provides researchers with a scientific and systematic approach to understand the behavioral determinants but also allows for quantitative analyses of occupant characteristics for a given built environment. The resulting knowledge can help decision-makers develop effective, sustainable, and economical energy intervention strategies to reduce energy consumption. These two research themes, thermal comfort and human behavior, are interrelated in nature. Occupants' interaction with the building HVAC systems is one of the main behaviors that affect building energy performance, especially when occupants' adaptive behaviors to achieve thermal comfort focus on continuously adjusting the HVAC setpoint. Thus, the MOA framework coupled with personalized thermal comfort has the potential to improve building efficiency and performance while reducing human discomfort and complaints.

In summary, the specific contributions of this research are as follows.

- A personalized HVAC control framework integrating heterogenous human and environmental data to determine the optimum setpoint and conditioning mode is developed and tested in single and multi-occupancy environments. This approach demonstrates the importance of including human data in comfort prediction.
- A non-intrusive thermal comfort sensing approach using a low-cost infrared thermal camera is developed. This approach identifies significant facial skin temperature features for comfort prediction.
- A robust thermal and RGB-D camera network for scalable and non-intrusive comfort prediction is developed. This approach has the highest flexibility compared to the existing and preceding approaches and can be applied in multi-occupancy environments.
- An HVAC control algorithm based on occupants' personal thermal profile and comfort predictive model is developed. This algorithm demonstrates how to integrate the preceding comfort sensing approaches into the HVAC control loop.
- An integrated MOA framework for identifying the determinants of energy-saving behaviors in a given context is proposed. The framework allows for designing targeted energy interventions to address the identified constraints in behavioral change.

- A clustering approach to quantitatively describe occupant characteristics in a given context based on individual MOA levels is proposed. This approach allows customized and multi-level interventions to be designed and delivered to occupants with different characteristics.

8.3 Directions for Future research

8.3.1 Validating the Comfort Sensing and Control Approaches in a Real Testbed

This research will build upon the non-intrusive comfort sensing and control approaches introduced in Chapter 2 to 5. A system prototype will be deployed in a real operational built environment (e.g., a shared office) to analyze its comfort performance and energy efficiency through a multi-day experiment. Several research questions will be investigated, such as Will occupants' experience of discomfort be reduced considering the response time of the HVAC system? Will occupants experience thermal oscillation due to this time lag? How is the energy consumed in the building affected by the proposed method compared to the conventional static setpoint strategy?

8.3.2 Investigating Thermal Comfort Sensing Approaches in Other Related Domains

This research will explore the non-intrusive approach to assess thermal comfort in other related domains, such as the thermal condition of nurses, construction workers, and truck drivers, to disseminate the research findings in thermal comfort and human wellness to a broader audience. In addition, a publicly available thermal comfort dataset consisting of facial thermal images, heart rate, occupants' thermal sensations and preferences, and ambient room conditions will be established to enable consistent evaluation and benchmarking of new methods in the future. This will significantly advance the current practice of thermal comfort prediction from an intrusive, intermittent approach to a non-intrusive and continuous method.

8.3.3 Exploring Methods to Assess and Improve Overall Indoor Environmental Quality

This research will extend the focus of satisfying and healthy built environments by exploring new methods to assess and control other indoor environmental quality factors beyond thermal comfort, such as healthy indoor air quality, pleasant lighting and acoustic conditions, and aesthetic indoor views. This research will explore the premise that human occupants can serve as the "sensors" to assess their surrounding environment and provide positive or negative feedback through different physiological signals. Therefore, other "human-in-the-loop" sensing approaches will be investigated to achieve a holistic evaluation of the indoor built environment.

8.3.4 Investigating the Interactions between Thermal Comfort and Occupant Behaviors

This research will investigate the interplays between personalized thermal comfort and occupants' behaviors in adjusting the HVAC setpoints. Occupants may abstain from their control behaviors if thermal satisfaction is improved through personalized thermal comfort, which will further affect the building energy performance. To understand this interactive mechanism, human thermal comfort-related actions, indoor thermal comfort analysis, and building energy simulation can be coupled to explore the influence of each component on the rest of the system (Thomas et al. 2016 and 2017).

8.3.5 Evaluating the Effectiveness of Occupancy-focused Interventions in Real Situations

This research will investigate the MOA framework in designing occupancy-focused energy-saving strategies (e.g., posters, non-cash incentives) and evaluate how building occupants with different characteristics (e.g., prone or resistant to change) react to these interventions in real situations. Specifically, the pre- and post-intervention MOA levels of the target occupancy clusters and their social networks within the building will be analyzed and compared. A longitudinal study will be conducted to assess the short-term and long-term intervention outcomes based on the energy reduction effect.

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