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Design and Implementation of AI-Based Thermal Comfort Sensing and Control for Adaptable Indoor Environments

by

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Abstract

Thermal comfort is a critical determinant of occupant well-being, productivity, and energy efficiency in modern buildings. Despite advances in building management systems, current control strategies often lack real-time adaptability and remain largely rule-based or model-driven, failing to account for the dynamic, individualized physiological needs of occupants. This research addresses these challenges by developing a comprehensive, AI-driven framework for thermal comfort sensing and adaptive control with a strong emphasis on occupant-centric intelligence and real-time responsiveness.

The work begins by identifying the limitations of conventional control models (such as schedule-based and PMV-driven approaches) and the pressing need for occupant-centric solutions in contemporary indoor environments. To bridge this gap, a novel low-cost RGB-T (Red, Green, Blue, Thermal) imaging system was designed and implemented, enabling non-contact, real-time measurement of facial skin temperature as a direct physiological proxy for thermal comfort. This system was further integrated with an open-source Raspberry Pi platform, transforming it into a BACnet-enabled controller and sensor node capable of closed-loop operation and seamless communication within real-time building automation networks. The integration demonstrates the practical feasibility of using affordable hardware not only for sensing, but also for adaptive control, within a standards-based automation environment.

Building on this foundation, the research advances the field by moving away from traditional face detection methods. Instead, it employs a deep learning approach and applies transfer learning with MobileNetV2 to enable lightweight, edge-deployable inference for robust and accurate facial temperature estimation. This methodological innovation significantly enhances the reliability and scalability of occupant comfort assessment, particularly in dynamic and heterogeneous indoor environments, paving the way for intelligent, real-time HVAC control based on physiological data.

Experimental validation in both simulated and operational settings using comparative baselines against conventional control strategies confirms the effectiveness of the proposed framework, with consistently improved comfort prediction accuracy and measurable gains in energy efficiency over traditional methods. The findings underscore the novelty and practical impact of integrating AI, low-cost sensing, and open communication protocols to realize adaptive, occupant-centric building management. This work lays a robust foundation for future research and deployment of smart, responsive indoor environments that are both energy-efficient and human-centered.

Declaration of Authorship

This thesis has been furnished according to the Massey University "PhD thesis with publications" guidelines. The thesis is based on the technical manuscripts either published or currently under review or in preparation for submission to the reputable academic journals. - Mozammil Ahsan

Publications

1. Mozammil Ahsan, Wajiha Shahzad, Khalid Mahmood Arif. (2024). AI-Based Controls for Thermal Comfort in Adaptable Buildings: A Review. *Buildings*, 14(11), 3519. <https://doi.org/10.3390/buildings14113519>
2. Mozammil Ahsan, Wajiha Shahzad, Khalid Mahmood Arif. (2025). Accurate Facial Temperature Measurement Using Low-Cost Thermal Camera for Indoor Thermal Comfort Applications. *Buildings*, 15(22), 4050. <https://doi.org/10.3390/buildings15224050>
3. Mozammil Ahsan, Wajiha Shahzad, Khalid Mahmood Arif. (2026). Low-Cost BACnet-Enabled Raspberry Pi Controller for Adaptive Indoor Environmental Management. The manuscript will be published, but it has not yet been submitted to a journal.
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Abbreviations

BMS	Building Management System
IOT	Internet of Technology
PMV	Predictive Mean Vote
STI	Short Term Issues
LTI	Long Term Issues
AI	Artificial Intelligence
DL	Deep Learning
BD	Big data
COPD	Chronic Obstructive Pulmonary Disease
ML	Machine Learning
HVAC	Heating, Venting and Air Conditioning
FL	Fuzzy Logic
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
NCBI	National Centre for Biotechnology Information
BMR	Basal Metabolic Rate
CI	Computational Intelligence
SEB	Smart Energy Buildings
FCM	Fuzzy Cognitive Map
FIS	Fuzzy inference system
DNN	Direct neural network
BPNN	Back propagation neural network
PPD	Predicted Percentage of Dissatisfied
RL	Reinforcement Learning
ANN	Artificial Neural Network

CNN	Convolutional Neural Network
PPM	Particles Per Minute
CO ₂	Carbon dioxide
IAQ	Indoor Air Quality
CA	Context Awareness
RNN	Random neural network
RENN	Recurrent neural network
DPNN	Deep neural network
ANF	Adaptive neuro fuzzy
GA	Genetic ALgorithm
ROI	Region of Interest
HOG	Histogram of Oriented Gradients
SVM	Support Vecrtor Machine
RTD	Resistance Temperature Detector
HLPM	Hierarchical Linear–Polynomial Mapping
MSL	Measurement Standards Laboratory
BACnet	Building Automation and Control Network
PLC	Programmable Logic Controllers
GUI	Graphical User Interface
NCBI	National Centre for Biotechnology Information
MSL	Measurement Standards Laboratory
VRF	variable refrigerant flow
IEQ	Indoor Environmental Quality
BCE	Binary Cross-Entropy
MSE	Mean Squared Error
FPS	Frames Per Second
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error

Chapter 1

Introduction

1.1 Introduction

Ensuring comfort for building occupants is a central goal in modern indoor environments. Traditional approaches, such as Fanger’s Predicted Mean Vote (PMV) model which estimates comfort based on fixed variables like air temperature, humidity, and clothing insulation—often fall short in capturing the dynamic and individualized nature of real world comfort [1, 2]. As a result, there is a growing need for adaptive, occupant centric solutions that respond to people’s actual experiences [3].

A review of the current literature reveals that while significant progress has been made in understanding thermal comfort, most existing models and building systems still rely on static assumptions and generalized setpoints [4–6]. Recent advancements in artificial intelligence are fundamentally transforming the landscape of smart buildings. The integration of modern era technologies is enabling unprecedented levels of efficiency, adaptability, and intelligence in building management and operations. Building Management Systems (BMS), which serve as the operational “brains” of modern facilities, are increasingly being enhanced with AI to enable real-time, personalized control of heating, ventilation, and air conditioning (HVAC) systems. Advancements in sensor technology and data analytics are making it possible to move beyond traditional comfort models and toward more responsive, individualized solutions.

Motivated by these trends, this work explores the integration of low-cost, non-contact thermal imaging for measuring occupant skin temperature, with a particular focus

on facial temperature as a direct indicator of thermal sensation. Affordable thermal cameras, when combined with AI-driven analysis, offer a practical pathway for real-time comfort assessment. The process begins with DLib, an open-source machine learning toolkit that provides robust facial detection in thermal images, even under limited image quality [7]. This foundation enables the use of a compact, low-cost platform such as a Raspberry Pi to be configured as a BACnet-enabled sensor and controller. By leveraging an RGB-T (Red, Green, Blue, and Thermal) camera and standard building automation protocols, the system can acquire real-time data and adaptively manage HVAC operation, making advanced comfort management accessible and scalable.

To improve detection accuracy and extract meaningful features from low resolution and affordable thermal cameras, deep learning models such as MobileNetV2 are used. MobileNetV2 is a lightweight convolutional neural network designed for efficient image analysis [8, 9]. Transfer learning is used to adapt pretrained models for the specific task of thermal image analysis, enabling reliable interpretation of physiological data in real-time.

The novelty of this work lies in the seamless integration of low-cost thermal imaging hardware, open-source facial detection algorithms, and advanced deep learning models within a unified, occupant centric comfort management framework. Unlike previous approaches that rely on expensive sensors or generic control strategies, this research demonstrates how affordable, embedded platforms can deliver real-time, non-contact physiological sensing and adaptive building control using industry-standard protocols. By bridging the gap between state of the art AI and practical building automation, this work enables scalable, personalized comfort solutions that are both accessible and robust for real time deployment.

By combining adaptive BMS control, advanced AI techniques, and affordable sensing technology, this work demonstrates a pathway toward more personalized, efficient, and intelligent indoor environments. Ethical considerations, including privacy, informed consent, and data security, are also addressed to ensure responsible deployment of next generation comfort solutions. Ultimately, this study presents a practical framework for occupant centric comfort assessment, leveraging state of the art AI and low-cost hardware to bridge the gap between traditional models and the evolving needs of modern building occupants.

1.2 Problem Statement

Achieving accurate and responsive thermal comfort assessment in modern buildings remains a significant challenge in buildings and smart environment management. Prevailing approaches, such as Fanger’s PMV model and conventional wall mounted temperature sensors, are fundamentally limited by their reliance on static, population averaged parameters and environmental proxies [10, 11]. These methods cannot capture how thermal sensation changes over time and across different areas within occupied spaces. As a result, building management systems often do not accurately represent the real comfort levels experienced by occupants.

The limitations of current BMS strategies are further exacerbated by their dependence on fixed setpoints, subjective feedback, and environmental measurements that are prone to placement errors, local heat anomalies, and temporal drift. These shortcomings undermine the accuracy and reliability of comfort assessment, leading to widespread occupant dissatisfaction, productivity loss, and unnecessary energy consumption [12]. Prolonged exposure to poor indoor thermal conditions has been linked to negative health effects, such as reduced cognitive performance, a higher likelihood of illness, and diminished overall well-being. These concerns are increasingly important in the management of modern buildings and public health [13–18].

Recent advances in non-contact physiological sensing, particularly low-cost thermal imaging of facial regions, offers a promising pathway for real-time occupant representative comfort assessment and adaptive environmental control. However, practical deployment is hindered by technical challenges such as low sensor resolution, calibration instability, and the lack of robust, automated facial region detection algorithms suitable for real time conditions. There is a pressing need for a validated, scalable, and ethically responsible framework that integrates advanced artificial intelligence with affordable sensing to enable accurate, real-time monitoring and adaptive control of indoor environments. This research tackles this important gap by creating and testing an AI powered, affordable system for accurate facial temperature measurement and its integration with adaptive BMS, moving forward the field of occupant focused comfort control in smart buildings.

1.3 Research Aim and Objectives

The primary aim of this research is to develop and validate a low-cost, AI-driven framework for accurate, non-contact assessment of occupant thermal comfort in indoor environments. This framework leverages affordable thermal imaging, advanced facial detection, and transfer learning to enable real-time, occupant centric building management.

The central research question guiding this study is: *How can affordable thermal imaging and advanced AI techniques be integrated to enable real-time, non-contact, and accurate assessment of occupant thermal comfort for adaptive building management?*

To achieve this aim, the following key objectives are established:

1. Critically review existing models, technologies, and limitations in occupant thermal comfort assessment, with a focus on AI and non-contact sensing approaches. This objective establishes the scholarly foundation for Chapter 2.
2. Design and implement a low-cost RGB-T camera system using DLib for automated facial detection and region of interest extraction. This objective provides the methodological and technical foundation for Chapter 3.
3. Integrate the RGB-T system with BACnet-enabled platforms to develop adaptive control strategies for real-time HVAC setpoint and room temperature management. This objective forms the foundation of Chapter 4.
4. Apply and validate MobileNetV2 with transfer learning for accurate facial temperature estimation from thermal images, supporting occupant comfort prediction. This objective constitutes the analytical and model-validation foundation for Chapter 5.

1.4 Research Design and Methodology

This research adopts an experimental approach in which a single participant is used throughout all phases of the study. By using the same individual for every experiment, the influence of participant related differences is minimized. This consistency strengthens

the validity of the results and underscores the true impact of the developed framework for contactless assessment of occupant thermal comfort. The methodology integrates hardware prototyping, algorithm development, and experimental validation, with a focus on practical deployment in indoor environments.

1.4.1 Research Design

The study is structured in the following phases:

1. **Literature Review:** To ensure systematic and rigorous coverage of the field, the literature review was conducted across three complementary databases: Google Scholar, Web of Science, and Science Direct. This multi-database approach was adopted to maximize coverage across peer-reviewed literature, grey literature, and conference proceedings. Google Scholar offers broad multidisciplinary indexing and captures a wide range of published work, including papers from smaller publishers and institutional repositories. Web of Science provides high-quality peer-reviewed articles with robust citation metrics, ensuring that foundational and influential studies in thermal comfort and building controls were identified. Science Direct gives direct access to Elsevier's comprehensive collection of engineering, materials science, and building research journals, including key publications in HVAC systems, occupant comfort, and thermal imaging technologies. The combination of these three databases enabled the review to capture seminal thermal comfort models, emerging.
2. **System Development:** An RGB-T (Red, Green, Blue, Thermal) camera system was developed, integrating a low-cost thermal camera (Topdon TS001) and a standard RGB camera with a Raspberry Pi platform.
3. **Facial Detection and Region Extraction:** DLib was employed for robust facial region detection in both RGB and thermal images. The system was specifically designed to automate region of interest (ROI) extraction, focusing on the forehead as the primary site for temperature measurement.

4. **Calibration and Validation:** Calibration protocols were established to improve the accuracy of facial temperature estimation from the thermal camera. Ground-truth temperature data was collected using a medical grade non-contact thermometer.
5. **Experimental Evaluation:** All experiments were conducted with a single healthy adult participant, who was exposed to a range of controlled indoor temperature conditions. The same participant was used throughout to ensure consistency and control for inter-individual variability.
6. **Transfer Learning:** Facial temperature was estimated from thermal images using a MobileNetV2 deep learning model, fine-tuned via transfer learning to perform both face detection and temperature regression within a unified framework.
7. **System Integration:** The validated system was integrated with a BACnet-enabled Raspberry Pi for real-time demonstration of adaptive HVAC control based on facial temperature.

1.4.2 Methodology

The methodology for this research is structured to address each major research objective through a sequence of targeted methods, analyses, and expected outcomes. Table 1.1 provides an overview of the approach taken for each chapter.

TABLE 1.1: Summary of research objectives, methods, analysis, and outcomes for occupant-centric thermal comfort assessment and control.

Research Objectives	Methods	Analysis	Outcome	Linkage
Critically review existing models, technologies, and limitations in occupant thermal comfort assessment, with a focus on AI and non-contact sensing approaches.	Comprehensive literature survey and comparative analysis	Synthesis of trends, limitations, and gaps	Clear motivation for improved occupant-centric solutions	Chapter 2
Design and implement a low-cost RGB-T camera system using DLib for automated facial detection and ROI extraction.	Hardware prototyping, DLib-based detection, ROI extraction	Functional testing and accuracy assessment	Reliable low-cost facial temperature measurement platform	Chapter 3
Integrate the RGB-T system with BACnet-enabled platforms for adaptive control.	System integration, BACnet communication setup, real-time control demo	Response analysis and qualitative performance assessment	Proof of real-time occupant-centric control in BMS context	Chapter 4
Apply and validate MobileNetV2 with transfer learning for facial temperature estimation.	Data preprocessing, model training, fine-tuning	MAE/RMSE and error analysis	Improved temperature prediction and comfort assessment	Chapter 5

1.4.3 Research Boundary and Scope

The boundaries and scope of this research are defined by a focus on developing, calibrating, and validating a low-cost, AI-driven framework for non-contact thermal comfort assessment in indoor environments. The study is intentionally limited in several key aspects to provide a clear foundation for future expansion into broader real time applications.

Environmental and Experimental Setting: All experiments were performed in a controlled indoor laboratory environment. Field trials, real-time deployment, and studies involving multiple or diverse participants are identified as future work.

Participant Scope: All experiments were conducted with a single healthy adult participant, who was involved in all phases of data collection and validation. As such, the findings are specific to this case and may not be directly generalizable to broader populations. Multi-participant studies are identified as future work.

Sensor Technology and Selection: The research is limited to the use of the Topdon TS001 thermal camera integrated with a standard RGB camera, forming an RGB-T imaging system. High end sensors and multi-sensor fusion approaches are outside the current scope.

Physiological Parameter: This study focuses on facial skin temperature, particularly in specific anatomical regions of the face, as the main physiological indicator of thermal comfort, while other signals like heart rate and sweat rate are not considered.

Algorithmic and Model Architecture: DLib is used to detect and extract faces and regions of interest (ROI) in both RGB and thermal images, as outlined in Chapters 3 and 4. For temperature estimation from thermal images, MobileNetV2 is fine tuned through transfer learning, as discussed in Chapter 5. This study does not examine other deep learning architectures or advanced sensor fusion techniques in detail.

Building Management Integration: The validated system is demonstrated using a BACnet-enabled Raspberry Pi for real-time HVAC control. Full-scale integration with commercial building management systems and deployment in operational buildings is beyond the current scope.

In summary, this research is bounded by its emphasis on a single-participant, affordable, and scalable solution for occupant centric comfort assessment, leveraging facial thermal imaging and AI. The work is intended to serve as a foundation for future expansion into broader, more diverse, and real time applications.

1.5 Research Ethics

Issues related to ethics have become a major concern for researchers when conducting their studies. There is a pressing need to carefully consider how to conduct research in an ethical manner, particularly during the data collection phase. These standards are shaped by social norms of behaviour and the philosophical basis of research ethics. For the purpose of this research, the code of ethics developed by the Massey University Human Ethics Committee (MUHEC) was strictly followed. The research observed the principles of ethics from start to finish. As the data collection phase involved human participation, an application requesting permission for data collection was submitted and subsequently approved by MUHEC. Approval was granted under the low-risk category, with the ethics notification number for this application being 4000031158.

Ethical principles of MUHEC were adhered to throughout the research. Actions required to address any issues arising in light of these principles were also considered. A Participation Information Sheet and Consent Form were presented to the participant to address the ethical principle of informed consent.

1.6 Overview of Research

To address the limitations of traditional thermal comfort assessment and the challenges associated with low-cost, non-contact physiological monitoring, this research proposes the development of an integrated, AI-driven framework for real-time occupant comfort evaluation and adaptive building management.

The proposed solution centers on the design and implementation of a low-cost RGB-T (Red-Green-Blue-Thermal) camera system, utilizing the Topdon TS001 thermal camera in conjunction with a standard RGB camera and a Raspberry Pi platform. This system

enables continuous, non-invasive monitoring of facial skin temperature, which serves as a direct and objective indicator of occupant thermal comfort.

Automated facial region detection is achieved using DLib, which provides robust and reliable extraction of the region of interest (forehead) from both RGB and thermal images. To further enhance the accuracy of temperature estimation, the research employs MobileNetV2 which is a lightweight convolutional neural network (CNN) that is fine tuned via transfer learning to predict facial temperature from thermal images, even in the presence of sensor noise and low resolution.

Calibration protocols are developed to align thermal camera readings with ground-truth measurements obtained from a medical grade non-contact thermometer, ensuring the reliability of the system across varying environmental conditions. The validated system is then integrated with a BACnet-enabled Raspberry Pi, enabling real-time communication with building management systems for dynamic HVAC control based on occupant comfort.

This approach not only improves the granularity and responsiveness of comfort assessment but also supports scalable, occupant centric building management. Ethical considerations, including privacy, informed consent, and secure data handling, are embedded throughout the research process to ensure responsible deployment of the proposed solution in real time environments.

1.7 Thesis Layout

The structure of this thesis is organized as follows:

- **Chapter 1** - Outlines the motivation, problem statement, research scope, objectives, ethical considerations, and the proposed solution for developing a low-cost, AI-driven framework for non-contact thermal comfort assessment in indoor environments.
- **Chapter 2** - Provides a comprehensive review of existing models and technologies for thermal comfort assessment, emphasizing the limitations of traditional approaches and the potential of artificial intelligence and non-contact sensing methods.

- **Chapter 3** - Building on the thermal comfort principles, physiological indicators, and measurement requirements discussed in Chapter 2, this chapter presents the design and implementation of a low-cost RGB-T imaging system using DLib-based facial detection, thereby translating the conceptual foundation into a practical, non-invasive sensing platform for reliable facial skin temperature measurement.
- **Chapter 4** - Extending the sensing platform established in Chapter 3, this chapter advances the research from temperature monitoring to building systems application by integrating the RGB-T system with BACnet-enabled platforms and developing adaptive control strategies for real-time, occupant-centric HVAC management based on detected thermal responses.
- **Chapter 5** - Building upon the theoretical basis introduced in Chapter 2, the RGB-T imaging and data acquisition framework developed in Chapter 3, and the real-time control application explored in Chapter 4, this chapter further enhances the overall system through the application of deep learning techniques, specifically MobileNetV2 and transfer learning, to improve the accuracy and robustness of facial temperature estimation from low-resolution thermal images.
- **Chapter 6** - Summarizes the key findings of the research, discusses the limitations, and outlines recommendations and directions for future work in the field of occupant centric thermal comfort assessment.
- **Appendices** include supplementary materials, with each research paper accompanied by its corresponding DRC16 form, documenting the ethical review and approval process for the research presented.

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Chapter 2

AI-Based Controls for Thermal Comfort in Adaptable Buildings: A Review

Chapter 2 is based on the published MDPI paper: Ahsan, M., Shahzad, W., and Arif, K. M. (2024). AI-Based Controls for Thermal Comfort in Adaptable Buildings: A Review. Buildings, 14(11), 3519. <https://doi.org/10.3390/buildings14113519>.

Abstract

Due to global weather changes and pandemics, people are more likely to spend most of their time in indoor environments. In this regard, the indoor environment quality is a very important aspect for the occupant well-being, which often gets ignored in modern building designs. Based on our research, thermal comfort is one of the essential items in building environments that can improve the mental stability and productivity of the occupants if the buildings indoor environment is created in a way that is aware of the occupant's comfort requirements. Buildings nowadays operate on adaptive or stationary models to attain thermal comfort, which is based on Fanger's model of the Predicted Mean Vote (PMV). Based on the literature review, limited work has been carried out to enhance the quality of the inside environment, and most research work has been devoted to building energy management. Moreover, there are no definite solutions so far that

have the capability to detect the thermal comfort requirements for multiple occupants in real time. Modern buildings tend to operate on predefined setpoint parameters to control the indoor environment based on the measured room temperature, which can be different from the thermal comfort requirements of the occupants. This paper discusses the limitations and assumptions that are associated with the existing thermal comfort solutions and emphasises the importance of having a real-time solution to address the thermal requirements for the occupants.

2.1 Introduction

Occupant comfort in a building environment is a very important index for defining the well-being and mental state of the occupant assignment going forward. In order to achieve occupant comfort, buildings are designed to operate the building services using either a building management system (BMS) or building automation applications via the Internet of Things (IoT) for having a controlled indoor environment. The controlled indoor environmental conditions are designed as per the building standards that define the minimum conditions to have a healthy indoor environment. The variables for occupant comfort can be listed in the following categories: thermal, visual, and acoustic comfort.

Thermal comfort in modern buildings is designed using the Fanger's model, which calculates the thermal comfort using a combined quantitative combination of environmental and individual variables, which then defines thermal comfort as the Predicted Mean Vote (PMV). The PMV index defines the occupant's desired thermal comfort zone within the range of -3 to +3. According to the PMV index, buildings are designed to achieve 0 PMV, as this is considered to be the most comfortable range [1].

In the building industry, thermal comfort is standardized through an analytical approach, that is, the thermal sensation scale which is derived by the Predicted Mean Vote (PMV) index. The PMV helps in forecasting the mean thermal sensation vote on a standardised scale for a group of occupants. Later on, the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) established a thermal comfort code, as shown below in Figure 2.1 [2]. This model is also adopted by ISO 7730 and CEN CR 172 [3].

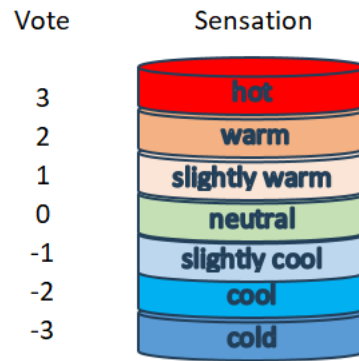


FIGURE 2.1: Seven-point thermal sensation scale.

Thermal comfort parameters can be classified into two categories, these are static variables and dynamic variables. Static variables are (1) air temperature, (2) radiant temperature, (3) air velocity, and (4) relative humidity, which are driven by the environmental conditions or the buildings characteristics.

Dynamic variables are (1) clothing insulation, (2) metabolic rate, (3) occupant age, and (4) gender. These are subject to change as they are driven by the actions of the occupants. Therefore, dynamic parameters like metabolic rate and clothing insulation are continuously fluctuating, as they are changing based on the activity level of the occupant [4].

Productivity, mental health, physical health, performance, social development, well-being, and comfort are the reactions of the static and dynamic variables, which then define the occupants' comfort level. Moreover, the environment has a lot of influence in defining the mental and physical state of the occupant. According to ASHRAE - "the mental condition that expresses satisfaction with the thermal environment is evaluated subjectively" [5]. In the building industry, there are two types of models that are used to analyse thermal comfort: (1) stationary models and (2) adaptive models. Stationary models are based on Fanger's model, which states that the human body undergoes a thermal balance with the surrounding building environment. Thermal comfort is then evaluated through Fanger's comfort equation, which is the incorporation of environmental and individual variables. This equation is then used as a tool to predict and represent the average vote of the thermal sensation on a conventional scale for many people under the certain combination of variables derived by the indoor thermal environment [1, 6]. 1) Air velocity, 2) radiant temperature, 3) air temperature, 4)

relative humidity, 5) clothing insulation and 6) metabolic rate are the main parameters for defining thermal comfort [7]. Figure 2.2 highlights the parameters that are used for calculating the PMV index.

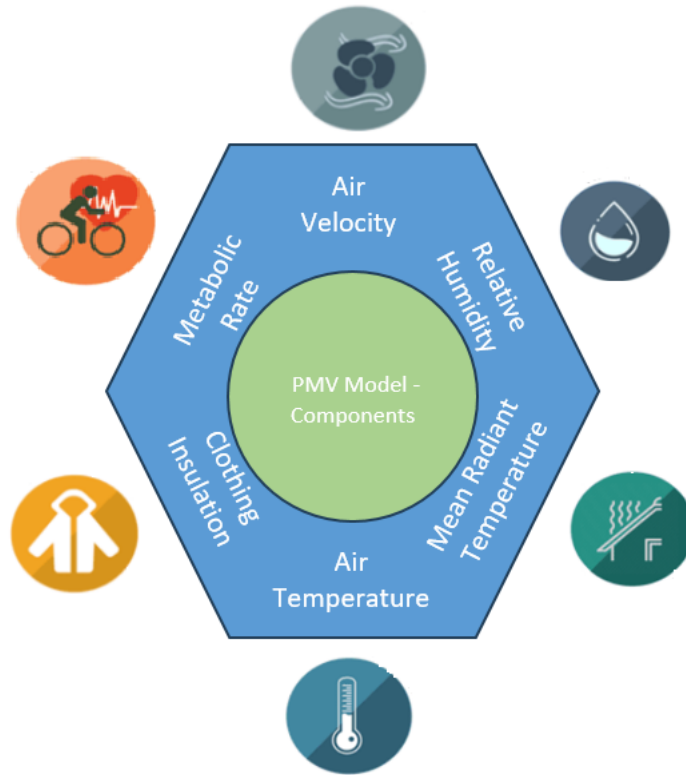


FIGURE 2.2: Component of PMV model.

Adaptive models are based on the theory that the occupant has the capability to alter the indoor environmental conditions in order to suit their thermal comfort preferences. In this model, the environmental conditions keep varying and are not assumed static. For example, the occupant can change the indoor environment conditions of a room by opening or closing the windows for ventilation [8, 9].

Artificial intelligence (AI) techniques have also been applied to address the occupant's thermal comfort issues in the building industry. Based on the literature review, there has been limited success in the results achieved for modelling occupants' thermal comfort. In most experiments, existing occupant databases have been used for training the AI model. There has been a lot of work carried out using AI techniques in energy management. The results are satisfactorily convincing in modelling building load usage, predictive controlling, optimization using deep learning (DL) techniques and Big data (BD) for storing data [1, 10–13]. Some of the parameters considered in energy management like

outdoor / indoor air temperature, humidity, CO₂ levels can be used in case studies for developing better AI models for thermal comfort. Table 1. lists the common parameters between the energy management and the thermal comfort models.

TABLE 2.1: Common Parameters used in Energy Management and Occupant Comfort Model.

Energy Management Model Parameters	Occupant Comfort Model Parameters
Outside Temperature	Outdoor Temperature
Supply duct Temperature	Room Temperature
Outside Humidity	Outdoor Humidity
Room Carbon dioxide	Room Carbon dioxide
Room Humidity	Room Humidity

This paper reviews a wide range of AI techniques that have been applied for achieving thermal comfort in an indoor environment. A bibliometric analysis have been done on thermal comfort. It has revealed that the published works have mostly addressed thermal comfort solutions by integrating it with other building discipline likes energy management. Over the years the definition of thermal comfort has evolved from simple to complex as other building disciplines also have a significant importance in defining sustainable buildings. One of the main factors that contribute in defining sustainable buildings is energy management. As a result, the relevance of thermal comfort has been compromised with other sustainable building challenges. In this review, we have focused on how AI models have contributed to addressing thermal comfort issues for occupants in indoor building environments. Some of the key terms used for article searches in databases and search engines included thermal comfort, artificial intelligence, occupant, air conditioning in modern buildings, and big data. Google Scholar, Web of Science, and ScienceDirect were the primary databases and search engines used for gathering research articles from 1990 to 2024. The main purpose of this article is to identify the limitations associated with existing solutions. Future challenges are also discussed to help researchers design new thermal comfort models that are universal, smart, aware, secure, and adaptable for all indoor environments.

Building on the preceding discussion, this section advances the overall research objective through a focused and complementary line of investigation.

2.2 Findings and Issues

As per the Chartered Institution of Building Services Engineers (CIBSE) standards, new buildings must undergo a fine-tuning process where air quality and thermal comfort parameters are checked. Air quality parameters are typically monitored via building management systems (BMS) and adjusted during the fine-tuning process to meet building standard requirements. In contrast, thermal comfort data is usually gathered through occupant feedback or smart applications, such as smartwatches and wristbands, which generally require input from the occupants. The data obtained for thermal comfort is often not accurate, as it relies on subjective feedback from occupants. This feedback can be influenced by factors such as feelings, mental health, and well-being, potentially affecting the accuracy of the results [14–18].

Based on the literature review, the main shortcoming of Fanger’s model is that it does not predict thermal comfort requirements in real time, as it is a calculated PMV index that is calculated based on assumptions and hypothetical data implemented during the building design stage [19].

The main variables for calculating PMV index are: (1) metabolic rate, (2) clothing insulation, (3) air velocity, (4) air temperature, (5) mean radiant temperature and (6) relative humidity as shown in Figure 2.2 [13].

Moreover, the adaptive thermal comfort requires occupant’s interference to adjust according to the room condition which may not be the practical method to alter the room conditions according to the thermal comfort requirement when there are multiple occupants [8, 9].

Modern buildings are equipped with BMS to operate the building services based on the predefined indoor parameters, but the system cannot adapt to the occupant comfort requirement as they are not smart to alter the plant operation outside the predefined indoor conditions to suit the occupant requirements in real-time.

BMS is designed to operate building services on predefined parameters. Generally, the BMS can be programmed to trend the plant operation which can then provide information on the plant performance during routine checks. But any alteration for the plant operation in real-time requires intervention from the plant operator to alter the

pre-defined conditions. Therefore, the modern buildings lack the capability to adapt to real-time conditions

Room sensors data can not be reliable in predicting the occupant comfort as the room temperature sensors measure the surface temperature of the RTD and it can be different to the desirable occupant temperature. Secondly, the physical location of the sensors in the room can be subjected to inaccurate results due to static heat sources being close to the sensor location like window glaze and electronic equipment like TV, printers, light bulbs, and radiant heaters close to the wall-mounted temperature sensor.

Based on our literature review, there is extensive research work being conducted to study the human body relationship with indoor temperature. There is insufficient data available to build the relationship of body skin temperature with indoor room temperature [6, 20–23].

There have been experiments conducted to measure thermal comfort via sweat rate. Smart wrist devices have been designed that can formulate the relationship between sweat dissipated and room temperature with an accuracy of 97 percent in real-time. This requires the occupant to wear a gadget that may not be a practical solution for all situations. For example when there are multiple occupants that contribute in defining the indoor environment conditions [24, 25].

The human body core temperature is 36.8 C and there is no easy way to measure the body core temperature. Human body is designed to maintain the body core temperature so that our organs function normally, but it is achieved on the cost of occupant comfort that is human body skin temperature, sweat rate and metabolic rate reacts to environmental changes for maintaining a constant body core temperature [23, 26–28].

There is a minor decrease in overall skin temperature with aging, which is due to the reduction in body core temperature. Older adults have significantly lower body temperature than the young adults. Based on medical research, males tend to have more significant effect of aging when compared between higher age groups [29, 30].

With aging there is impaired thermo-regulation due to reduced function of sweat glands and skin vasodilatory response to heat. Therefore, it is difficult to obtain a definite relationship between aging and thermal comfort [20, 31].

Metabolic rate is a part of the PMV equation, and it is a crucial component of the thermal comfort studies. However, recent research studies have shown that it is probably the most inaccurate component of the heat balancing model as the thermal comfort index is calculated on a constant value for metabolic rate. According to the Fanger's model for PMV, metabolic rate is one of the six components. Thermal studies conducted in the last 50 years have shown that metabolic rate is calculated based on the assumption that the occupants are seated or standing in an office environment cite. Table 2.2. recommends the metabolic rate as per ASHRAE and ISO 773 standards [32]. Generally, females tend to have a slightly lower metabolic rate than males [33].

TABLE 2.2: Recommended Met standards based on activity level [32]

Standards	Activity	Metabolic Rate (Met)
ASHRAE Standard 55	Sitting	1.0
	Standing	1.2
	Walking at 3.2 km/h	2.0
	Walking at 4.3 km/h	2.6
	Walking at 6.8 km/h	3.8
ISO 7730	Sitting	1.0
	Standing	1.2
	Walking at 2 km/h	1.9
	Walking at 3 km/h	2.4
	Walking at 4 km/h	2.8
	Walking at 5 km/h	3.4

When calculating PMV, the metabolic rate is generally defined as a constant value based on the group of occupant age and body surface area. However, in real-time the occupant age, gender, and activity level changes the metabolic rate. Metabolic cart measures resting metabolic rate. Metabolic carts measure the carbon dioxide (CO₂) exhaled and oxygen inhaled by an individual when breathing to assess metabolic fuel usage (carbohydrates versus fats) [34].

Human heat production is a combination of several factors. The heat produced due to any human body activity is then defined as a function of metabolism. One of the key factors in calculating metabolic rate is Basal Metabolic Rate (BMR) [23, 35]. BMR is explained as the energy required for living that is the energy required to maintain body temperature, cardiac and respiratory functions.

2.3 Health Effects

Occupant comfort is a critical aspect of indoor environmental quality, with health impacts that range from subtle short-term discomforts to severe long-term diseases. Occupant comfort issues can be categorised into two groups as shown in Table 2.3.

TABLE 2.3: Health Impacts of Indoor Environmental Quality: Short-Term vs. Long-Term Effects [2, 36].

Short term effects	Long term effects
Headaches	Stroke
Dizziness	Ischaemic heart disease
Respiratory diseases	Lung cancer
Irritation of ear, nose and throat	Chronic obstructive pulmonary disease
Decision making	Mental state
	Psychological issues

Short term effects are usually unnoticed but it does have an impact on the occupant's daily life routine. When the short-term issues are not addressed and if the occupant is exposed to an unhealthy environment for long time, it leads to long-term effects that can result in permanent health damages. Productivity, headaches, dizziness, respiratory diseases, decision making process and irritation of the nose, throat and eyes are some of the common short-term effects. If ignored, the long term effects can result in stroke, ischaemic heart disease, chronic obstructive pulmonary disease (COPD), lung cancer, mental state, and psychological feelings [37–42].

2.4 Evolution of Thermal Comfort

Figure 2.3 shows the clustering results of the bibliometric analysis for the last 50 years of how various themes were connected and developed through each time slice. From 1970s to 2000, the relevant keywords related to thermal comfort were relatively simple and few. However, from 2000 to 2010, thermal comfort was modelled with other building challenges such as energy management. Since 2010 onwards, a wider range of disciplines were introduced for modelling thermal comfort such as (1) climate change/model, (2) architectural design, (3) thermal performance, (4) personal control, (5) occupant behaviours, etc. This implicates that in recent times, economic and social activities and green building/ sustainability/energy saving methods have played a significant role in redefining thermal comfort [8, 43].

One of the most important aspects in the field of thermal comfort in the last 20 years is the acceptance of re-improvising the model of thermal comfort. In the early 1970s, Fanger's model for PMV/PPD was considered to be a global solution for thermal comfort and it was included in various building comfort standards. Most notably, the ISO 7730 (1984) and ASHRAE 55-1992, allowing the HVAC engineers to use Fanger's model in designing the HVAC comfort parameters for the building. Later on, from mid 1990s, Nicol and Humphrey's proposal for adaptive models was also considered in building designs. That is to consider the building occupants as an integral component for the 'comfort system'. It is to note that the original papers for the adaptive model was also published in the early 1970s. Brager and de Dear later attributed physiological, behavioural, and psychological parameters to be a part of the development process of the adaptive models [44–47].

With the ongoing urgency for decarbonising the built environment and rapid changes to the environment due to global warming, thermal comfort will further evolve in the upcoming years. Demand for increasing building energy efficiency and sustainable building will also play an important role in further evolving thermal comfort [48, 49].

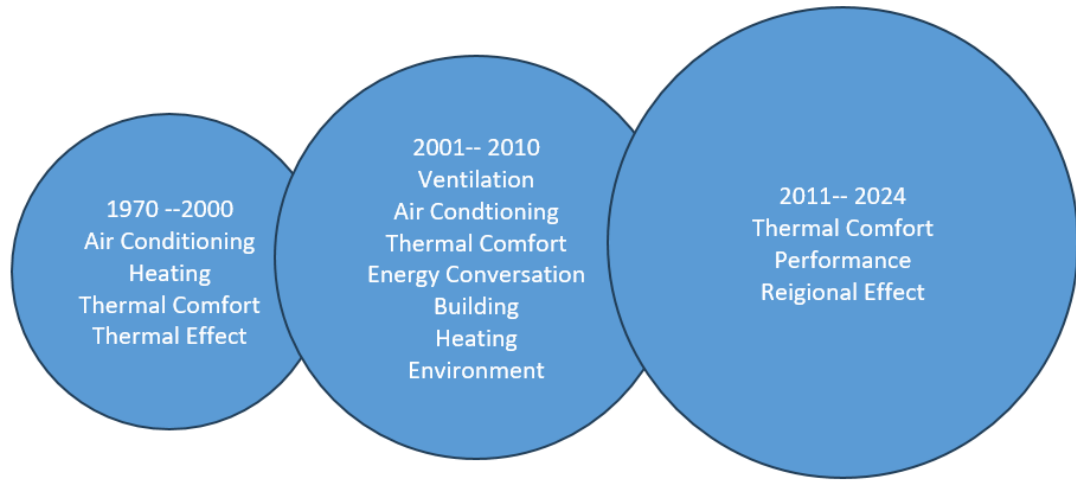


FIGURE 2.3: Evolution of thermal comfort.

2.5 Literature Analysis

Based on our literature review, neural network techniques have been commonly used for controlling building thermal comfort. Some of these techniques have been integrated with building energy management. Our main aim during literature review was to investigate and identify AI/ML assisted techniques that have already been used for thermal comfort models in building industry. Moreover, it is also to identify research challenges on how AI/ML techniques shall be improvised to have more efficiency in achieving thermal comfort. Finally, we would also like to study whether the thermal comfort model can be integrated with other building disciplines and acceptable results for thermal comfort are achieved. Limitations and assumptions associated with each reviewed paper are also discussed in this section. This paper will help researchers in designing a thermal comfort solution that considers the limitations and assumptions associated with the existing solutions.

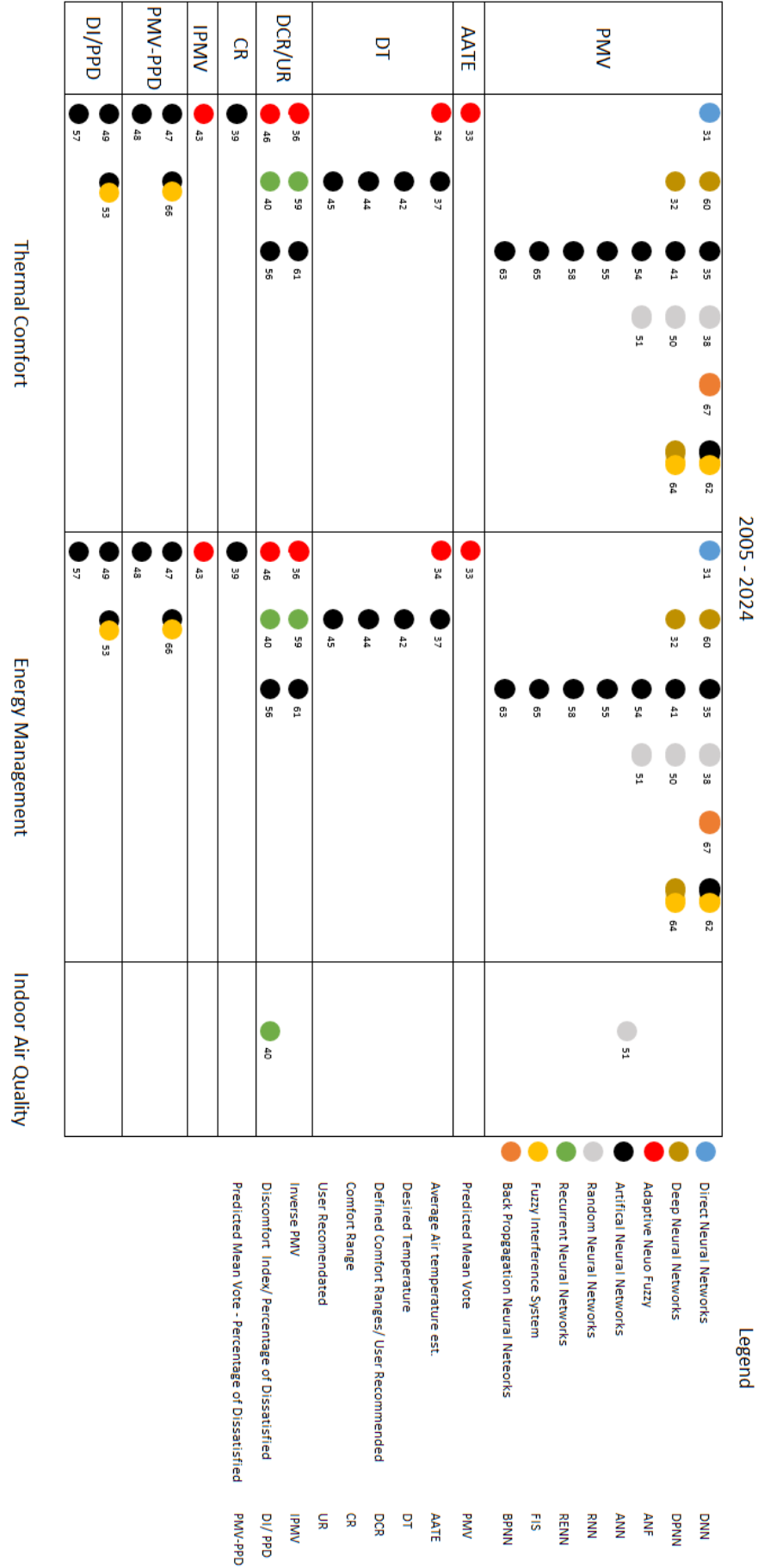


Figure 2.4 summarises the ongoing research in controlling thermal comfort either by integrating thermal comfort with energy management or attributing a solution to it as stand alone. The most focused topics that have been for smart sustainable buildings are optimising HVAC controls [50], improving building control techniques, collecting Big data [51, 52], predicting thermal comfort models and integration of thermal comfort model with energy management [5, 53–57]. Some of the main key words that were used for searching the articles were 1) “thermal comfort”, 2) “artificial intelligence”, 3) “Big data”, 4) “occupant”, and 5) “heating, ventilation and air-conditioning systems in modern buildings”.

2.5.1 Types of Neural Networks

ANN consist of distinct layers of successive neurons: the inputs, the hidden layers (not accessible outside the network) and the output layer(s). This technique’s architecture is derived on the concept of biological neuron. Figure 2.5 shows a typical functional block diagram for an ANN controller. The extent of the ANN is estimated by the number of hidden layers [58].

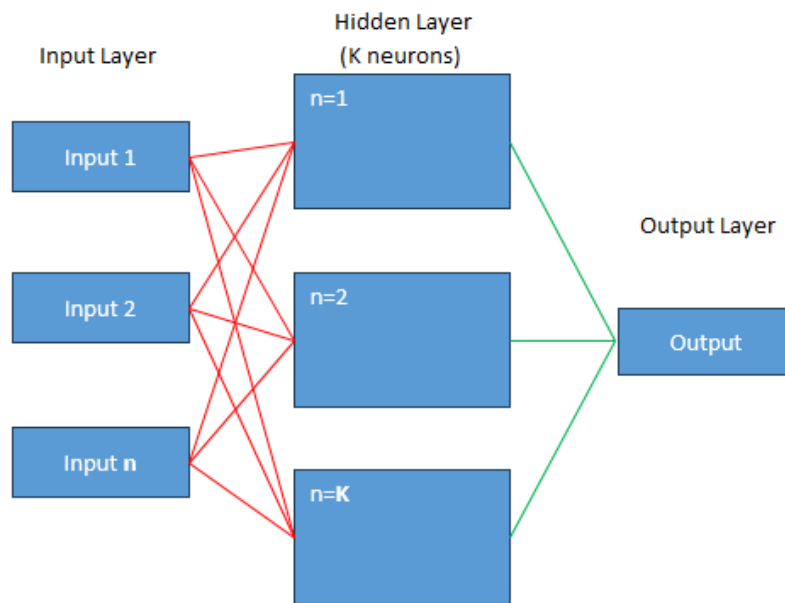


FIGURE 2.5: Functional Block diagram for an Artificial neural network.

Direct neural network (DNN) is a controller which itself is a neural network that does not require the identification of the application. The DNN controller is trained directly based

on the I/O data points where there can be multiple inputs but single output [59]. Figure 2.6 shows a typical functional block diagram for a DNN controller. Deep neural network (DPNN) is also a neural network type that consist of multiple levels of network that has the ability to execute high complexity functions provided enough training datasets are available for training the model [60]. Adaptive neuro fuzzy (ANF) is a kind of ANN that integrates both neural network and fuzzy logic principles. Fuzzy inference system (FIS) is a type of AI that helps with prediction, modelling, and inference [61]. Random neural network (RNN) is a representation of an interconnected layers that can compromise of multiple networks for an application. RNN models are generally low complexity supervised algorithm and is a universal approximator for bounded continuous functions [62] Recurrent neural network (RENN) has a unique feature that is when it is extended over a time period; it is characterised by the direction of the flow of information between its layers. It is a bi-directional ANN that allows the output from some nodes to affect subsequent input to the same nodes [63]. Back propagation neural network (BPNN) is also from the family of neural network that is good for fine tuning a model based on the error rate obtained in the preceding cycle of the AI algorithm. BPNN involves taking the error rate of a forward propagation and feeding it to the neural network layer which then fine-tunes the complete process [64].

2.5.2 Thermal Comfort Modelling using DNN

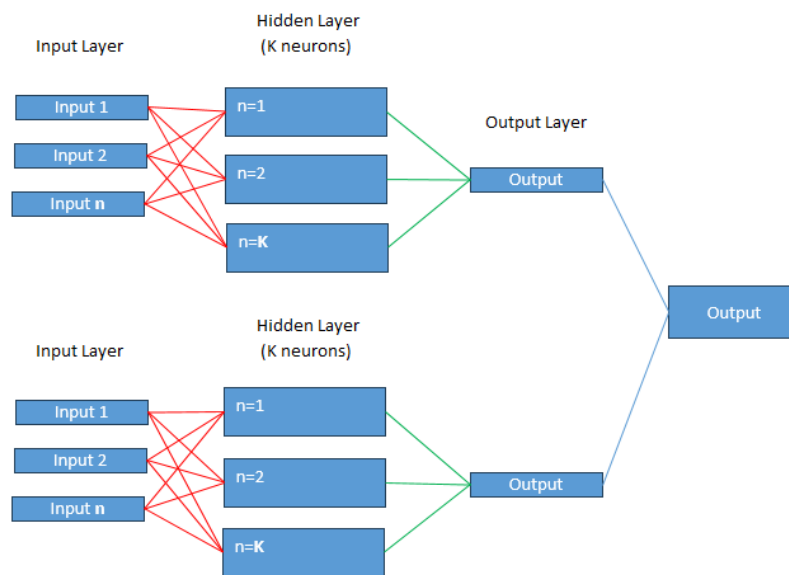


FIGURE 2.6: Functional Block diagram for an Direct neural network.

In 2005, Liang and Du conducted a research for optimizing and controlling individual thermal comfort and energy management using DNN technique for a HVAC system that was designed using variable air volume box (VAV) [65]. The outcome of using this technique showed high comfort level when the HVAC system was controlling PMV index between the bandwidth of 0.5 and +0.5 and conserving energy when there was no demand from the occupant. However, the main limitation in this design was that the building parameters were not considered.

In 2008, Liang and Du conducted another research for an intelligent control system that used an algorithm with the capability of learning the occupant's behaviour and monitoring energy usage for HVAC using DNN [53]. This resulted in better energy management and satisfactory results for thermal comfort when applied for HVAC-VAV applications. Similarly, a learning-based optimization framework was developed by Gao et al., for a HVAC systems in smart buildings using DNN [66]. However, the main limitation in both the case study was that the occupant's database used for modelling the AI was estimated rather than measured. Not only this other PMV variables like air speed and mean radiance for an occupant were also predetermined that is the air speed was set to constant and the occupant distance from the air supply spigots were also assumed as a fix distance.

2.5.3 Thermal Comfort Modelling using ANF

Adaptive neuro fuzzy (ANF) is an important AI technique that has proven its capabilities in medical diagnosis, image recognition and control system. ANF combines neural networks and fuzzy logic to create an intelligent decision-making model. It has the capability to learn from feedback or self learning over a period of time to adjust the model's parameters for more efficient results. In order to improve its efficiency, it needs a big database for self learning thus making it more robust and handling complex problem. Figure 2.7 shows a typical functional block diagram for an ANF controller.

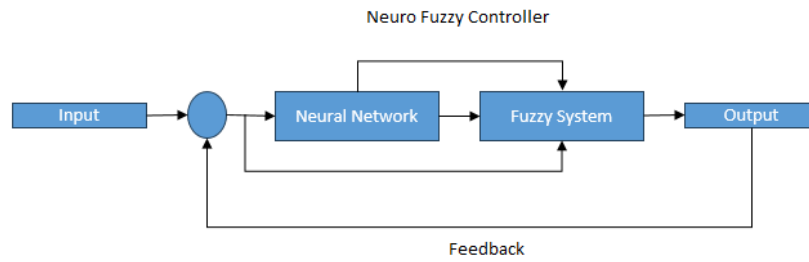


FIGURE 2.7: Functional Block diagram for an Adaptive neuro fuzzy Network.

In building industry, HVAC control systems are designed using ANF for controlling occupant thermal comfort and energy management. Jassar et al. have proposed a neural fuzzy controller using ANF to control and learn the building HVAC behaviour by eliminating occupant decision for thermal comfort [67]. The aim was to improve the HVAC plant efficiency by managing the energy requirements and have better thermal comfort controls when compared to traditional HVAC plant operation. Similar study was also conducted to improvise the HVAC operation by using ANF to control the fan and damper operation rather than using PID controls for energy management and thermal comfort [68]. However, in both the above studies, occupant preference for thermal comfort was not considered and the model was trained based on assumptions for the occupant thermal comfort. Simulation results highlighted that the ANF model can be effective and can be used as a replacement for HVAC control system. Building HVAC is a wide domain where AI techniques can be applied to the whole HVAC system or a particular design of the system for achieving certain goals like energy management, thermal comfort, equipment reliability, load diversification, etc.

Generally, specific plant system is integrated with AI capabilities as there are financial boundaries, lack of available data and the deployment time frames that contributes in deciding the area of interest. Another algorithm was developed using ANF to control the HVAC operation by modelling the thermal comfort based on the PMV index [52]. ANF techniques have also been applied on residential buildings to improve thermal comfort and to manage energy consumption of the HVAC system. However, in some case studies existing database were used for modelling the thermal comfort requirement [69]. In another case study, occupants were given control to adjust the room temperature setpoint and the ANF algorithm would model the HVAC parameters in order to maintain thermal and manage energy consumption [70]. However, the main limitation in all

these studies using ANF was either an existing database was used for modelling the occupant thermal comfort requirement or assumptions were made like having constant parameters for metabolic rate and clothing insulation. Moreover, none of the occupant thermal comfort parameters were measured in real-time, therefore; there is an ambiguity in whether the model was able to achieve the occupant thermal comfort requirement. Secondly, the ANF models were not aware of the occupant thermal comfort in real-time.

2.5.4 Thermal Comfort Modelling using ANN

Artificial neural network (ANN) technique has also been commonly deployed in building energy management and thermal comfort applications because of its ability to learn over time and derive conclusions from a complex set of information that is provided via big data. In some case studies, ANN has been integrated with fuzzy controllers for forecasting the thermal comfort requirements [71]. Magnier and Haghighat designed a fuzzy controller that was used for predicting the thermal comfort requirement based on the meteorological information provided. ANN was used in gathering the feedback from the occupant as hot or cold via touch screen to process the occupant comfort mode which would then regulate the indoor room temperature. Fuzzy controller in this case study was used as a tool to model energy management of the HVAC and predict when the HVAC could be turned off based on the predicted building environment temperature and meteorological information. ANN was mainly used for thermal comfort that could override the predicted indoor temperature based on the occupant feedback as hot or cold. Another study was conducted for a residential building to optimize thermal comfort and energy consumption via multi-objective optimization using ANN [72]. However, in this study occupant discomfort database was taken from ASHRAE adaptive thermal comfort model to calculate the number of hours that occupants generally define as uncomfortable.

In some cases, ANN techniques have been modelled with double skin envelope curtain wall that were installed in the building structures. The double skin envelope is a combination of internal and external envelopes. There are open slots for air inlets and outlets in each envelope. To help in reducing heating and cooling loads, a cavity is created between the internal and external envelopes, and the shading devices [51, 55]. As a result, this will minimize energy usage and provide thermal comfort to the occupants. ANN models take feedback from the curtain envelope as too cold or too hot which then

controls the HVAC operation. Moon et al. have defined too hot as greater than 26 degrees and less than 23 degrees as too cold and this is used as the thermal comfort setpoints for the occupant [55]. ANN has been widely used for energy management in non-residential buildings by diversifying HVAC load demand. Generally, when AI models are trained for only energy management purpose, occupant demand for thermal comfort is simplified by either using existing database to model occupant comfort requirement or making generic assumptions based on feedback and stats available in order to reduce the complexity of the problem [50]. In another research done by Yuce and Rezgui, ANN and genetic algorithm (GA) was used in developing an algorithm for managing the building energy usage. Based on the results, 25% energy saving was achieved and it also resulted in occupant comfort. However, in the case study occupant comfort was not the main focus and occupant comfort achieved was as a consequent part of the rules applied for achieving energy saving [73]. ANN techniques have also been configured to adapt to seasonal requirement. For instances, Moon and Jung developed an algorithm to improve thermal comfort and building energy efficiency in the cooling season via ANN [74]. The algorithm was developed on defined setpoint temperature and a setback temperature during vacant hours. However, in this research thermal comfort parameters were not considered for training the model.

When occupant thermal requirement is assumed as a constant parameter or is not the main focus of the research, the reliability and efficiency of modelling thermal comfort is not accurate as the AI models are not able to simulate the real-time requirements for thermal comfort. Therefore, further research is required in developing models where the controllers and the AI technique being applied are smart, adaptable, and aware of the occupant thermal requirements in real-time.

Similarly, another model was developed to predict the optimal temperature setpoint during occupied hours using ANN so that the thermal comfort and the building energy efficiency can be achieved. In this study, occupants were considered as constant heat load and the internal gain was calculated assuming a fixed number of occupants during occupied mode and no occupant present during unoccupied mode [57].

In some research, occupant thermal comfort database has been built by measuring skin temperature/metabolism rate through devices/gadgets connected to human body either through sensors or wrist band. Image processing technique has been used to determine

clothing insulation. Zhia and Soh have developed an AI based algorithm via ANN to achieve energy saving and thermal comfort in a HVAC system through computational intelligence techniques [75]. Zhia and Soh have suggested to measure the occupant's metabolism via peripheral devices like wrist band and clothing insulation via image processing technique and then take the average for metabolic rate and clothing insulation to calculate the PMV index. However, in this article the author does not discuss the results of wrist band and data collected for occupant clothing type. An average value for each occupant metabolism and clothing insulation have been calculated. Two scenarios have been model in this study. In Scenario 1, occupants with sedentary activities, the average metabolic rate was measured as $60\text{W}/\text{m}^2$ and the average clothing insulation factor was taken as $0.07\text{ m}^2\text{K}/\text{W}$ (i.e. casual short T-shirts and light long pants). In Scenario 2, occupants with light activities, the mean metabolic rate was measured as $93\text{W}/\text{m}^2$ and the mean clothing insulation factor was taken as $0.1\text{ m}^2\text{K}/\text{W}$ (i.e. casual long shirts and casual long pants). Results show that the maximum energy saving that can be achieved is 31% and the thermal comfort is with in the defined comfort zone of PMV index that is $\text{PMV} = 0$. However, there are few limitations in this case study that need to be reviewed. First, the experiment was conducted in a lab environment where all the control parameters were simulating an office space and in order to keep the metabolic rate constant for the occupant they were instructed to sit. Secondly, the experiment was conducted to simulate the environmental conditions for equator climate. Thirdly, the conceptual aim of this study was to optimize the whole building HVAC system so it was assumed that all rooms in the building are identical with same energy and thermal comfort demand for simplicity purpose. Based on the above limitation, it can be concluded that the model lacks the capability of being aware of the surrounding environment as the environment and the occupant activity level database was created in a controlled lab facility. Similarly, Chaudhuri et al. developed a framework using ANN for controlling the building HVAC system for thermal comfort and energy saving [76]. To gather the occupant database, twenty occupants were randomly selected and their skin temperature, skin conductance, pulse rate and oxygen saturation were measured using wearable sensors in a seated position. The experiment was conducted for 100 min and a database was developed to train the model. Meanwhile, environmental parameters that are air temperature, air speed, relative humidity and mean radiant temperature were measured. This resulted in 36.5% energy saving and 25°C was found as the desirable temperature for the occupants residing in Singapore. Expectation to wear sensors for

measuring occupant parameters in normal daily routine is not a practical solution as people can forget to wear them and there is a possibility for the devices to be mishandled by the occupant which can result in inaccurate results.

In order to build a data base for the occupant comfort, some experiments have been conducted for research purpose in controlled environment rooms where air speed and air quality have been controlled to predefined values. Room conditions are created to have a constant metabolic rate and occupant clothing are also predefined. Zhong and Choi have developed an AI based algorithm via ANN to control the thermal environment of the building [77]. In this study, a controlled environment chamber was used at the University of California where five occupants participated for the thermal comfort experiment. During the experiment CO₂ density was set within the range of 700 - 800 ppm and the airspeed was controlled within 0.1 m/s as per the ASHRAE 55-2013 Standard. All the occupants clothing insulation index were 1.0 clo. In order to simulate the occupant metabolic rate to be 1.0 met, they were asked to sit in front of an office desk. The temperature in the experiment chamber was gradually increased from 18.0 °C to 30.0°C while the relative humidity varied between 40% to 45%. The total duration for the experiment was 65 mins and during the experiment every 5 mins a survey was conducted where the occupants were asked to state their thermal comfort condition. Occupants were asked to participate in the validation experiments, and the results of the experiment were used to analyze the performance of the ANN model. Under controlled parameters of the occupant comfort (metabolic rate and clothing insulation) the control method displayed upto 45% reduction in energy usage and upto 44.3% desirable thermal comfort when compared to traditional PMV model. Shan et al., have also conducted a similar experiment for improving thermal comfort by measuring three physiological parameters of the occupant (the skin temperature of the wrist, the neck and the temperature of the point 2 mm above the wrist) and then applying ANN to model the thermal comfort using the measured database [78]. A thermocouple sensor was connected to the occupant skin to measure the temperature which was then integrated to the ANN algorithm. The suggested model indicated better response to predict thermal comfort demand by an average of 89.2% and a standard deviation around 2.0%. This is not a practical solution as this design requires skin contact for measuring the skin temperature which is not possible in daily life routine.

ANN has also been used in modelling HVAC systems with VAV design in controlling

building indoor air temperature [79]. Although in the research conducted by Ghofrani et al. the main agenda was to improve the response time of VAV system based on fix room temperature setpoints. The suggested model did overall improve the control and optimization of buildings indoor cooling. However, in this research the occupant thermal comfort requirement was assumed constant which in real-time conditions is not possible as it provides an inaccurate information on the thermal comfort requirements. Moustris et al. have developed an algorithm via ANN for predicting cooling load demand so that the occupant thermal comfort demand can be achieved. Existing database for the occupant comfort-discomfort index database was used for training the model which then helped in reducing the cooling load demand errors for short- and medium-term prognoses. The main purpose for this research was to manage energy for short and medium term using an existing database to train the model. There is ambiguity on the accuracy for the database used for training the model as it was not collected in real-time. Therefore, the model may not be exhibiting the same conditions when the data was collected.

2.5.5 Thermal Comfort Modelling using DPNN

Deep neural network (DPNN) models have also been used in the building industry for various building related applications. DPNN is a type of ANN that is having many input and output layers of the network. The term deep refers to multiple layers in the network. DPNN has the capability to trained on big data and has the capability of making predictions and decisions. Figure 2.8 shows a typical functional block diagram for a DPNN controller.

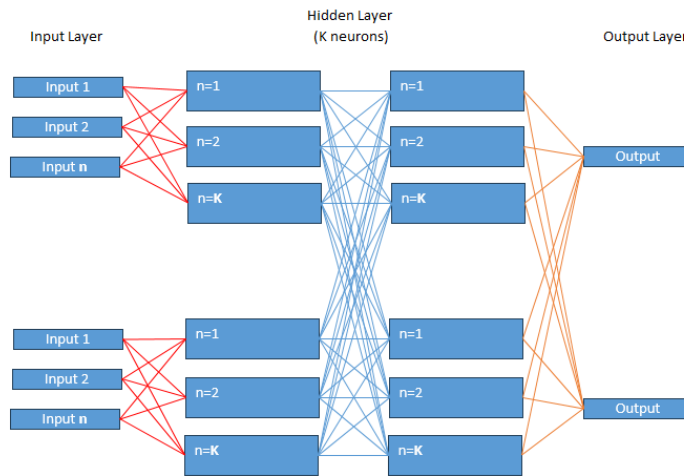


FIGURE 2.8: Functional Block diagram for an Deep neural network.

Moon and Ahn developed a model for building HVAC system so that the energy consumption for the building can be reduced and also the thermal comfort requirements for the occupants can be achieved via DPNN [80]. Moon and Ahn collected occupants feedback for validating their thermal comfort results. They did not measure thermal comfort in real-time due to occupant's privacy concerns. This method is not reliable as it is relying on occupant's feedback and this can be subjected to the occupant's mental state, feelings, and emotions.

2.5.6 Thermal Comfort modelling using RNN

Figure 2.9 shows a typical functional block diagram for RNN model.

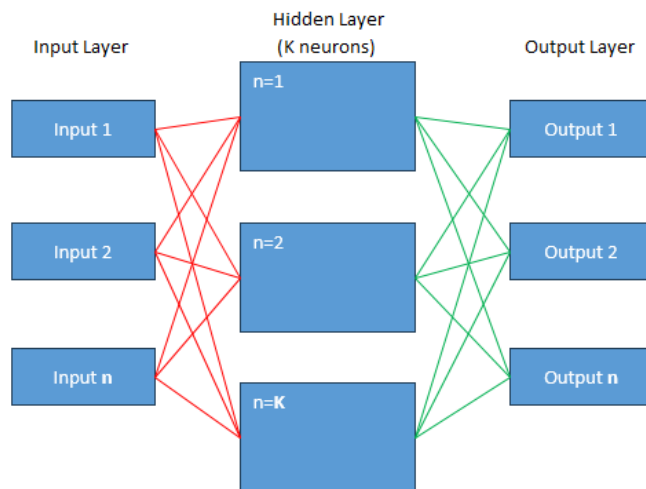


FIGURE 2.9: Functional Block diagram for an Random neural network.

Javed et al. developed a RNN model for maintaining the thermal comfort requirement and reducing the energy usage for a residential building that provides heating to the building through radiator based heating system [54]. To calculate the thermal comfort for the occupant, Javed assumed that the heat gain for each occupant is 100W. Based on the assumptions made for the occupant's heat gain, the proposed model provides a mean square error of 38.87% for particle swarm algorithm which is less than the genetic algorithm (GA). Mean square error for particle swarm algorithm is 21.19% less than sequential quadratic programming. According to Javed, when RNN is combined with GA it allows in achieving acceptable thermal comfort conditions with minimum energy usage of 400.6 MWH provided that the occupant's heat gain is 100 W. In another case study [80], a study was conducted by designing and implementing a smart controller via wireless sensors that could operate on internet of things (IoT) applications and features cloud computing for HVAC within an environment chamber using RNN as ML technique. RNN algorithm was developed to predict the number of occupants in the environment chamber using PIR sensors and CO₂ sensor. The HVAC controller will predict the thermal comfort requirement via mode selection that will either be done by the physical interference of the occupant to set the temperature setpoint or using RNN based temperature setpoint estimator that will regulate the setpoint for heating and cooling. Results highlight that the hybrid RNN-based occupancy estimation algorithm was accurate by 88% in achieving thermal comfort and 27.12% reduction in energy use when compared to the simple rule-based controllers. RNN based temperature setpoint calculator compromises of a relationship between predefined temperature range and the number of occupants counts via PIR sensor and measured CO₂. This relationship is not developed based on the PMV index scale, therefore, the comfort mode (PMV = 0), may not be the true temperature representation of the occupant thermal comfort requirement. Similarly, another study was conducted by Javed et al. for developing a RNN based smart controller by integrating it with IOT application featuring cloud computing and web services for the building HVAC system [81]. CO₂ readings were measured via sensors to estimate the number of occupants which was then integrated into the RNN model for determining thermal comfort. Cloud computing was used for storing data received from CO₂ sensor and the other PMV/ HVAC related parameters that was essential for training the RNN model. However, the occupant will have to set the temperature setpoint based on the PMV scale via web services which would then control the heating, cooling, and ventilation of the HVAC. Results highlight that

energy saving can be achieved and the RNN HVAC controller achieved the desired thermal comfort based on the information provided by the occupant. Based on the cloud computing data, the model would then control the HVAC operation and manage energy requirements for ensuring thermal comfort of the occupant based on the defined temperature setpoint via web services. This model does not have the ability to determine the thermal comfort requirement by itself and is dependent on the occupant input for determining the comfortable temperature range.

2.5.7 Thermal Comfort Modelling using RENN

Figure 2.10 shows a typical functional block diagram for RENN model.

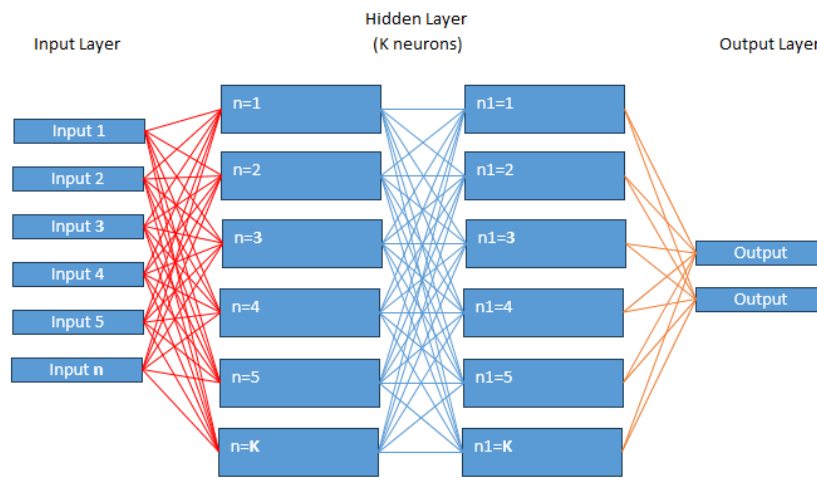


FIGURE 2.10: Functional Block diagram for an Recurrent neural network.

Javed et al., developed a RENN-based smart controller for achieving thermal comfort by managing energy usage for HVAC services in a testing chamber [56]. For achieving thermal comfort, the controller is programmed to alternate between thermal comfort mode and user defined mode. Hybrid particle swarm optimisation with sequential quadratic programming is used for training RENN. Based on the results obtained via simulations, the controller has acquired the knowledge of the human preferences with an accuracy of 94.87% for heating, 98.39% for cooling and 99.27% for ventilation. The occupancy assessment using RENN is about 83.08%. RENN models have been trained for energy management in buildings with smart meters and they have proven efficiency in buildings for thermal load management [82]. In this case study, the model is dependent on the input from the occupant as temperature setpoint to learn the thermal comfort

requirement. This is not a universal solution as it is occupant oriented for a direct input to drive the system. If there are multiple occupants the system will lack the capability to provide thermal comfort for all the occupants.

2.5.8 Thermal Comfort Modelling using Combination of Neural Network Types

Moon et al. developed an ANN-based deterministic model to respond to the ever changing occupants thermal demand that causes thermal discomfort and also increase energy load [83]. They carried out several experiment for creating a PMV dataset based on the time the room is occupied and tested different operational modes for obtaining maximum efficiency. The model results reflected in improving thermal comfort by 4.3% rather and 44.1% of energy efficiency. However, Moon has discussed one of the model's main limitations that is the model does not have the capability to portray results to real-time changes. The model is designed to operate different modes on predefined parameters; therefore, thermal requirements outside the defined parameters can not be achieved.

Reynolds et al., developed a smart heating setpoint scheduler for an office building control using ANN and genetic algorithm (GA). The purpose for the scheduler was to obtain a feedback in occupied mode from the occupants so that the heating/cooling load data can be used for training the AI model [84]. This resulted in reducing energy usage by 4.93% and improving thermal comfort by reducing the PPD by an average of 0.76%. The design was mainly for energy management. Thermal comfort was a byproduct of the design as the model was being trained on the feedback obtained from the occupant. In another study conducted by Sung and Ahn, thermal comfort was a byproduct of the energy management mode [85]. They developed a ML model to forecast the energy performances in heating loads and cooling loads of residential buildings. In this study, the model was trained by collecting data for 1) relative compactness, 2) surface area, 3) wall area, 4) roof area, 5) overall height, 6) building orientation, 7) glazing area, and 8) glazing distribution. A comparison between DNN and ANN technique has been carried and based on the results; they concluded that DNN provided better results when compared to ANN for predicting heating and cooling load demand. Similarly, Sadeghi et al., developed a context-aware model for a multi-objective decision making process in

an ambient intelligence that is designed for regulating thermal comfort while optimizing energy-efficiency in an office building using FIS and ANN [86]. Feedback from the occupants were collected to see the affect of the control rules applied for energy saving. This resulted in saving 27% of energy while maintaining occupant thermal comfort demand. Again, in this the design thermal comfort demand has been determined based on the feedback from the occupants.

2.5.9 Discussion and Observation

As per our review, the most well known techniques that have been applied are ANN, RNN, RENN, FIS, GA, DNN, DPNN, BPNN and ANF.

ANN is the most widely and commonly used technique in building industry for supervised or unsupervised domains. It was first introduced by McCulloch and Pitts in 1943. In 1950s, ANN was further developed with further types of ANN and new learning methods [87–89]. ANN techniques have been widely used for energy management in buildings as they provide substantial accuracy than conventional methods provided a large database is available for executing the ANN algorithms [90–94].

However, the conclusion that is derived from this literature review is that there is no real-time solution for achieving thermal comfort when there are multiple occupants in a shared space/zone. Secondly, wearing gadgets for multiple occupant application is not a practical solution. Thirdly, occupant's feedback may not provide an accurate solution as occupant feedback is subjected to their mental state and emotions which results in error for calculating thermal comfort. Traditionally, research in building design has primarily focused on energy management, often treating thermal comfort as a secondary outcome. The research method used by the authors of the published work was mainly empirical case-study. Data collected for thermal comfort and energy usage was through questionnaires, interviews with participants, making use of existing publicly accessible database or by measuring data. Based on the above findings, further research is required in designing a smart, aware, and adaptable AI design where the occupant parameters can be measured in real-time without any physical touch or use of gadget. In order to achieve a real-time smart, aware and adaptable thermal comfort building design, big data is required for training the AI models. Moreover, the AI thermal comfort model

should be a practical solution that is designed as per the building standards so that it can be integrated with the building HVAC services.

2.6 Industry Challenges

Now based on the literature review, there are still some open research challenges in the field of energy management and occupant comfort techniques. They have been identified as the following:

- 1) Smart and connected buildings.
- 2) Storage and process Big data for complex smart buildings
- 3) Cybercrime issues in smart buildings
- 4) Context awareness computing in building disciplines
- 5) Comfort modelling and dynamic temperature setpoint adjustment
- 6) Getting comfort requirement from the occupant.

2.6.1 Smart and Connected Buildings

The concept of integrating multiple buildings comes from the concept of diversified load. From the energy management view, connected buildings will play an important role in enhancing energy efficiency [95, 96]. Connected buildings will help energy sectors in further developing smart grid applications [97]. Similarly with diversified load, the buildings will be aware on the thermal comfort requirement of the occupants and thus have the ability to share the demand requirement of heating/cooling to suit the occupant comfort requirement.

2.6.2 Storage and Process Big Data for Complex Smart Buildings

Sensing devices in smart buildings produce a lot of data which then requires storage. There are ways already being implemented for storing data like through flexible cloud computing and virtualisation solutions. But this needs to be further improved because

for solving complex algorithms in real-time, huge amount of historical data is required for precision and accuracy [98]. Large amount of data is required for ensuring the datasets are balanced and need to be representative of the application, or else the model will make inaccurate decisions based on the available data. Therefore, it is important that storage and collection of datasets is improvised further and for solving complex problems there is enough data available.

2.6.3 Cybercrime Issues in Smart Buildings

Any communication devices can be vulnerable due to software bug or exploitation [99, 100]. This is because writing a software code is both hard and time consuming. In some cases, manufacturers take shortcuts for developing security policies which then results in software's being easy targets for cybercrime related activities [101]. Generally, five design conditions are considered for protecting the privacy as shown in the below Figure 2.11.

NIST Framework for cyber physical systems strongly advise that the five design conditions should be studied in an interdisciplinary holistic manner at various levels of components (be it physical, analogue, or at the more abstract cyber level) [19].

Smart building's design needs to adhere to the importance of protecting occupant's privacy and devices used for gathering data will need to comply with cybersecurity policies. Moreover, data that will be used for training AI models will also need to adhere to the security regulations.

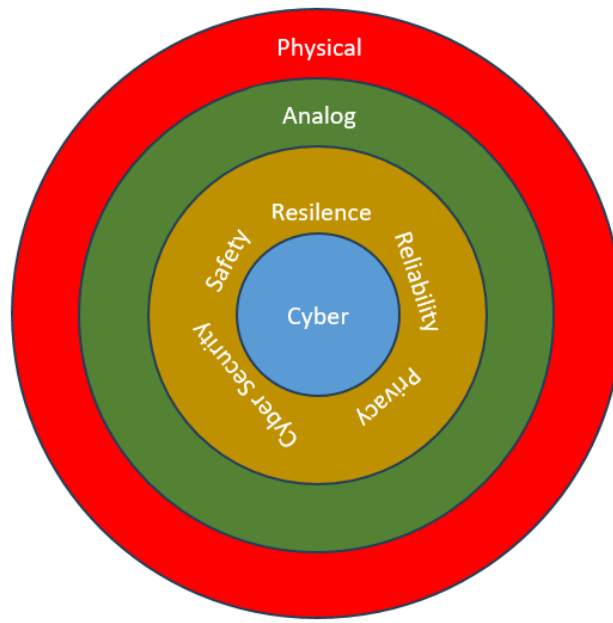


FIGURE 2.11: Framework for Cyber security.

2.6.4 Context Awareness Computing in Building Disciplines

Context awareness (CA) means that the building control system has the capability to detect and forecast the changes that is required for maintaining a comfortable indoor environment in real-time. These changes can be direct systems inputs such as outside air temperature, humidity, lux levels, sound. It can also be indirect systems inputs such as forecasting the occupant behaviours or securing knowledge for building events, calculating precise heat/ cooling demand. CA is the most important part of the building intelligence [102].

2.6.5 Comfort Modelling and Dynamic Temperature Setpoint Adjustment

The evaluation of thermal comfort in building environments is essential for the development of environmental and energy related policies in buildings which is usually achieved in compliance with the ASHRAE 55 standard [103]. Research has shown that the comfort conditions for the occupant differs based on the geographical location and the way in which the buildings are designed and managed.

Some research suggest that the occupants feel more comfortable when they have got access to the building management system and they will set the indoor conditions to suit their comfort requirement [104, 105]. However, this is not a practical solution when there are multiple occupants sharing the same zone/ room. Occupant comfort parameters need to be set to a tolerant setpoint to which the system design will try to operate based on the thermal comfort requirements.

2.6.6 Getting Comfort Requirement from the Occupant

Several studies have been conducted for developing an individual comfort-based AI model that allows user defined characteristics for a given environments [103, 106–111]. This solution may be applicable on specific building types like the retirement villages, where the system can be designed to suit the occupant requirements based on their personal feedback. In some building's, occupants feedback is taken through apps which may or may not be accurate as it is linked to emotional, psychological, and physiological condition of the individual occupant [111]. The user defined environment has got some limitations and it can not be used in situations when there are multiple occupants sharing the same environment. Each occupant has their own comfort range and thus the accuracy of achieving comfortable indoor environment is questionable.

Further research is required on how the thermal comfort parameters are measured for multiple occupants without having direct input from the occupant as feedback or surveys via app or handwritten notes.

2.7 Conclusion

This paper provided a comprehensive analysis of literature review on the topic of thermal comfort in buildings. The research themes of the existing studies are identified through scientometric analysis. They are the following:

- 1) Fanger's model use for calculating thermal comfort - PMV index
- 2) Defined comfort ranges
- 3) Integration of energy management with thermal comfort

Fanger's model for PMV is the most common method to calculate thermal comfort in indoor environments. Metabolic rate and clothing insulation are two important components of the PMV equation. It cannot be generalised with a constant value as the values for the metabolic rate and clothing insulation changes on a very frequent basis due to the reason that it is dependent on the occupant activity level. Literature review, suggest that studies have been conducted to analyse this issue and it has shown that thermal comfort for individual occupant can be summarised as successful that is achieved via wearable gadgets, personalised feedback gadgets or via fine tuning HVAC controls to suit individual occupant preference.

However, further work is still required when there are multiple occupants in a zone that requires thermal comfort in real-time. Moreover, a more practical solutions needs to be derived where there is no dependency on occupants wearing gadgets or via feedback's. Further research is required on having a smart, aware and adaptable thermal comfort model with no direct contact driven feedback from the occupant.

Data security and privacy needs further attention in order to avoid data leaks from the gathered database. With new challenges being created from cyber-crime activities, protection of the occupant database is vital and this may require collaboration with IT and security consultants to address this issue. However, with challenges there is also opportunities to integrate thermal comfort with other building models like integration with energy management models or with diverse load models where services are shared with multiple building disciplines. With integration of models, multiple building related issues can be addressed simultaneously provided there is a good collection of big data to train the AI models.

The review highlights that AI technology in building industry is still an ongoing research topic. Mainly for the reason that little data is available for analysing the building and occupant related parameters. Inorder, to achieve acceptable solution fast computer processing, integrity and security of the database is essential for training the AI models.

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Chapter 3

Accurate Facial Temperature Measurement Using Low-Cost Thermal Camera for Indoor Thermal Comfort Applications

Chapter 3 translates the conceptual review from Chapter 2 into an experimental sensing framework by presenting the design, calibration, and validation of a low-cost RGB-T imaging system with DLib-based facial detection, with results demonstrating the reliability and practical feasibility of non-invasive facial skin temperature measurement for indoor comfort applications; this chapter is based on the published paper: Ahsan, M., Shahzad, W., and Arif, K. M. (2025). Accurate Facial Temperature Measurement Using Low-Cost Thermal Camera for Indoor Thermal Comfort Applications. Buildings, 15(22), 4050.

Abstract

Non-contact measurement of human skin temperature is an important area of research. Infrared temperature devices have played a critical role in measuring skin temperature without physical contact. Thermal cameras have also been employed for non-contact skin temperature measurements. However, both infrared devices and thermal cameras have limitations that restrict their use in the building industry for assessing occupant

thermal comfort. The building industry requires sophisticated equipment capable of measuring human temperature non-invasively and, through integration with building control systems, adjusting the environment to meet occupants' thermal comfort needs. Unfortunately, standard thermal cameras and infrared temperature sensors are not designed with building applications in mind. This paper proposes an affordable and building-compatible thermal camera designed to measure occupant skin temperature via a non-contact method, enabling better integration with building control systems to support occupant comfort. Experimental results demonstrate that the proposed system can reliably capture facial skin temperature and establish a quantifiable relationship between facial and room temperatures. Moreover, this provides a foundation for future real-time thermal comfort and building-control applications.

3.1 Introduction

Thermal comfort is essential for building occupants' productivity, mental state, and well-being [1]. Modern building designs often account for thermal comfort by applying Fanger's Predictive Mean Vote (PMV) model to calculate the required comfort levels for occupants [2]. However, Fanger's explicit model requires customization to meet occupants' thermal comfort needs in real time [3, 4].

Researchers have proposed using thermal cameras to collect real-time temperature data from occupants, which can then be used to train AI models to operate the building's Heating, Ventilation, and Air Conditioning (HVAC) systems in accordance with occupants' comfort requirements. Existing room temperature measurement solutions, however, have certain limitations. Most rely on RTD (Resistance Temperature Detector) wall sensors, which are prone to inaccuracies due to their physical installation locations and exposure to other heat sources, such as window glazing or electronic equipment [5–8]. Similarly, gadgets and occupant feedback are often inaccurate, either because of limited temperature measurement range or because feedback is influenced by personal feelings and emotions, resulting in an unreliable database for training AI models [9, 10].

Thermal cameras are preferred for real-time occupant temperature measurement. However, they are generally expensive, prompting many researchers to develop customized

thermal cameras [11]. With limited building budgets, these custom solutions allow researchers to adapt the cameras to specific building designs and geographic locations.

Given this context, this paper presents a solution for measuring occupants' temperature using a customized, non-contact thermal camera. The camera is programmed to capture temperature from commonly exposed body parts, specifically the facial skin. A relationship will be established between wall-mounted RTD sensors and the thermal camera to identify facial comfort temperature and predict overall occupant comfort.

3.1.1 Concept of Calculating Thermal Comfort in Modern Buildings

In the 1970s, Fanger proposed two models for assessing and predicting thermal comfort in indoor environments: the Predicted Mean Vote (PMV) and the Predicted Percentage Dissatisfied (PPD). The PMV quantifies the average thermal sensation of a large group of people on a seven-point scale, ranging from -3 (cold) to $+3$ (hot), with 0 representing neutral. PPD estimates the percentage of people likely to feel uncomfortable in a given environment. The design parameters for both models include air temperature, mean radiant temperature, relative humidity, air velocity, clothing insulation, and metabolic rate for a given environment. Both models are widely used in building design and are incorporated in ASHRAE Standard 55 [12] and ISO 7730 [13] as international thermal comfort standards. However, a key limitation is that all design parameters are calculated based on fixed values and do not reflect real-time variations in thermal comfort [14].

3.1.2 Skin Temperature Relationship with Indoor Comfort

Studies have shown that human skin temperature is closely related to indoor comfort, which is not uniform and can vary over time depending on indoor air parameters, metabolic activity, and clothing. Research indicates that skin temperature is a strong indicator of occupants' perceived thermal comfort, and certain body parts, such as the face, can help identify comfort levels [15, 16].

The inner core body temperature for a healthy human is approximately 36.7°C . To maintain this core temperature, the body engages in several automated responses, adjusting blood flow under the skin to regulate heat [5, 17–20]. These changes in blood

flow manifest as sensations such as warmth, sweating, cold, or shivering, which are reflected in skin temperature and thus indicate the occupant's comfort level [21–23].

In one study, an experiment was conducted to examine the relationship between skin temperature and occupant comfort using wireless temperature sensors (thermistors) attached to multiple body locations, including the forehead, chest, upper arm, thigh, calf, and hand. Skin temperature was continuously monitored alongside environmental measurements and occupants' subjective comfort assessments. The results confirmed that skin temperature is a reliable predictor of thermal sensation and can be used to assess indoor comfort in buildings [24].

Table 3.1 summarizes the observed relationship between indoor air temperature and mean skin temperature, illustrating how changes in the indoor environment correspond to variations in occupants' skin temperature and, consequently, their perceived thermal comfort.

TABLE 3.1: Measured indoor air and mean skin temperature during the experiments

Indoor Air Temperature (°C)	Mean Skin Temperature (°C)
20	32
22	32.5
24	33
26	33.5
28	34

Clothing, metabolic rate, air velocity, humidity, radiant temperature, and air temperature all influence thermal comfort for occupants. Indoor air quality (IAQ) parameters, such as CO₂ (ppm), also play a role in comfort [2, 14, 25, 26]. Frontczak and Wargocki note that achieving optimal indoor comfort requires a holistic approach, as occupant comfort results from the combination of multiple factors [27]. During the experiments conducted in this research, CO₂ (ppm) and humidity (RH) are monitored to observe their effect as indoor air temperature changes.

3.1.3 Current Methods of Measuring Indoor Room Temperature

The most common method to measure and control indoor environments is through wall-mounted temperature sensors. These sensors are typically RTD types, which measure the resistance of the sensor's surface to determine the indoor temperature. They are integrated into the Heating, Ventilation, and Air Conditioning (HVAC) system as part of a closed-loop feedback mechanism. The wall-mounted sensors measure room temperature and send feedback via programmable logic controllers (PLC) to modulate the HVAC system according to predefined parameters.

This approach is prone to inaccuracies. The sensor's location can produce false readings if installed near windows or close to heat-generating sources such as TVs or printers. In other words, the wall-mounted RTD sensor controls the indoor environment based on its surface temperature, which may not reflect the actual room conditions [28].

In addition to wall-mounted temperature sensors, modern smart-building systems increasingly deploy distributed Internet-of-Things (IoT) sensor networks for monitoring ventilation performance, indoor air pollutants, and occupancy behavior [29]. These systems typically track variables such as CO₂ concentration, humidity, and airflow patterns to support ventilation control and indoor-air-quality management, rather than measuring individual occupants' thermal state. Such approaches provide environmental context but do not directly assess personal thermal comfort, motivating alternative sensing techniques such as non-contact facial temperature monitoring.

Another method for regulating indoor temperature is through occupant-based monitoring devices such as smart watches. With advancements in medical technologies for skin temperature measurement, researchers have proposed solutions to measure occupants' sweat rates via smart watches. This data can then be used to modulate HVAC operation through IoT-based communication between the watch and the control system. Sweat rate sensors operate by integrating miniaturized thermo-pneumatic actuators, which measure humidity evaporation caused by sweat. These sensors typically include two components: a humidity chamber for collecting sweat-induced humidity and a humidity sensor within the chamber to measure the collected moisture [16].

Natural ventilation-based sweat sensors are categorized into open and closed chamber types. Open chamber types include two humidity sensors, with one open to measure

the humidity difference, while the generated sweat naturally ventilates through the open end. These are highly sensitive to even gentle airflow (≥ 0.5 m/s), limiting their use in mobile monitoring applications. Closed chamber types use a single humidity sensor to measure the rate of humidity rise while in contact with the skin [30]. While effective for individual occupants, this solution cannot ensure thermal comfort for those not wearing the watch.

A third method relies on direct occupant feedback. This is commonly done during building fine-tuning, typically three to six months after commissioning or during routine maintenance [31]. However, this method is highly subjective, as occupant responses are influenced by stress, well-being, and mental state [32–34].

Since the COVID-19 pandemic, thermal imaging has emerged as a method for measuring facial temperature. Nevertheless, researchers have achieved limited success due to challenges in face detection, calibration, and environmental variables, which affect measurement accuracy [35–40].

This paper focuses on non-contact facial temperature measurement using thermal images and calibrating these thermal readings against room temperature obtained from wall-mounted sensors. AI-driven comfort models require diverse and reliable field data; however, wearable sensors and RTD-based measurements can suffer from practical limitations such as user compliance, placement constraints, motion artifacts, and location-dependent inaccuracies. These factors reduce real-world data robustness, making non-contact sensing a promising alternative.

To address this gap, we propose a low-cost RGB-T thermal imaging system integrated with a Raspberry Pi to continuously measure facial skin temperature and align these measurements with ambient indoor temperature. This approach provides spatial thermal information without requiring user-mounted devices and supports automated region-of-interest detection, offering a practical, occupant-centric solution for indoor comfort studies.

To guide this study, the following research questions (RQs) are addressed:

RQ1: Can a low-cost RGB-T thermal imaging system reliably measure facial skin temperature in indoor environments?

RQ2: What is the relationship between room air temperature and facial skin temperature under controlled conditions?

While this paper focuses on measurement and calibration, these findings also lay the groundwork for future research on integrating facial temperature sensing with HVAC control strategies.

The present work extends prior findings by researching an indirect method to measure occupant temperature, thereby strengthening the continuity of the thesis argument.

3.2 Proposed System Design

Previous studies have shown that indoor temperature can be measured in multiple ways; however, occupant thermal comfort remains a concern, as highlighted in Section 3.1.3, which identifies limitations in the discussed techniques. To address this, an experiment was conducted to establish the relationship between facial temperature, measured using a thermal camera, and indoor temperature, recorded by RTD sensors. The Topdon Thermal Camera TS001 (Topdon Technology Co., Ltd., Shenzhen, China) was used to measure facial temperature.

Thermal cameras are limited in detecting objects, as they capture heat signatures rather than visible light images. As a result, fine details of an object are often too complex to be accurately captured by a thermal image. For face detection, the Grandstream GUV3100 (Grandstream Networks, Inc., Boston, USA) was employed, while the Netatmo indoor modules (Netatmo S.A., Boulogne-Billancourt, France) were used to measure indoor air temperature, CO₂, and humidity. The combination of the webcam and thermal camera is referred to as the RGB-T camera (Figure 3.1).

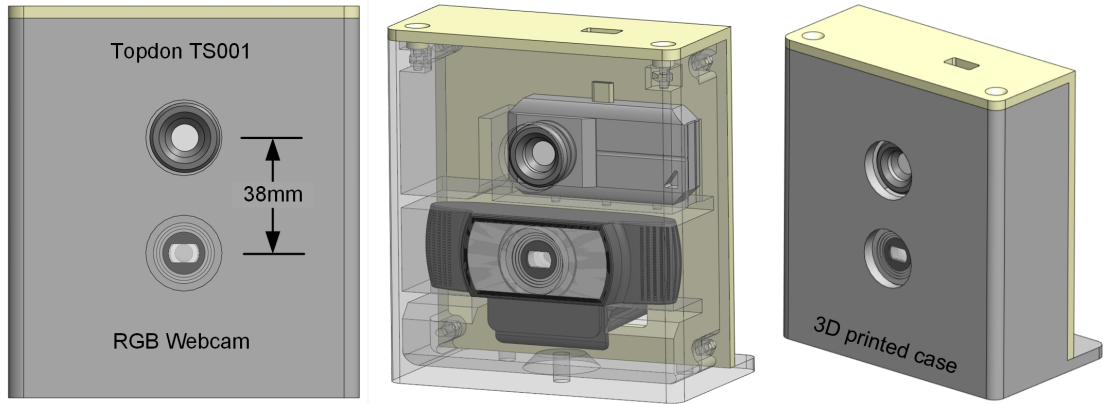


FIGURE 3.1: Graphical model of the RGB-T camera, developed by integrating a low-cost thermal camera (Topdon TS001) with a high-definition webcam. Both cameras are housed in a 3D-printed enclosure to maintain a fixed position.

Both cameras are aligned so that the region of interest remains consistent, as shown in Figure 3.2. The dimensions of the area of interest are set during the calibration process to ensure that the occupant's face can be accurately detected in each frame.

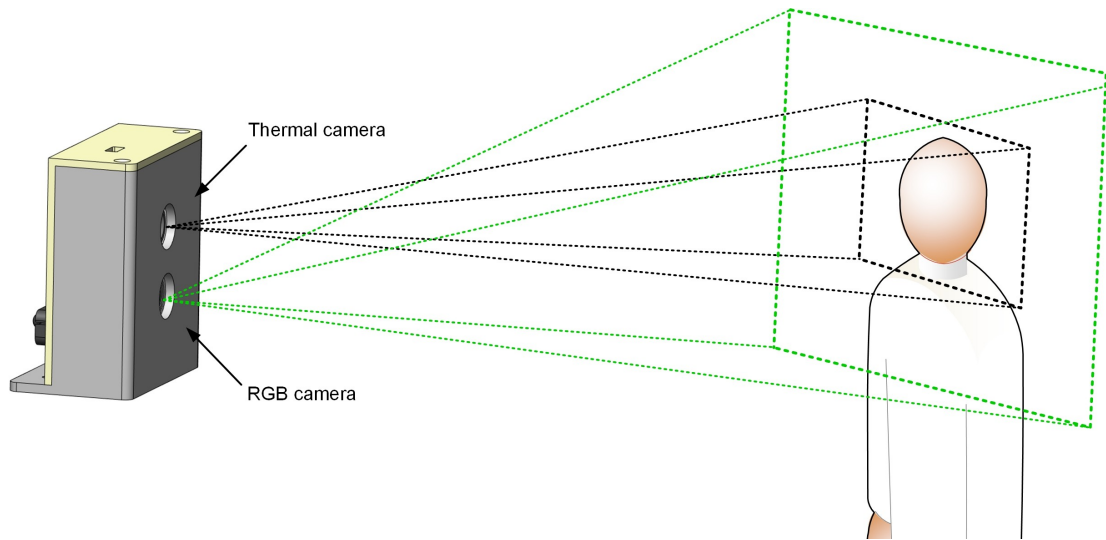


FIGURE 3.2: Field of view (FOV) of the RGB and thermal cameras in the RGB-T system. The larger FOV of the RGB camera (indicated by the green dashed line) enables facial recognition, while the narrower FOV of the thermal camera (indicated by the black dashed line) captures temperature data for the facial region.

A Raspberry Pi 5 was programmed with an algorithm to detect a face. Once a face is detected, the algorithm triggers the thermal camera to measure facial temperature and the Netatmo sensors to record indoor temperature, CO_2 , and humidity. The readings are recorded in a text file whenever a face is detected. A relationship is then established between the Netatmo sensor and the Topdon thermal camera readings. The positions

of the cameras and Netatmo indoor sensors remain fixed throughout the experiment. Figures 3.1 and 3.3 illustrate the camera design and experimental setup.

Several alternative sensing approaches were evaluated. Low-cost thermopile devices (e.g., AMG8833 (Panasonic Corporation, Osaka, Japan)) were initially considered due to their affordability, but they provide only single-point temperature readings and therefore lack the spatial resolution needed to monitor multiple occupants or detect local facial thermal variations. Wearable skin-temperature sensors and low-cost IR spot sensors reported in literature can provide accurate skin temperature readings, but they require user compliance and are impractical for passive indoor comfort monitoring. Higher-end thermal cameras (e.g., FLIR A20V (FLIR Systems Inc., Wilsonville, Oregon, USA)) offer superior accuracy but are expensive and, in some cases, discontinued or unsupported.

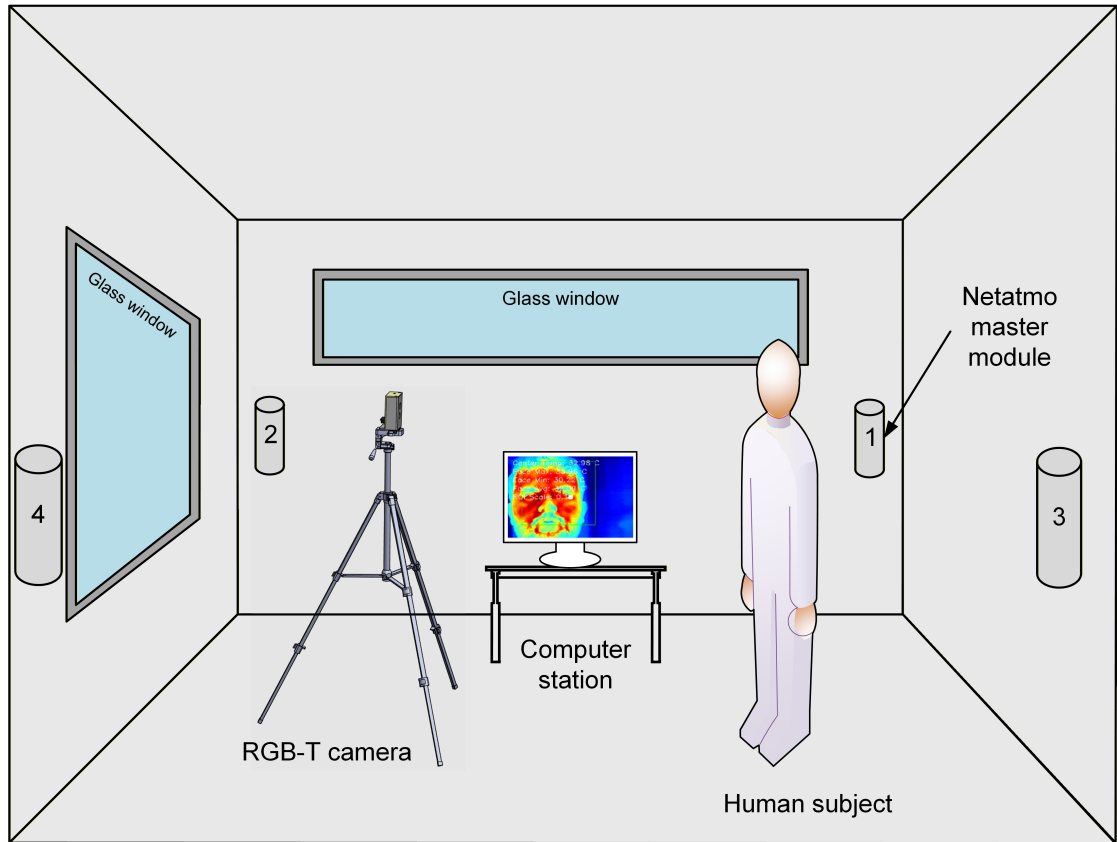


FIGURE 3.3: Experimental setup for facial temperature measurement using a webcam and a thermal camera. Four indoor air quality units (Netatmo) were installed on the walls to record temperature at multiple locations within the room. Netatmo 1 served as the master module, while Netatmo 2–4 operated as slave modules. The room contained two glass windows, and the camera-to-participant distance was maintained at approximately 0.5 m.

The proposed system adopts a low-cost RGB-T camera platform combined with a

Raspberry Pi for real-time acquisition, spatial temperature mapping, and automated ROI-based facial temperature extraction. This enables continuous non-contact temperature measurement with sufficient spatial resolution to support indoor comfort studies, distinguishing our approach from both single-point thermopile devices and wearable-based methods.

Four wall-mounted Netatmo temperature sensors are installed to accurately monitor the room temperature, as shown in Figure 3.3. The human body's inner core temperature is approximately 36.7°C , which is necessary for normal organ function. To maintain this core temperature, skin temperature across different body parts must be regulated. This experiment focuses on average facial temperature, measured using the Topdon TS001 thermal camera.

Studies indicate that, for indoor environments, thermal comfort corresponds to facial temperatures in the range of 32°C to 34°C . When facial temperature rises above 35°C , occupants may begin to feel warm or hot, whereas temperatures below 32°C may lead to sensations of coolness or cold [15, 16]. Figure 3.4 presents the sequential workflow for implementing a facial temperature monitoring system.

The face detection model was trained using an open-source deep learning library called Dlib. Dlib employs Histogram of Oriented Gradients (HOG) features along with a linear Support Vector Machine (SVM) classifier, making it suitable for real-time face-detection applications. In addition, Dlib includes a deep learning model for face embeddings, which can be used for face identification and verification tasks, such as creating customized indoor comfort models for individuals. For more accurate face detection, Dlib leverages a conventional neural network (CNN) technique [41]. The primary advantage of using Dlib is that it is lightweight and fast, making it well-suited for deployment on a Raspberry Pi 5.

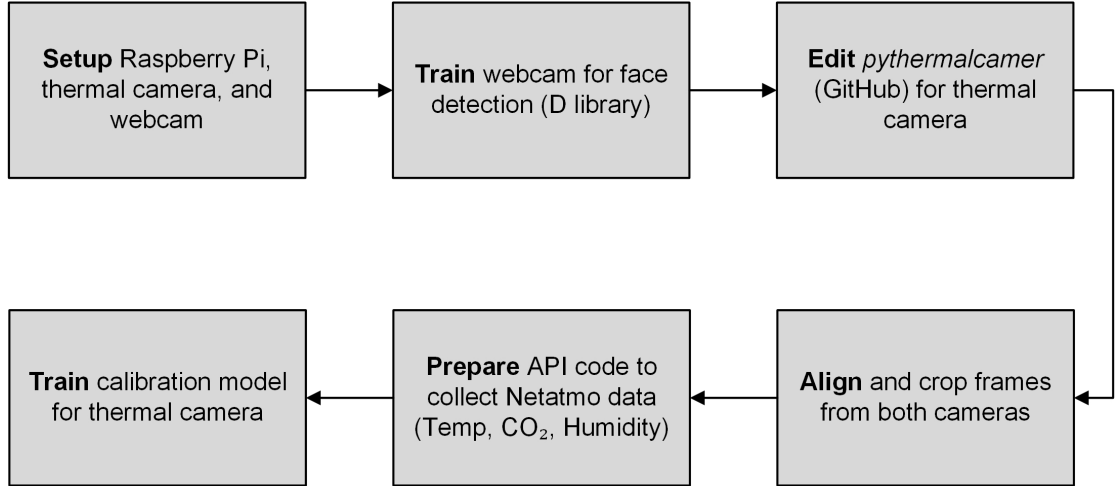


FIGURE 3.4: Workflow for facial temperature measurement using the RGB-thermal (RGB-T) sensing system implemented on a Raspberry Pi platform. The pipeline includes hardware setup, webcam face-detection model configuration, thermal-camera software adaptation, and data alignment between thermal and RGB frames. Netatmo sensor data are collected via API, and a calibration model is trained to map thermal readings to reference temperature measurements.

A Python (3.11) script was developed to measure average facial temperature using the Topdon TS001 thermal camera. The core communication logic, diagnostics, and data parsing routines were adapted from the open-source PyThermalCamera repository by Les Wright, originally designed for the Topdon TC001 camera [42]. The script was further extended to include data saving, Netatmo sensor integration, and facial recognition using the DLib library.

Both cameras were aligned to focus on the same region of interest (ROI). Table 3.2 summarizes the characteristics of both cameras. The ROI and cropping were adjusted to ensure that the frames from both cameras matched accurately.

TABLE 3.2: Characteristics of Topdon TS001 thermal camera and GUV3100 webcam.

Parameter	GUV3100	TS001
Focal Length	3.6 mm (fixed focus)	3.2 mm (fixed focus)
Field of View (FOV)	84° (diagonal)	56° (H) × 42° (V)
Focus Type	Fixed focus (optimal range: 50 cm–3 m)	Adjustable focus (manual adjustment)
Sensor Resolution	1080p Full HD (1920 × 1080 pixels)	256 × 192 pixels (thermal)
Minimum Focus Distance	50 cm	30 cm

For calibration purposes, a ROI function was implemented, allowing the average facial temperature measurement area to be adjusted by scaling the side length of the square ROI between 0.1 and 1. The ROI size is defined relative to the bounding box detected by the face detection algorithm (i.e., an ROI of 1 corresponds to the full bounding box). A smaller ROI provides more accurate results, as the maximum and minimum temperatures are measured within a reduced area. The average facial temperature is calculated as the mean of the maximum and minimum temperatures recorded within the ROI. Figure 3.5 illustrates the difference between ROIs with scaling factors of 1 and 0.1, where the latter corresponds to an area 100 times smaller. The red square represents the ROI in the thermal image, while the green square indicates the bounding box around the face detected by the RGB camera. An offset feature was also incorporated for the maximum and minimum temperatures, which was set to 0 °C in the experiment.

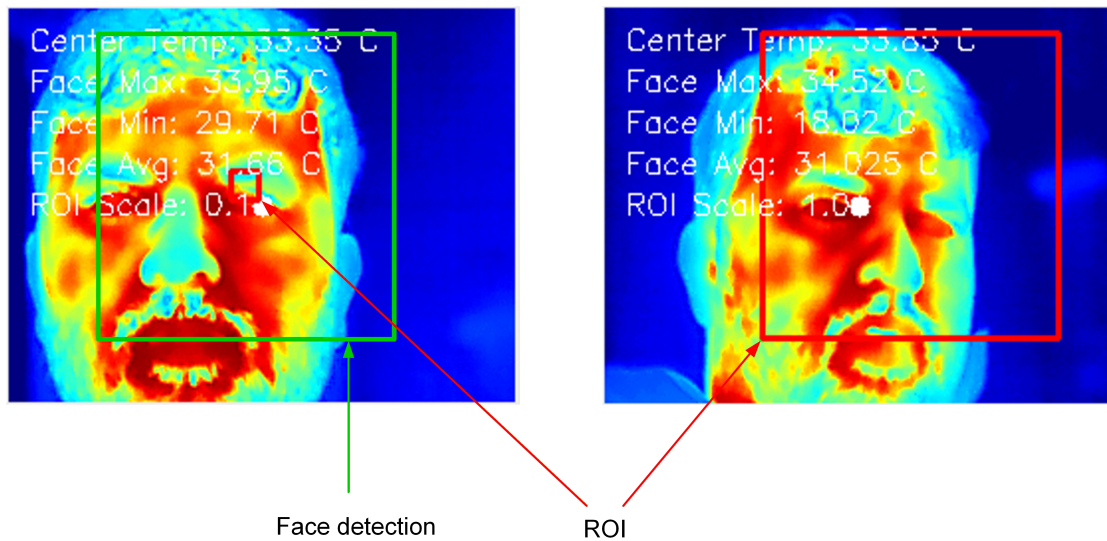


FIGURE 3.5: Comparison of face detection and region-of-interest (ROI) selection in thermal imaging. The green bounding box indicates the detected face, while the red box represents the ROI used for temperature extraction (scaling factor = 0.1 on the left and 1.0 on the right). The smaller ROI (0.1) corresponds to an area 100 times smaller than the full bounding box, enabling more localized and precise temperature averaging. The overlaid labels on the images indicate the maximum, minimum, and center facial temperatures, and the ROI scale is also displayed.

Netatmo readings were collected simultaneously with face detection. These measurements were integrated into the logic via the Netatmo API. Whenever the webcam detects a face within the frame, both the average face temperature and Netatmo sensor measurements are recorded with time and date in a text file, which is updated every 5 seconds. Figure 3.6 presents the corresponding logic flow chart.

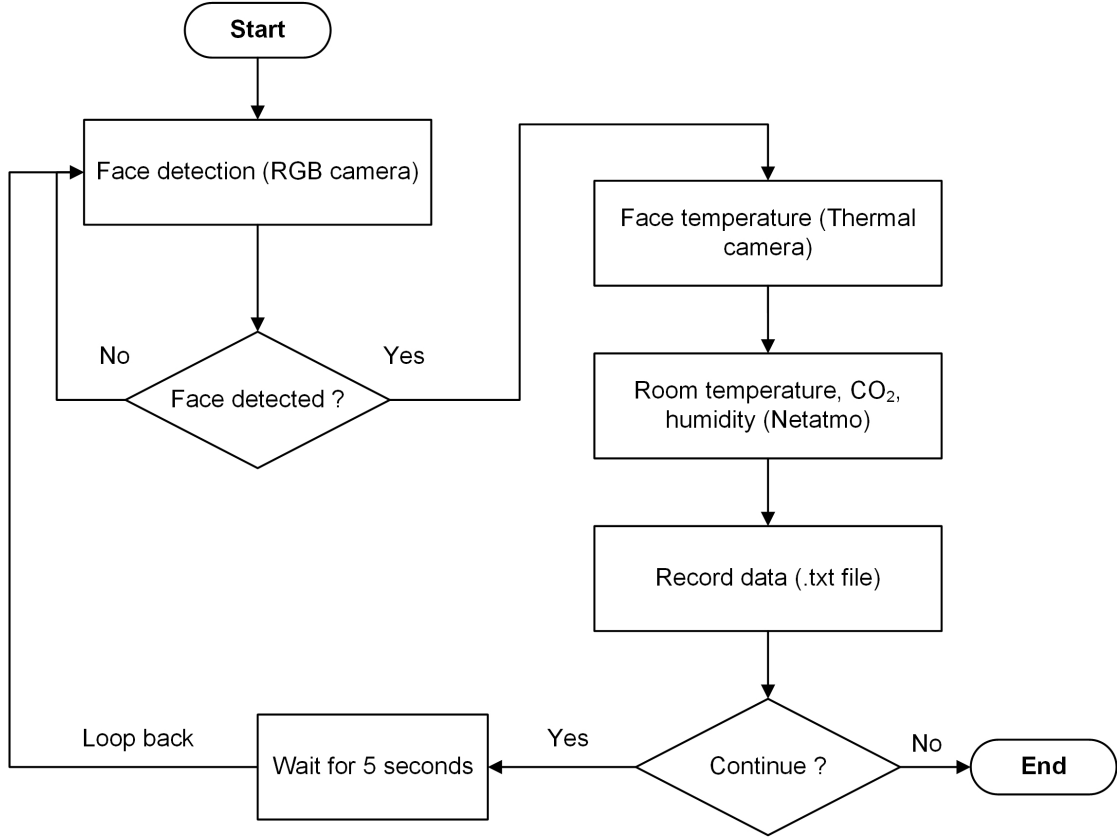


FIGURE 3.6: Face detection and thermal measurement process flowchart. The RGB face detection loops run continuously and upon detection of a face triggers the remaining steps in the workflow. To avoid overloading the processing unit and air quality sensors, a five second wait is added after each successful reading.

Calibration of the Topdon TS001

Prior to the experiment, the Topdon TS001 was checked for temperature accuracy. Calibration was performed against a Sentry TS663 (Sentry Optronics Corp., Ban-Ciao (Taipei), Taiwan, R.O.C.) infrared temperature sensor using the Hierarchical Linear-Polynomial Mapping (HLPM) method. Measurements are traceable to the SI via the Measurement Standards Laboratory (MSL), New Zealand. A blackbody with a 35 mm aperture (0–90 °C range) was used; ambient conditions were maintained at 20 ± 2 °C and instrument readability was 1 °C. For the TS001 calibration, temperatures from the TS001 and TS663 were recorded at five setpoints between 30 °C and 35 °C, with both instruments positioned 0.5 m from the target and an indicated readability of 0.5 °C. Measured values were within the ± 1 °C tolerance.

At a camera-to-subject distance of 0.5 m, the thermal camera field-of-view covers approximately $0.53 \text{ m} \times 0.38 \text{ m}$ (H $\times$ V), while the RGB camera covers approximately

0.78 m $\times$ 0.44 m. This FOV ensures full facial coverage in both modalities, providing sufficient resolution for accurate region-of-interest-based temperature extraction.

3.3 Results and Discussion

The experimental setup was tested over a period of one week to ensure that the temperature readings remained within the expected range. The test was carried out multiple times to ensure that the results were consistent for validation purposes. Each test lasted 40 minutes, with the participant seated in front of the camera to ensure proper face detection while the thermal camera recorded the average facial temperature. The distance between the participant and the thermal camera/ web camera was maintained at 0.5 m in a sitting position. The camera tripod was set at a height of 1.2 m. The age of the participant was 36 years and a slight beard was preferred to see the thermal affect and notice variation in temperature on the facial measurements. As shown in Figure 3.3, windows were opened or closed, and the heat pump setpoint temperature was adjusted to modify the room temperature. The wall-mounted Netatmo sensors recorded these temperature changes. Once the room temperature stabilized and the occupant adapted to the indoor environmental conditions, the average face temperature was measured, and thermal images of the face were captured. The room dimensions were 3 m (L) $\times$ 3 m (W) $\times$ 2.4 m (H). The ambient temperature for the room was in the range of 17°C to 19°C. Before the start of the experiment, the ambient temperature for the room was controlled to 15°C by opening the windows as the outside ambient temperature was lower than the room temperature. Once the room temperature was set to 15,°C, the windows were closed, and an electric heater (2 kW) was used to gradually increase the room temperature to 25,°C. The entire process took approximately 40 minutes, and the results were recorded.

During the testing period, the outside ambient temperature ranged from 1°C to 6°C at night and 8°C to 13°C during the day. The participant wore casual clothing. The results were recorded in a text file every 5 s, resulting in 480 measurements over each 40 minute test. Table 3.3 summarizes the results, which were also recorded at 5 minute intervals during the testing period.

During the test, the participant's facial temperature changed in response to variations in room temperature. The thermal images captured at each degree of change reflected these variations. On the thermal scale, yellow indicates cooler regions of the face, while red indicates warmer areas. According to Fanger's PMV model parameters, air velocity and clothing insulation remained constant throughout the experiment. However, relative humidity, air temperature, mean radiant temperature, and metabolic rate varied.

Although real-time metabolic rate was not measured in this experiment, changes in metabolic rate can be inferred from the facial thermal images, as metabolic rate corresponds to the rate at which the body produces heat. The shifting yellow and red regions on the face indicate biological responses to maintain core temperature, contributing to occupant comfort.

TABLE 3.3: Summary of room temperature, facial temperature, CO₂, humidity, and thermal images. Each block shows four repeated measurements followed by a mean $\pm$ standard deviation row.

Room Temp (°C)	Face Temp (°C)	CO ₂ (ppm)	RH (%)	Thermal Image
15.2, 15.8,	28.79, 29.20,	667, 673,	52, 53,	
15.9, 15.3	28.90, 28.70	673, 680	53, 53	
1-4 15.55 $\pm$ 0.36	28.90 $\pm$ 0.22	673 $\pm$ 6	53.0 $\pm$ 0.0	
16.2, 16.4,	29.89, 30.84,	533, 631,	61, 61,	
16.7, 16.7	30.43, 30.45	626, 680	61, 61	
1-4 16.50 $\pm$ 0.24	30.40 $\pm$ 0.39	615 $\pm$ 68	61.0 $\pm$ 0.0	
17.0, 17.1,	29.44, 29.61,	626, 621,	60, 60,	
17.3, 17.8	29.81, 30.90	626, 680	60, 60	
1-4 17.30 $\pm$ 0.36	29.94 $\pm$ 0.66	638 $\pm$ 26	60.0 $\pm$ 0.0	
18.0, 18.1,	30.72, 30.90,	722, 726,	59, 59,	
18.3, 18.8	31.10, 30.72	745, 748	59, 59	
1-4 18.30 $\pm$ 0.36	30.86 $\pm$ 0.18	735 $\pm$ 26	59.0 $\pm$ 0.0	
19.0, 19.3,	30.65, 31.10,	722, 726,	59, 59,	
19.4, 19.8	31.89, 32.05	745, 748	59, 59	
1-4 19.38 $\pm$ 0.33	31.42 $\pm$ 0.66	735 $\pm$ 26	59.0 $\pm$ 0.0	
20.7, 20.7,	30.89, 31.18,	752, 760,	58, 58,	
20.7, 20.8	30.49, 32.08	769, 763	58, 58	
1-4 20.73 $\pm$ 0.05	31.16 $\pm$ 0.68	761 $\pm$ 7	58.0 $\pm$ 0.0	
21.4, 21.4,	32.61, 33.72,	780, 797,	56, 56,	
21.9, 21.9	33.03, 33.65	795, 800	56, 56	
1-4 21.65 $\pm$ 0.29	33.25 $\pm$ 0.53	793 $\pm$ 10	56.0 $\pm$ 0.0	
22.3, 22.3,	33.29, 33.02,	805, 810,	55, 55,	
22.6, 22.6	32.98, 33.39	821, 821	55, 55	
1-4 22.45 $\pm$ 0.15	33.17 $\pm$ 0.20	814 $\pm$ 9	55.0 $\pm$ 0.0	
23.5, 23.5,	33.57, 33.51,	1020, 1020,	48, 48,	
23.5, 23.5	33.84, 33.66	1020, 1020	48, 48	
1-4 23.50 $\pm$ 0.00	33.64 $\pm$ 0.14	1020 $\pm$ 0	48.0 $\pm$ 0.0	
24.5, 24.5,	33.85, 33.96,	1031, 1031,	48, 48,	
24.5, 24.5	33.43, 33.29	1031, 1031	48, 48	
1-4 24.50 $\pm$ 0.00	33.63 $\pm$ 0.32	1031 $\pm$ 0	48.0 $\pm$ 0.0	

In Fanger's model, mean radiant temperature is typically calculated from the surface temperatures of the environment without considering skin temperature. However, recent research supports combining environmental parameters with physiological measurements, such as skin temperature, to achieve more accurate and personalized assessments of thermal comfort [43, 44]. In this experiment, environmental temperatures were not calculated; the focus was solely on analyzing real-time changes in facial temperature to determine occupant comfort.

Figure 3.7 shows screenshots of the participant's thermal images at different room temperatures. The thermal images illustrate that as room temperature decreases, the red regions on the face (indicating higher temperature) diminish while yellow regions (indicating lower temperature) appear. An increase in yellow regions corresponds with the participant feeling cold, while an increase in red regions corresponds with the participant feeling warm.

The following factors must be considered when analyzing the results, as they can affect the accuracy of the data presented:

1. Accuracy of the thermal measurement via the thermal camera;
2. Accuracy of the indoor temperature sensor;
3. Location of the sensors;
4. Participant distance from the camera;
5. Metabolic rate of the participant.

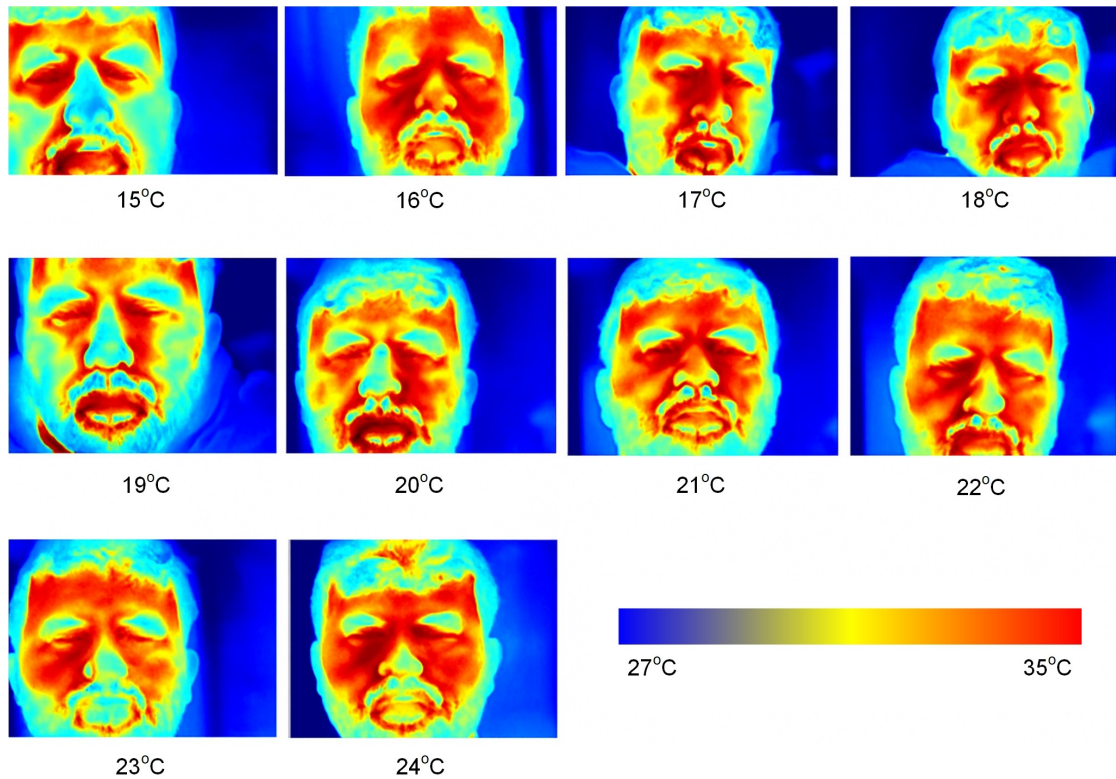


FIGURE 3.7: Thermal images of the participant's face at different room temperature setpoints, illustrating changes in facial heat distribution. Pixel-level temperature extraction and averaging within the defined region of interest (ROI) were performed algorithmically. A horizontal color bar is included to indicate the temperature scale used across all thermal images. Image labels denote the corresponding average room temperatures.

During the experiment, the participant's position, as well as the locations of the thermal camera and indoor temperature sensors, were kept consistent. However, the accuracy of the equipment must still be considered. With the limited budget for this experiment, results could have been more precise if devices with higher accuracy and lower tolerance had been used. According to the datasheet for the Topdon TS001 thermal camera, the accuracy is $\pm 3^{\circ}\text{C}$ [45]. Another limitation that need to be considered, while analyzing the results is metabolic rate. For the research purpose, metabolic rate measurement was not considered as at the time of the experiment, we did not have the setup to measure it. However, in order to keep the metabolic rate consistent, the participant's measured data was collected in sitting conditions (1.0–1.2 m) during the complete experiment [46]. The participant was given the same set of clothes during the experiment and his distance from the measuring device was kept constant. The experiment was conducted during night time to avoid any influence of window glare/reflection. Figure 3.8 shows the plots for all Netatmo sensors, while Figure 3.9

shows the average room temperature and its relation to average facial temperature. The plot shows a general upward trend: as room temperature increases, average face temperature also increases. Although the relationship is not perfectly linear, it suggests a stepwise response, indicating that facial temperature reacts to changes in room temperature.

The “stepwise” pattern observed in the relationship between room temperature and facial temperature (Figures 3.8 and 3.9) can be attributed to both physiological responses and measurement artifacts. Physiologically, the human body regulates skin blood flow and sweating in discrete steps as environmental conditions change, leading to non-linear, stepwise adjustments in facial skin temperature [47, 48]. This is consistent with thermoregulatory literature, where skin temperature does not always change smoothly but can exhibit plateaus or sudden shifts in response to thermal stimuli [49]. Alternatively, the stepwise pattern may partially result from measurement artifacts, such as the resolution limits of the TS001 thermal camera ($\pm 3^\circ\text{C}$ accuracy), or from averaging effects when calculating mean facial temperature across frames.

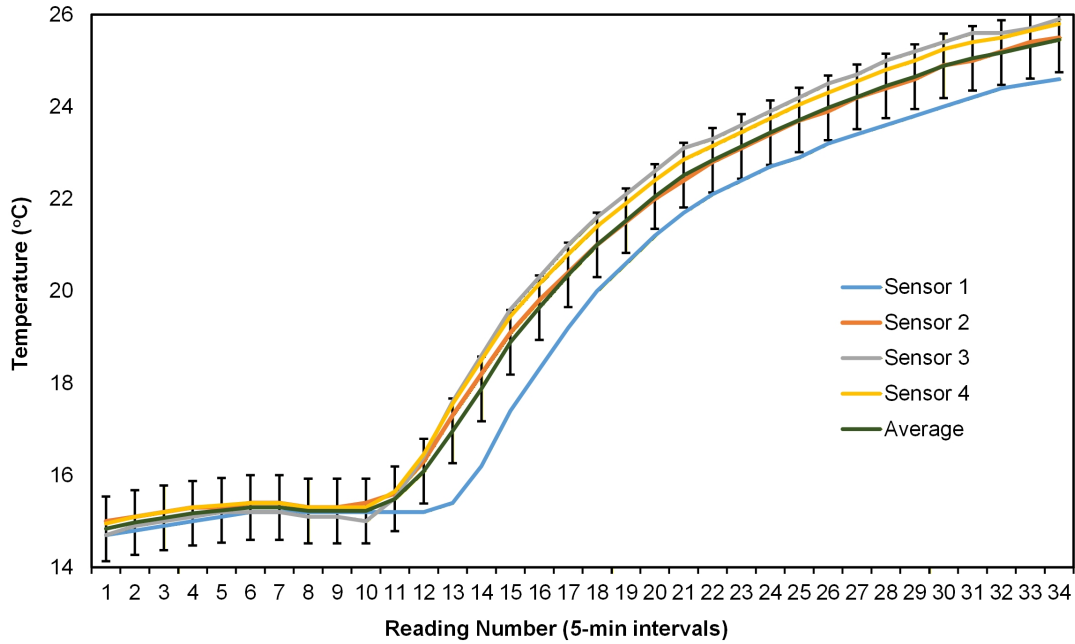


FIGURE 3.8: Temperature measurements recorded by four Netatmo indoor air-quality sensors placed at different locations inside the test room. Each line represents the temperature profile at 5-min intervals during the controlled heating cycle. Error bars represent variability across repeated measurements and are shown for both individual sensors and the averaged temperature curve. The results demonstrate consistent spatial temperature trends as the room warmed from 15°C to 24°C .

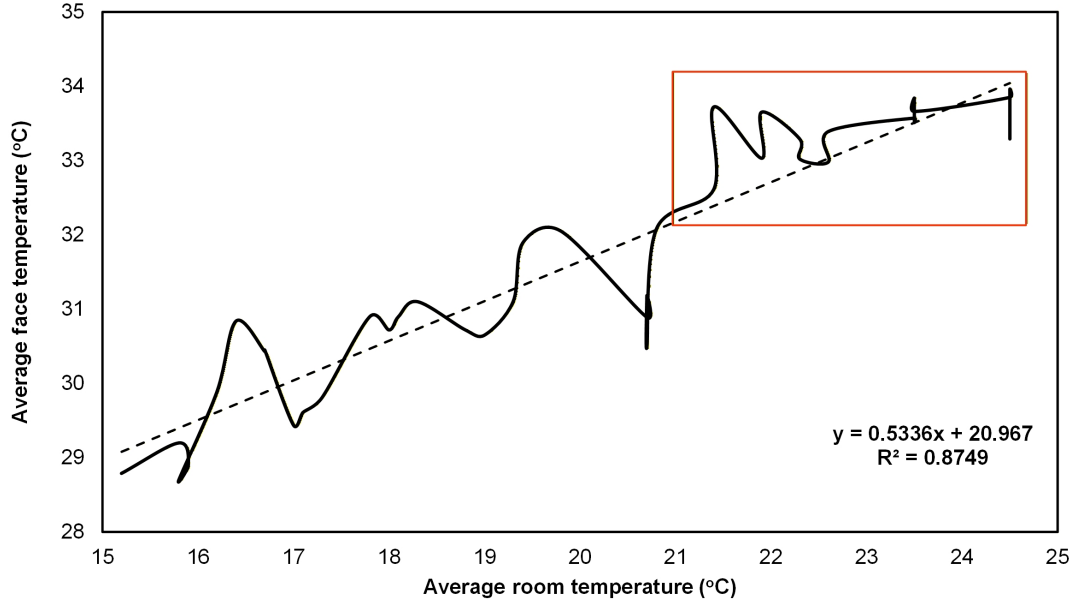


FIGURE 3.9: Relationship between average room temperature and average facial temperature during a experiment. The solid line represents the facial temperature response, and the dashed line indicates a linear trend fit ($R^2 = 0.8749$). The highlighted region indicates the upper-temperature range where facial temperature stabilizes as room temperature approaches warmer comfort levels.

Our findings align with previous studies: Zhang [24] and Brager & de Dear [14] both report that facial skin temperatures in the range of 32–34 °C are associated with thermal comfort. The observed comfort range in this study (room temperature 21–25 °C, facial temperature 32–34 °C) is consistent with these references, supporting the validity of our approach. However, the experiment was conducted during winter with a single subject, which limits the generalizability of the results to other seasons and populations.

From a practical perspective, the demonstrated relationship between room and facial temperature suggests that real-time facial temperature monitoring could be integrated into HVAC control logic. By targeting occupant facial comfort, building systems could adapt setpoints dynamically, potentially improving both comfort and energy efficiency. However, the accuracy limitations of the TS001 camera and the single-subject, winter-only dataset mean that further validation is needed before widespread adoption.

Based on the observed facial temperature range of 32 °C to 34 °C, the corresponding room temperature was between approximately 21 °C and 25 °C. This range can be considered satisfactory for occupant comfort, consistent with findings from previous studies. Zhang [24] reports that 32 °C to 34 °C is a comfortable facial temperature,

and Brager and de Dear [14] indicate that comfort facial skin temperature is around 33°C .

As highlighted with a red box on the average room temperature vs. average facial temperature plot in Figure 3.9, it can be concluded that during hot days, occupant facial comfort should be maintained around 32°C (indoor room temperature 21°C), and during cold days, facial comfort should be maintained around 34°C (indoor room temperature 24°C). From Figure 3.7, facial temperature was observed within the range of 21°C to 24°C . Since the experiment was conducted during winter, these findings primarily reflect comfort in colder conditions. The participant reported facial discomfort when the room temperature dropped below 18°C but reported no discomfort at temperatures above 20°C .

This experimental result allows researchers to control room temperature for occupant comfort based on facial temperature. Depending on the chosen control strategy, temperature regulation can be implemented using two methods:

1. Temperature control directly via face temperature;
2. Temperature control via wall-mounted temperature sensors using a face temperature factor.

In Option 1, the system continuously adjusts the room temperature based on facial temperature measurements from multiple occupants or frequent changes in an occupant's metabolic rate (e.g., during exercise). The temperature setpoint responds rapidly, as the HVAC unit's heating and cooling valves are constantly modulated to achieve the desired comfort temperature.

In Option 2, the system operates more stably, as room temperature is adjusted using a face temperature factor. This factor defines a bandwidth for the temperature setpoint, allowing adjustments in intervals and resulting in a smoother transition to the occupant's comfort temperature.

In complex building temperature control systems, other factors, such as IAQ parameters and humidity, are also considered when designing control strategies. In this experiment, only the relationship between room temperature and facial temperature was established, as temperature primarily determines how hot or cold the air feels and directly affects

occupant comfort. IAQ and humidity are generally homogeneous within a space, with minimal variation observed in the measured results. As room temperature increases, CO₂ levels also rise, indicating that the mechanical system should increase fresh air flow to maintain acceptable CO₂ levels. Humidity remained within the acceptable range. In cases of high indoor humidity, the mechanical system should dehumidify the air, whereas excessively dry conditions require humidification.

3.4 Conclusions

This paper presents an experimental analysis of facial temperature versus wall-mounted temperature sensors using a low-cost thermal camera. The results indicate a stepwise relationship between facial temperature and room temperature. Other factors, such as clothing and metabolic rate, must also be considered, as they can influence the results. It should be noted that to maintain the body's core temperature, rapid changes in blood flow occur across different body parts, which can further affect the relationship between facial temperature and indoor room temperature. The primary reason for measuring facial temperature as a reference for occupant comfort is that the face is generally uncovered and directly exposed to the indoor environment, making it a reliable indicator of thermal conditions.

The experimental results provide an alternative method to measure occupant temperature in real time. This approach allows for continuous monitoring of facial temperature for multiple occupants whenever a face is detected. Furthermore, it enables early detection of discomfort, as the measurements are directly obtained from occupants rather than inferred from average room temperature. Based on the thermal camera specifications, this method allows for a wider range of temperature measurements compared to wall-mounted sensors, occupant feedback, or wearable devices. Finally, this approach offers the potential to optimize HVAC control by delivering real-time occupant comfort data to the control logic rather than relying solely on return air temperature or average room temperature. Using facial temperature measurements for HVAC control can improve occupant focus, productivity, and well-being.

The study identified a clear link between room temperature and facial skin temperature, with optimal comfort generally occurring when facial temperatures are between 32 and

34 °C. The RGB-T system, built on a Raspberry Pi platform, proved effective for continuous facial detection and temperature tracking. This approach holds potential for integration with building management systems to support HVAC adjustments based on occupant comfort. Nonetheless, factors such as where sensors are placed, the distance from the camera, and individual physiological variations can still impact measurement accuracy.

For future work, it is important to conduct studies involving multiple occupants, assess system performance throughout different seasons, and develop closed-loop control mechanisms to further improve energy efficiency and comfort, in line with best practices in the buildings sector. Moreover, incorporating skin temperature data into the calculation of mean radiant temperature within Fanger's PMV model could enable dynamic, real-time adjustments to indoor temperature settings. By merging real-time skin temperature readings with environmental data, thermal comfort evaluations can become more precise and tailored to occupant needs. As this investigation involved a single participant in winter conditions, the findings should be viewed as preliminary; broader seasonal and demographic studies are required to validate and generalize the observed trends.

Future research should explore integrating skin temperature into the mean radiant temperature calculation in Fanger's PMV model. This integration would enable real-time adjustments to temperature setpoints in indoor environments to better meet occupant thermal comfort needs. Combining skin temperature with environmental factors in real time will further enhance the accuracy and personalization of thermal comfort assessments.

This research explores the use of an affordable RGB-T system for tracking facial temperature in real time, supplying supplementary data to inform building HVAC operations. The study's key innovation lies in integrating accessible hardware (Topdon TS001, webcam- Grandstream GUV 3100, Raspberry Pi) with a facial detection workflow to monitor how occupants' thermal states respond to environmental changes. Future investigations should address calibration with standard references, assess performance with multiple occupants across different climate scenarios, and implement closed-loop HVAC trials to determine actual benefits for energy efficiency and occupant comfort.

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Chapter 4

Low-Cost BACnet-Enabled Raspberry Pi Controller for Adaptive Indoor Environmental Management

Chapter 4 builds on the validated sensing outcomes of Chapter 3 by integrating the RGB-T platform into a BACnet enabled control architecture and reporting system level experimental results on adaptive, real-time occupant centric HVAC operation, thereby showing how physiological sensing can be converted into actionable control decisions in building environments.

Abstract

This study presents a comprehensive evaluation of adaptive control strategies for building management systems (BMS), emphasizing the integration of low-cost, open-source hardware and real-time physiological sensing. The research systematically investigates the capabilities of the Raspberry Pi as a BACnet-enabled device, demonstrating its dual functionality as both a master controller and a sensor for occupant-centric building automation. A RGB-T facial temperature monitoring setup is implemented, enabling direct measurement of occupant thermal comfort and facilitating dynamic

HVAC control through adaptive control strategies for room temperature. Experimental validation in both simulated and operational environments confirms seamless BACnet interoperability, rapid object updates, and reliable network performance. The system utilizes real-time facial temperature data as the primary input for dynamic HVAC setpoint adjustment, with a robust fallback mechanism based on room temperature trends to ensure continuous comfort when there is no facial detection. Results reveal that traditional static thermal comfort models, such as Fanger's PMV, are limited in capturing the dynamic and personalized nature of human comfort. Incorporating real-time physiological data and adaptive control logic significantly improves comfort prediction and energy efficiency. The findings underscore the potential of affordable, flexible solutions to advance occupant-centric, energy-efficient building management in modern environments.

4.1 Introduction

In modern buildings, building management systems (BMS) are designed to control, optimize, and monitor building services. BMS can enhance operational efficiency, reduce building energy consumption, and improve occupant comfort in real time. Based on building designs, BMS can provide integrated solutions for controlling heating, ventilation, and air conditioning (HVAC), security, lighting, and energy management [1–3].

With the introduction of adaptive control in BMS, building services can dynamically respond to real-time changes in occupancy, environmental conditions, and user preferences [4]. Adaptive control enables low-cost sensors and processing devices to integrate with the BMS via open communication protocols such as the Building Automation and Control Network (BACnet) to collect data for analytics and to control and optimise services such as HVAC to suit occupant comfort in real time. Proper utilization of adaptive control in BMS can result in smart, aware, and adaptable buildings [5, 6].

BACnet communication enables flexible deployment across various network structures, including IP-based and serial communication. Both physical and virtual data points are defined in an object-oriented architecture that can be monitored or controlled by building controllers in reliable, scalable, and vendor-neutral automation solutions [7].

Implementation of adaptive control in BMS for facilities is often limited by the high cost of control and monitoring sensors, leading to poor energy management and occupant comfort. Low-cost solutions offer clients the option to integrate open-source hardware, such as Raspberry Pi, to enable intelligent building automation [8, 9]. These solutions reduce initial investment and maintenance expenses, making adaptive control and real-time monitoring feasible for a broader range of buildings.

In this paper, the capabilities of the Raspberry Pi as a BACnet-enabled device were systematically evaluated to demonstrate its effectiveness as a low-cost building controller, successfully replicating the core functionalities typically found in commercial building automation systems. Complementing this, the study presents the practical integration of a low-cost RGB-T facial temperature monitoring setup, with the Raspberry Pi configured as a BACnet sensor to enable real-time acquisition and transmission of occupant thermal comfort data. This dual demonstration highlights the versatility of the Raspberry Pi, confirming its suitability as an adaptive sensor platform for occupant-centric building management, while also evaluating its capability as a master controller for future adaptive control applications, offering a promising low-cost alternative to conventional high-cost solutions. The results demonstrate the significant potential of affordable, open-source hardware to enhance adaptive control strategies and enable real-time optimization of occupant thermal comfort in modern building environments.

This contribution is positioned as a logical progression of the earlier evidence by developing a framework to enable integration with building controllers, while preserving alignment with the central objective.

4.2 Literature Review

Contemporary building environmental control systems exhibit considerable diversity in complexity and functionality. Basic systems typically comprise individual components such as light switches, thermostats, and standalone indoor air quality monitoring devices. In contrast, advanced building management systems provide comprehensive integration of HVAC controls, lighting systems, security infrastructure, and environmental monitoring stations [10].

Room and building sensors are physically connected to programmable logic controllers (PLCs), which are then networked via Ethernet or serial communication to other PLCs and to a supervisory system such as a graphical user interface (GUI) or Supervisory Control and Data Acquisition (SCADA) platform. Additionally, smart home devices and IoT applications can manage indoor environments. However, IoT-based applications and smart home devices often lack robustness and reliability and have limited real-time control compared to BMS [10, 11].

The BACnet protocol is accepted worldwide due to its open, interoperable, and vendor-neutral design. Its object-oriented structure enables the exchange of standardized data and control commands, simplifying the implementation of control and monitoring systems. BACnet enables facility managers to optimise building performance, enhance occupant comfort, and improve energy efficiency through GUI-based BMS setup. ASHRAE Standard 135 and ISO 16484-5 recognize BACnet as an international standard for building and automation controls [12, 13].

Room temperature is commonly measured using wall-mounted temperature sensors, but these often fail to reflect true occupant comfort due to poor placement and interference from heat sources. To address this limitation, a Raspberry Pi BACnet sensor system using RGB-T facial temperature monitoring will be used. This approach enables direct measurement of occupant thermal comfort and allows for more precise HVAC control [14]. Limited attention is given to low-cost, open-platform solutions that can be achieved using computers like Raspberry Pi. Raspberry Pi remains underexplored, particularly for adaptive and real-time control in buildings [15–17].

Facial monitoring system (RGB-T), when integrated with Raspberry Pi platforms as a sensor, enables direct measurement of facial temperature for real-time occupant comfort assessment [14]. Thermal image processing and face detection allow these systems to convert temperature data into BACnet format, facilitating adaptive HVAC control. This approach offers improved accuracy compared to traditional wall-mounted sensors and enables more responsive real-time building management.

Occupant thermal comfort is an essential parameter for indoor building environments. Wall-mounted temperature sensors measure the surface temperature of the RTD (resistance temperature detector), which may be an inaccurate indicator of the occupant's thermal comfort requirements. Moreover, wall-mounted sensors can measure false room

temperature when located in areas with multiple energy sources, such as a heater, printer, table lamp, or window glaze, which can alter the actual room temperature conditions [18, 19]. To overcome these challenges and achieve more precise room thermal comfort for occupants, facial temperature measurements can be utilized as a direct indicator to derive occupant thermal comfort.

Occupant thermal comfort is calculated using the Fanger predictive mean vote (PMV) model during the building design stage. Fanger established a mathematical formula for thermal comfort with six parameters: air temperature, radiation temperature, relative humidity, wind speed, clothing thermal resistance, and metabolic rate [20, 21]. Recent research highlights that Fanger’s PMV model often fails to capture the complex, dynamic nature of human thermal comfort in buildings. In Fanger’s model, clothing thermal resistance and metabolic rate are assumed to be constant, which may not reflect real-time thermal comfort requirements [22].

A healthy individual typically has an internal core body temperature near 36.7°C . To maintain this temperature, the body automatically initiates various processes, such as altering blood flow near the skin to balance heat levels [17, 23–26]. These adjustments result in physical sensations like feeling warm, sweating, feeling cold, or shivering—which can be observed as changes in skin temperature and serve as indicators of how comfortable a person feels indoors [27–29].

Systematic reviews and revised models demonstrate that incorporating nonlinearity and real-time physiological data—such as skin temperature and metabolic rate—significantly improves the accuracy and responsiveness of comfort predictions [22, 30, 30, 31]. Real-time facial temperature is a direct measurement of skin temperature. Skin temperature is a key indicator of thermal balance, as it is influenced by metabolic rate and clothing insulation [32, 33]. Advanced approaches, including machine learning and adaptive physiological models, enable control systems to reflect occupant needs under varying and personalized conditions more effectively. These findings underscore the critical importance of adaptive control strategies that dynamically respond to both environmental and occupant-specific variables, thereby ensuring personalized comfort and greater energy efficiency in modern building environments.

Table 4.1 summarizes the relationship between facial skin temperature, clothing insulation, and metabolic rate according to Fanger’s thermal comfort model.

TABLE 4.1: Relationship between metabolic rate, clothing insulation, and mean skin temperature (adapted from Fanger, 1970).

Metabolic Rate (met)	Clothing Insulation (clo)	Mean Skin Temperature (°C)	Example Activity
1.0	0.5	32.5	Seated, light clothing
1.0	1.0	33.0	Seated, standard clothing
1.0	1.5	33.5	Seated, warm clothing
1.2	0.5	32.0	Standing, light clothing
1.2	1.0	32.5	Standing, standard clothing
1.2	1.5	33.0	Standing, warm clothing
2.0	0.5	31.5	Light exercise, light clothing
2.0	1.0	32.0	Light exercise, standard clothing
2.0	1.5	32.5	Light exercise, warm clothing

Generally, when an occupant engages in physical activity, their internal heat production increases. As a result, the facial skin temperature decreases due to increased sweating and vasodilation, which promote heat loss from the skin. When clothing insulation is low, body heat dissipates quickly, thereby lowering facial skin temperature. However, when clothing insulation is high, body heat is trapped, and the facial skin temperature rises due to reduced heat dissipation. In comfortable environments, the facial skin temperature typically ranges between 32 °C and 34 °C [25].

In summary, when metabolic rate increases, the occupant’s facial skin temperature decreases due to increased internal heat dissipation. As clothing insulation increases, the facial skin temperature rises because the body heat is trapped.

4.3 Materials and Methods

The experimental methodology was structured in two distinct phases, each aimed at rigorously assessing the BACnet communication capabilities of the Raspberry Pi as both a sensor and a controller, which are fundamental to the implementation of the adaptive control strategy detailed in the results section. In phase one, the Raspberry Pi was configured as a BACnet sensor, with occupant facial temperature measurements programmed as primary thermal comfort indicators. This approach demonstrated the feasibility of integrating low-cost physiological sensing into commercial building automation systems, directly supporting the adaptive setpoint determination reported in the results section.

Phase two focused on controller capabilities, reconfiguring the Raspberry Pi as a BACnet master controller to enable command and control over networked devices. The controller function was tested on a simulated local network, validating the supervisory control functions within the BACnet network hierarchy of a low-cost controller. Due to potential security and operational concerns, the implementation of the Raspberry Pi as a controller within the commercial building network was not pursued. For future applications, the Raspberry Pi can be used as a building controller to implement the adaptive control strategy, as demonstrated by its configuration as a sensor in this study.

Systematic validation of BACnet communication on a low-cost device as both a sensor and a controller highlights its capability to support adaptive control strategies, enabling real-time responsiveness and dynamic setpoint adjustment as demonstrated by the experimental outcomes.

4.3.1 Experiment Stage 1: Adaptive Control via Raspberry Pi Sensor Integration

4.3.1.1 BACnet Setup

The Raspberry Pi was configured as a BACnet-compliant sensor, serving as the core of the adaptive control strategy by enabling synchronous acquisition of facial thermal and ambient measurements. These data were processed into BACnet-readable format for seamless integration with commercial building controllers, supporting real-time adaptive setpoint determination. Figure 4.1 illustrates the experimental network topology, which uses Ethernet-based protocols to enable robust data exchange between the thermal monitoring system and the building management infrastructure.

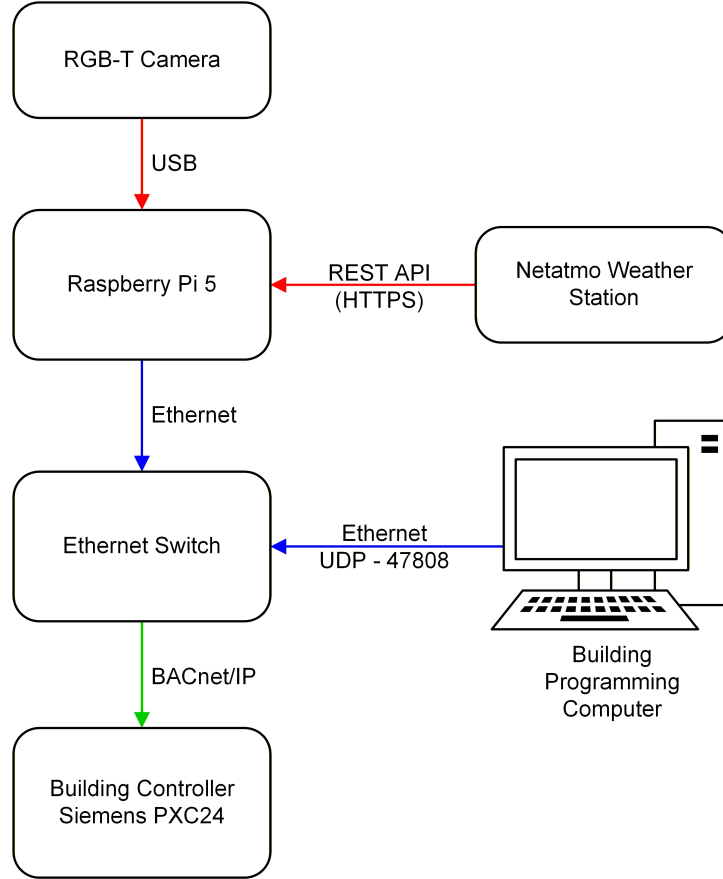


FIGURE 4.1: System/Network Architecture.

This implementation builds upon previously established facial temperature measurement methodology [14], extending it with novel BACnet protocol integration for building automation. The BACnet communication protocol was established using Python's BACpypes library, creating a building automation-compliant sensor node (see Figure 4.2). Device initialization included standardized parameters for compatibility, and advanced network auto-detection algorithms ensured robust connectivity across diverse infrastructures.

The system implemented 14 BACnet objects, including analog value objects for thermal and environmental measurements and binary value objects for system status monitoring. The critical innovation was the ultra-high-frequency update rate (10 Hz), which enabled real-time adaptive comfort control and full BACnet stack operation, facilitating integration with existing building management systems.

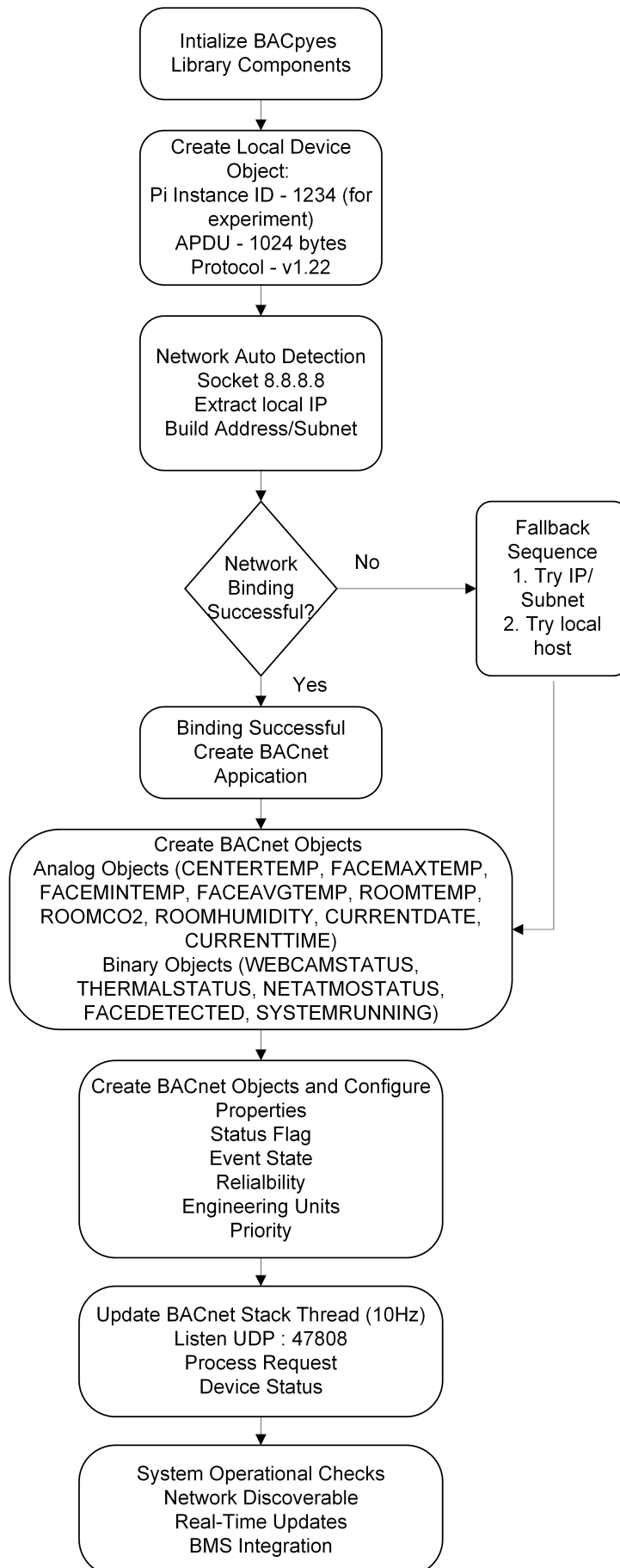


FIGURE 4.2: BACnet communication protocol establishment flowchart illustrating systematic device initialization and network auto-detection for robust connectivity.

4.3.1.2 Sensor Setup

Netatmo API integration utilized OAuth2 authentication for secure environmental data acquisition, targeting the `getstationsdata` endpoint at synchronized intervals:

$$\text{API Request Rate} = \frac{1}{t_{\text{interval}}} = \frac{1}{5 \text{ seconds}} = 0.2 \text{ Hz} \quad (4.1)$$

Thermal sensor calibration converted 16-bit data to absolute temperature:

$$T_{\text{celsius}} = \frac{(H_{\text{byte}} + L_{\text{byte}} \times 256)}{64} - 273.15 \quad (4.2)$$

Environmental validation ensured data quality through range-checking:

$$T_{\text{ambient,valid}} = \{T_{\text{amb}} : -40^{\circ}\text{C} \leq T_{\text{amb}} \leq 60^{\circ}\text{C}\} \quad (4.3)$$

$$\text{CO}_{2,\text{valid}} = \{\text{CO}_2 : 400 \text{ ppm} \leq \text{CO}_2 \leq 5000 \text{ ppm}\} \quad (4.4)$$

$$\text{RH}_{\text{valid}} = \{\text{RH} : 0\% \leq \text{RH} \leq 100\%\} \quad (4.5)$$

Coordinate transformation aligned RGB facial detection with thermal resolution:

$$x_{\text{thermal}} = x_{\text{RGB}} \times \frac{W_{\text{thermal}}}{W_{\text{crop}}} \quad (4.6)$$

$$y_{\text{thermal}} = y_{\text{RGB}} \times \frac{H_{\text{thermal}}}{H_{\text{crop}}} \quad (4.7)$$

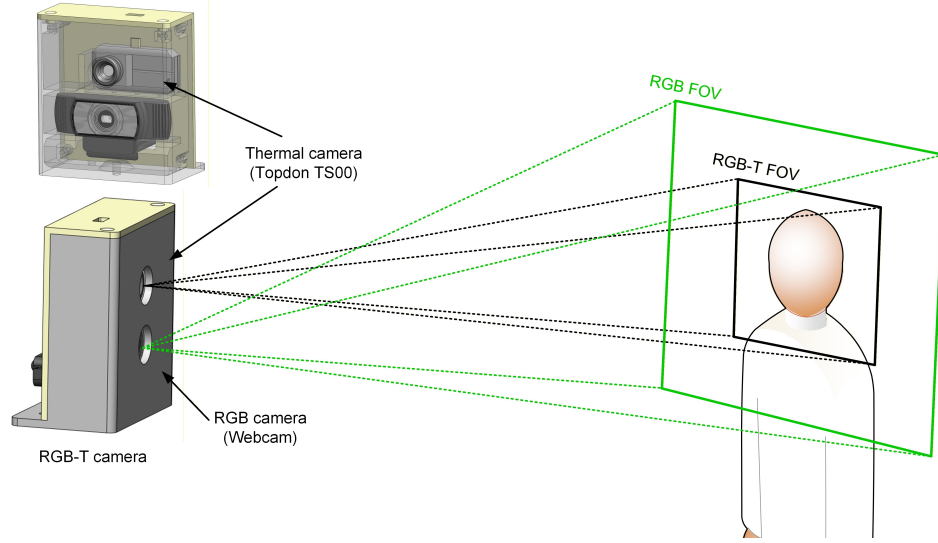


FIGURE 4.3: RGB-T camera setup with ROI. The visible (RGB) frame is used for face detection and the detected bounding box is mapped to the thermal frame; the scaled forehead ROI (shown) is used for robust temperature extraction.

Building upon established methodology [14], ROI mapping (Figure 4.3) enabled geometric correspondence between RGB facial detection and thermal temperature measurement. Synchronized environmental monitoring was achieved with 2-second temporal correlation:

$$\Delta t_{\text{sync}} = |t_{\text{facial}} - t_{\text{netatmo}}| \leq 2 \text{ seconds} \quad (4.8)$$

Data logging captured synchronized measurements for BACnet transmission:

$$\text{Data Record} = \{t, T_{\text{facial}}, T_{\text{ambient}}, \text{CO}_2, \text{RH}, \text{Status}\} \quad (4.9)$$

Post-experimental statistical analysis enabled quantitative assessment of parameter interdependencies through Pearson correlation coefficients:

$$\text{Correlation Matrix} = \begin{bmatrix} \rho(T_{\text{facial}}, T_{\text{ambient}}) & \rho(T_{\text{facial}}, \text{CO}_2) & \rho(T_{\text{facial}}, \text{RH}) \\ \rho(T_{\text{ambient}}, \text{CO}_2) & 1 & \rho(\text{CO}_2, \text{RH}) \\ \text{sym} & \text{sym} & 1 \end{bmatrix} \quad (4.10)$$

Figure 4.4 presents a comprehensive breakdown of the system process flow in a block diagram format, illustrating the sequential data processing stages from sensor inputs to building management system integration.

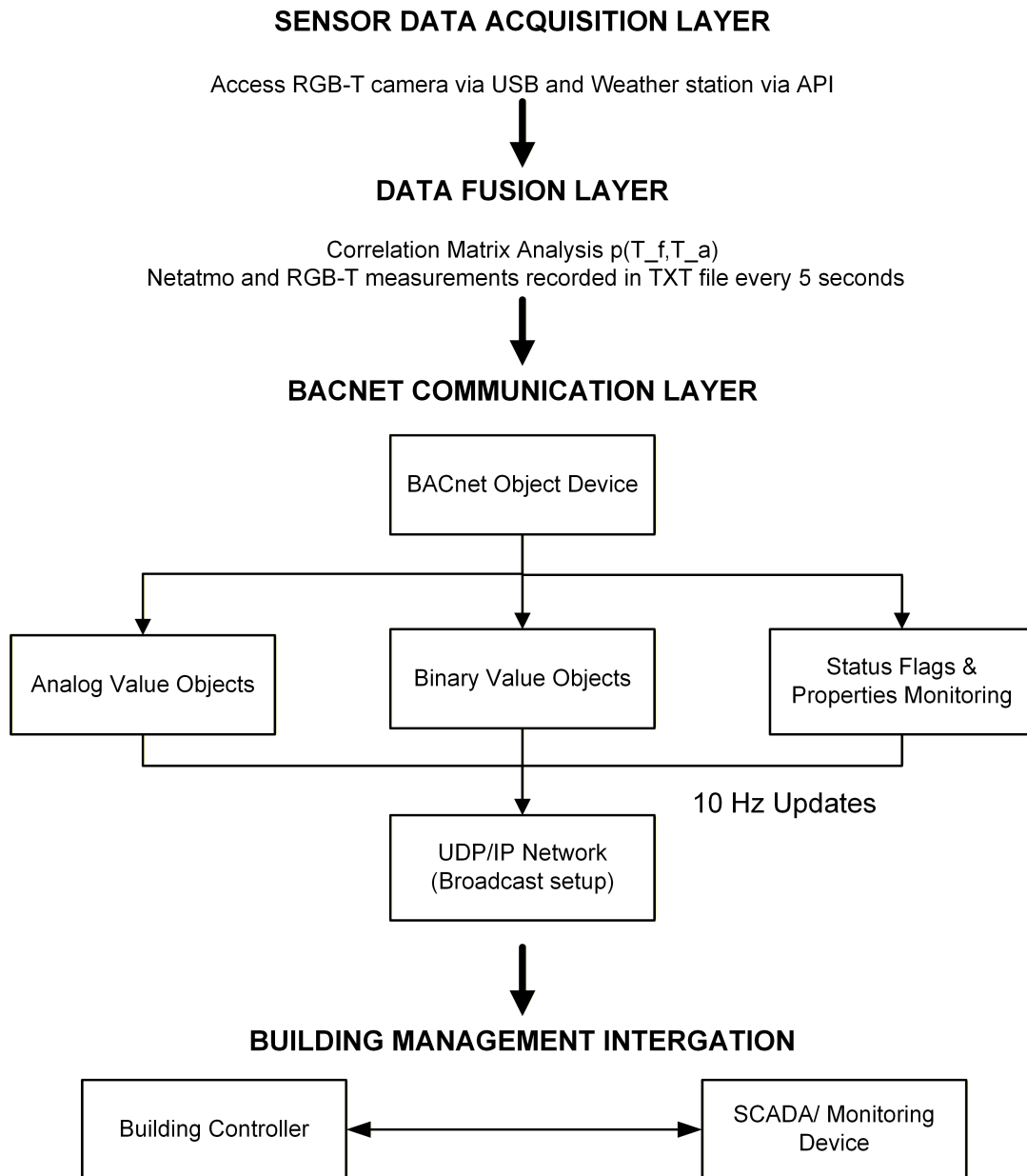


FIGURE 4.4: Integrated RGB-T thermal monitoring system with BACnet communication. The flowchart illustrates the complete data processing for building automation integration.

This stage demonstrates a novel approach to integrating low-cost thermal monitoring systems with commercial building automation infrastructure via BACnet protocol. The Raspberry Pi, configured as a BACnet sensor, enabled real-time adaptive control

by providing continuous physiological feedback for setpoint determination, laying the groundwork for future controller-based implementations.

4.3.1.3 Time Stamping

The BACnet communication layer is configured at 10 Hz to ensure that the Raspberry Pi sensor can communicate seamlessly with the building controllers at a sufficiently high network update rate, thereby minimizing traffic-related communication delays. In contrast, the API acquires environmental data every 5 seconds (0.2 Hz), and the thermal camera records facial temperature every 2 seconds (0.5 Hz). Since these subsystems operate at different sampling frequencies, all measurements are aligned through precise time stamping to preserve temporal consistency during data fusion. Importantly, HVAC temperature regulation is a slow-loop control process rather than a fast-loop process; therefore, the slower API and thermal-camera update intervals do not introduce significant control delays or degrade practical temperature-control performance.

4.3.2 Experiment Stage 2: Adaptive Control via Raspberry Pi Master Controller

4.3.2.1 BACnet Master Controller Configuration

In this stage, the Raspberry Pi was configured as a BACnet-compliant master controller, enabling supervisory control within the building automation network hierarchy. The experimental network topology comprised the Raspberry Pi as the primary BACnet master device, with a commercial building automation controller operating as a subordinate node. This arrangement facilitated bidirectional communication and control command execution, as illustrated in Figure 4.5, and established the technical foundation for implementing adaptive control strategies at the supervisory level.

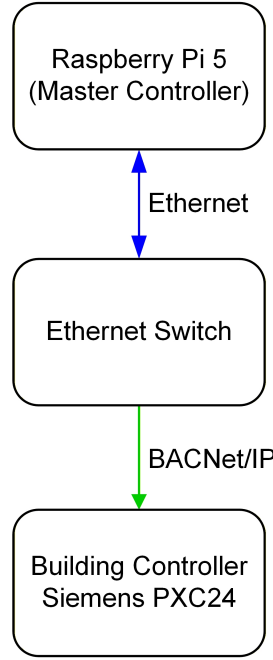


FIGURE 4.5: Experimental BACnet network topology demonstrating bidirectional communication between the Raspberry Pi master controller and commercial building automation controller.

4.3.2.2 Adaptive Control Logic and Communication Protocols

The Raspberry Pi was programmed to function as a BACnet master controller, supporting seamless bidirectional communication with building controllers over a local IP network. Utilizing the BACpypes library, the device was instantiated as a BACnet master and dynamically configured for network compatibility, with robust fallback mechanisms to maintain connectivity. The system architecture supported real-time building automation by updating BACnet object values and exchanging control commands at a frequency of 10 Hz, ensuring rapid and reliable communication for adaptive control.

Bidirectional BACnet communication was achieved through dedicated functions for reading and writing object properties, supporting both tuple-based and name-based addressing conventions. Multithreading enabled concurrent execution of the BACnet stack, adaptive control loop, object updates, data logging, and keyboard input handling, ensuring responsive and uninterrupted operation. The adaptive control logic was designed to dynamically adjust temperature setpoints and operational modes based on real-time sensor inputs, mirroring the strategy validated in Stage 1.

4.3.2.3 System Monitoring, Notification, and Data Management

An integrated email notification subsystem monitored temperature deviations and automatically sent formatted HTML alerts to designated recipients when the setpoint differed from the room temperature by a specified threshold. All system actions—including control events, alarms, and manual interventions—were persistently logged to text files with timestamped entries, supporting operational transparency and post-experimental analysis. This comprehensive architecture enabled the Raspberry Pi to function as a master controller, orchestrating real-time building control, alarm notification, and data management within a BACnet-enabled environment, as shown in Figure 4.6.

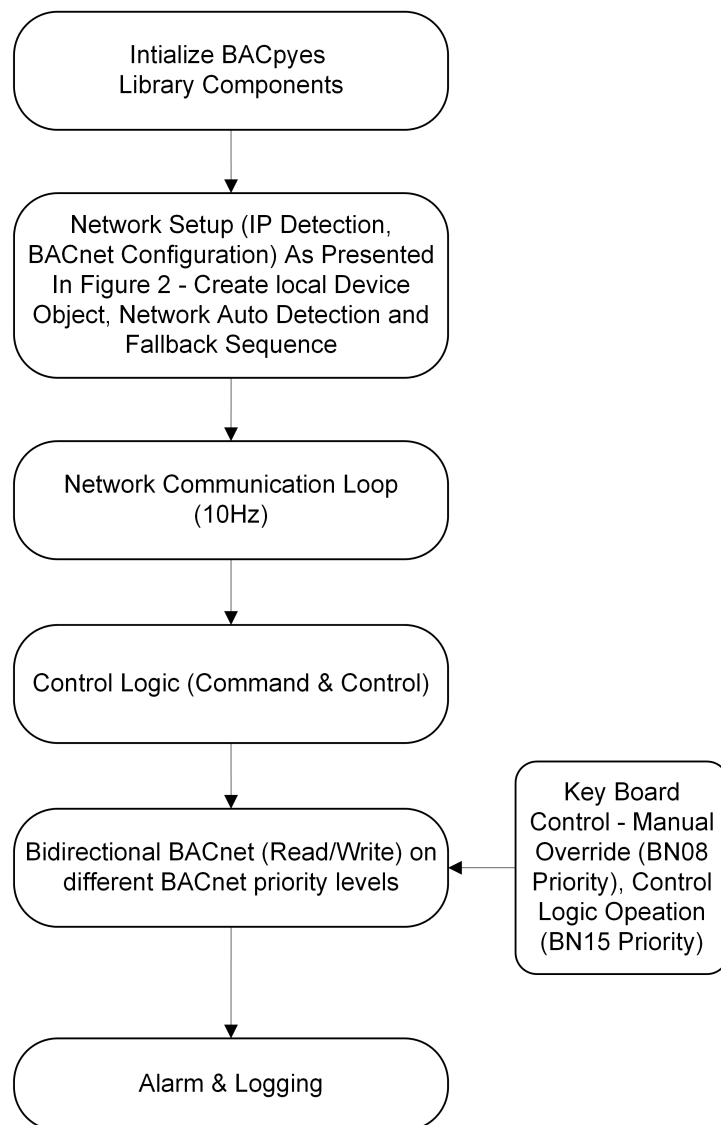


FIGURE 4.6: Block diagram illustrating the bidirectional BACnet communication process, fallback logic, priority control, and keyboard override in the Raspberry Pi master controller system.

Note: While the Raspberry Pi master controller was validated on a simulated local network in this study, future work may extend its deployment to commercial building networks to directly implement adaptive control strategies, as demonstrated by sensor-based integration in Stage 1.

4.4 Results

Scenario testing assessed the adaptive control strategy employed via the facial temperature monitoring BACnet sensor on a commercial building automation network. Each scenario test was performed with systematic data collection at 5-minute intervals, ensuring sufficient temporal resolution for statistical analysis while maintaining manageable data volumes. The adaptive control strategy experiment was implemented in an operational open-space office environment measuring 21.0 m $\times$ 10.5 m $\times$ 3.0 m to evaluate system functionality under multiple scenarios.

The office-based testing was conducted during after-hours periods with window blinds in the closed position, resulting in ambient temperatures ranging from 24 °C to 25 °C. This configuration simulated the elimination of external thermal influences from solar radiation. Comprehensive environmental monitoring was achieved through systematic deployment of Netatmo sensors at each corner of both test environments, ensuring spatial representation of room temperature, CO₂, and relative humidity distributions.

4.4.1 Scenario 1: Continuous Facial Temperature Tracking

This test established the relationship between facial temperature and room temperature in a lab environment. As part of the adaptive control strategy, facial temperature was designated as the primary input to set the temperature setpoint, and a lookup table was used to determine the setpoint. The building controller was programmed with the lookup table shown in Figure 4.7, which presents a graph generated by plotting environmental temperatures against facial temperature values. The graph facilitates the determination of optimal temperature setpoints based on direct physiological indicators.

The laboratory facility measured 3.0 m $\times$ 3.0 m $\times$ 2.4 m (length $\times$ width $\times$ height). The space was initially cooled to approximately 20 °C using the HVAC system, after which

the HVAC was turned off. Window blinds and windows were opened to allow outdoor air to enter, with ambient outdoor air temperature between 24 °C and 27 °C, gradually warming the room. Netatmo sensors were positioned at each corner to monitor room temperature, CO₂, and relative humidity, with placement avoiding direct solar exposure. Testing was conducted over four days, with each session lasting more than 3 h.

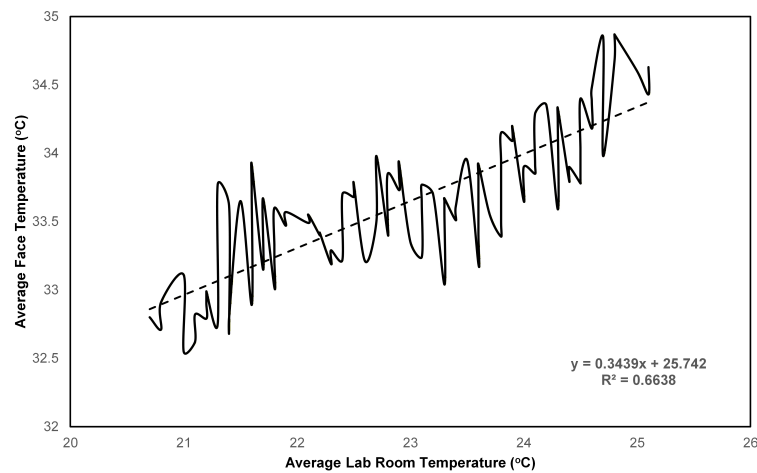


FIGURE 4.7: Stepwise linear correlation between ambient room temperature and occupant facial temperature measurements.

The experimental data demonstrated a stepwise linear relationship between Netatmo sensor measurements and facial temperatures, revealing distinct thermal comfort plateaus that align with human thermoregulatory responses, in which facial temperature transitions occurred at specific ambient temperature thresholds rather than exhibiting continuous linear variation.

Experimental conditions were standardized to maintain occupant activity parameters, with the participant engaged in typical office computing tasks while seated throughout the measurement period. The experimental termination criterion was met when the participant reported physiological discomfort necessitating hydration, thereby indicating the threshold of acceptable thermal conditions and providing a clear endpoint for determining the thermal comfort boundary.

The facial temperature monitoring system was positioned at a fixed height of 1.2 m via tripod, corresponding to standard seated occupant sight lines in commercial building environments. The test subject was a 36-year-old male participant with facial hair, selected to evaluate thermal measurement accuracy under realistic physiological

conditions in which facial temperature patterns may exhibit spatial heterogeneity due to varying hair density and skin exposure characteristics across facial regions. During the experiment, clothing and seating conditions were kept constant to hold the metabolic rate approximately steady.

4.4.2 Scenario 2: Fixed Temperature Setpoint Control with Facial Temperature Measurements

4.4.2.1 Facial Monitoring Sensor Integration to the Office Network

The facial monitoring sensor was integrated with a BACnet-enabled building controller on an operational commercial office building automation network. The network configuration involved modifying the IP addresses of both the Raspberry Pi controller and the building controller to ensure compatibility with the office network topology and to enable stable BACnet communication.

4.4.2.2 Office HVAC BMS Control Topology

The experimental validation was conducted in an engineering office equipped with variable refrigerant flow (VRF) HVAC systems comprising four Mitsubishi heat pump units. The building automation architecture utilized dual communication protocols: two heat pump units operated via Modbus interfaces, while the remaining units communicated through BACnet. System coordination was managed by a Siemens PXC5 Ethernet-based controller, which implemented centralized control logic for all thermal conditioning equipment.

The control strategy applied a unified temperature setpoint methodology across all four heat pump units, with a ± 2 °C operational bandwidth to accommodate spatial temperature variations and system response characteristics. Operational mode selection was configured for automatic operation, with available modes including heating, cooling, dehumidification, fan-only, and automatic mode selection based on thermal load requirements. Fan speed control was similarly configured for automatic operation, with manual overrides for low, medium, and high speed settings. Comprehensive alarm monitoring was implemented to support preventive maintenance scheduling, with a

focus on filter status to ensure optimal system performance and indoor air quality. CO₂ concentration and relative humidity measurements acquired through the Netatmo environmental monitoring system were excluded from the experimental control algorithm because the existing office building automation infrastructure lacked indoor air quality control programming within the operational logic framework.

All HVAC units operated under a coordinated time schedule, with seasonal temperature setpoint defaults of 21 °C for summer and 23 °C for winter. The control logic incorporated an economy-cycle operation mode that activated when the measured room temperature reached the setpoint, with regular operation resuming when the room temperature deviated by 0.5 °C from the setpoint, thereby ensuring energy-efficient operation while maintaining comfort.

4.4.2.3 Operational Limitations

Experimental validation was constrained by the need to preserve building-system integrity and to avoid network conflicts with other subsystems. Editing of the HVAC controller logic was permitted only for specific BACnet data points, namely temperature setpoint adjustment and the integration of facial temperature with room temperature. Network isolation protocols were enforced to prevent disruption of field devices, and temperature setpoint adjustments were restricted to the 21–23 °C range, with override capabilities disabled to preserve established comfort control strategies.

The experiment was conducted in three stages:

- Stage 1: Fixed temperature setpoint control with facial temperature measurements monitored alongside average wall-mounted temperature sensor measurements.
- Stage 2: Fixed temperature setpoint control with a heating source introduced to disrupt average room temperature; temperature monitoring relied solely on wall-mounted sensors.
- Stage 3: Fixed temperature setpoint control with heating source disruption, utilizing the average of both wall-mounted and facial temperature sensors to assess the effect of physiological feedback on control performance.

4.4.2.4 Stage 1

Table 4.2 present the results obtained during the two-day test, each conducted over one hour with temperature recorded at five-minute intervals.

TABLE 4.2: Setpoint, averaged room and facial temperature for two days

Setpoint (°C)	Day 1 (Outside air 27.1°C)		Day 2 (Outside air 25.4°C)	
	Room (°C)	Facial (°C)	Room (°C)	Facial (°C)
21	21.3	33.7	21.1	32.4
21	21.3	33.9	21.1	32.1
21	21.3	32.4	21.1	32.1
21	21.3	33.8	21.1	32.4
21	21.3	33.5	21.1	32.9
21	21.3	33.9	20.9	32.9
21	21.3	33.9	20.9	32.9
21	21.3	32.9	20.9	32.9
21	21.15	33.1	20.9	33.1
21	21.15	33.2	20.9	32.9
21	21.15	33.2	20.9	32.9
21	21.15	33.8	20.9	32.7

Room temperature remained consistent throughout both test days, as reflected in the stable facial temperature readings. With only one participant present in the office space, no significant changes in average room temperature or setpoint were observed, suggesting limited variability under these controlled conditions.

4.4.2.5 Stage 2

Table 4.3 present the results obtained during the two-day test, each conducted over one hour and incorporating an electric fan heater placed 1 m from the participant's desk.

TABLE 4.3: Impact of a localized heater on average room and facial temperature with fixed temperature setpoint at 21 °C.

Setpoint (°C)	Day 1 Outside air 28.4 (°C)		Day 2 Outside air 25.4 (°C)	
	Room (°C)	Facial (°C)	Room (°C)	Facial (°C)
21	21.15	35.1	20.9	34.7
21	21.15	35.7	20.9	34.9
21	21.15	35.7	20.9	35.6
21	21.19	35.8	20.9	35.6
21	21.19	35.6	21.1	35.6
21	21.19	35.7	21.1	35.7
21	21.19	35.7	21.1	35.7
21	21.2	35.7	21.1	35.5
21	21.2	35.7	21.1	35.7
21	21.2	35.7	21.1	35.7

The participant reported thermal discomfort during the test, despite minimal variation in the setpoint and the average room temperature, indicating limited responsiveness of wall-mounted RTD sensors. The effect of the 1 kW electric fan heater was negligible compared to the 6 kW rated cooling capacity of each heat pump, resulting in only a minimal change in average room temperature. This highlights the limitations of conventional wall-mounted temperature sensor placement for detecting localized thermal discomfort.

4.4.2.6 Stage 3

Table 4.4 present results from a two-day experiment, with temperature measurements recorded every five minutes over one hour. The test utilized a 1 kW electric fan heater positioned 1 m from the participant's desk, and average room temperature calculations incorporated facial temperature readings.

Due to the large size of the office environment, a direct correlation between facial temperature and overall room temperature could not be established. To address this, four Netatmo sensors were positioned at the corners of the participant's desk (1.5 m × 0.6 m) to obtain localized environmental measurements. This arrangement enabled a robust

correlation between facial temperature and desk-level room temperature, with deviations limited to ± 0.3 °C of the plotted measurements in Figure 4.7. A linear regression model was derived from Scenario 1 results, and the PPCL logic was programmed to replicate the relationship between anticipated room temperature and facial temperature:

$$\text{Facial temperature} = 0.3439 \times \text{Anticipated room temperature} + 25.742 \quad (4.11)$$

TABLE 4.4: Integration of facial-calculated temperature with wall-mounted measurements for average room temperature.

Setpoint (°C)	Day 1 Outside air 28.4 (°C)				Day 2 Outside air 25.4 (°C)			
	Wall sen- sor (°C)	Avg. room (°C)	Calc. room (°C)	Facial (°C)	Wall sen- sor (°C)	Avg. room (°C)	Calc. room (°C)	Facial (°C)
21	21.2	22.81	29.24	35.8	21.1	22.96	30.4	36.2
21	21.2	22.58	28.08	35.4	21.1	22.79	29.5	35.9
21	21.2	22.46	27.55	35.1	21.1	22.75	29.0	35.6
21	20.9	22.28	27.79	35.1	20.9	22.45	28.7	35.3
21	20.9	22.27	27.65	35.0	20.9	22.42	28.6	35.0
21	20.7	22.06	27.21	35.1	20.7	22.23	28.4	34.9
21	20.6	21.69	26.94	35.0	20.6	21.69	26.9	34.3
21	20.5	21.73	26.62	34.9	20.5	21.73	26.6	34.3
21	20.5	21.61	25.62	34.7	20.5	21.53	25.5	34.3
21	20.3	21.57	25.46	34.9	20.3	21.33	25.2	34.4

The experimental data reveal discrepancies between room temperature measurements obtained from wall-mounted sensors and localized facial temperature readings, despite a consistent room temperature setpoint of 21 °C. Calculated room temperature based on facial readings was significantly elevated, ranging from 24.3 °C to 30.4 °C, and facial temperatures consistently exceeded 34 °C. These findings suggest that the participant experienced localized thermal conditions substantially warmer than those indicated by conventional room sensors. The elevated facial temperatures and calculated room temperatures align with participant reports of thermal discomfort, particularly due to direct exposure to the electric fan heater and uneven temperature distribution in

the room. Overall, the results underscore the limitations of relying solely on wall-mounted temperature sensors for occupant comfort assessment and highlight the value of integrating localized physiological measurements.

4.4.3 Scenario 3: Fallback Logic Activation

The experimental approach replaced traditional ambient temperature-based setpoint control with parameters reflecting physiological thermal comfort, specifically using facial temperature measurements. The anticipated room temperature was determined using the relationship described in Scenario 1, enabling the selection of optimal setpoints based on physiological indicators. Office temperature setpoints were constrained by the control logic to the range of 21 °C to 23 °C. For primary control, the relationship between facial temperature and expected room temperature served as the reference for temperature setpoint selection in the PPCL logic. In secondary control, when no face was detected, the setpoint was determined by the wall-mounted room temperature sensor.

Figure 4.8 presents the adaptive control strategy employed for setpoint temperature, whereas Figure 4.9 summarizes the logic for average room temperature measurement.

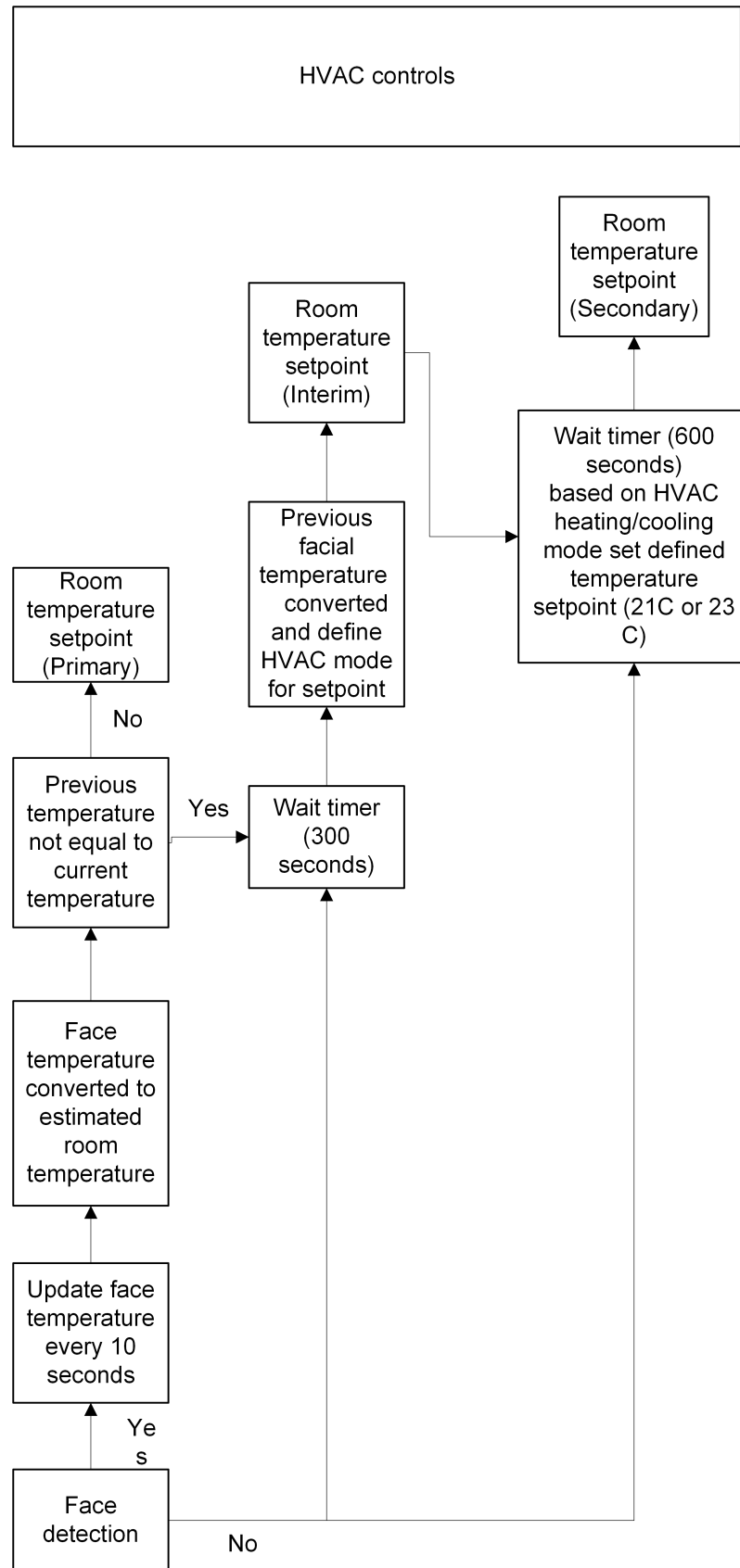


FIGURE 4.8: Adaptive HVAC control logic integrating facial temperature and room sensor feedback for dynamic setpoint selection.

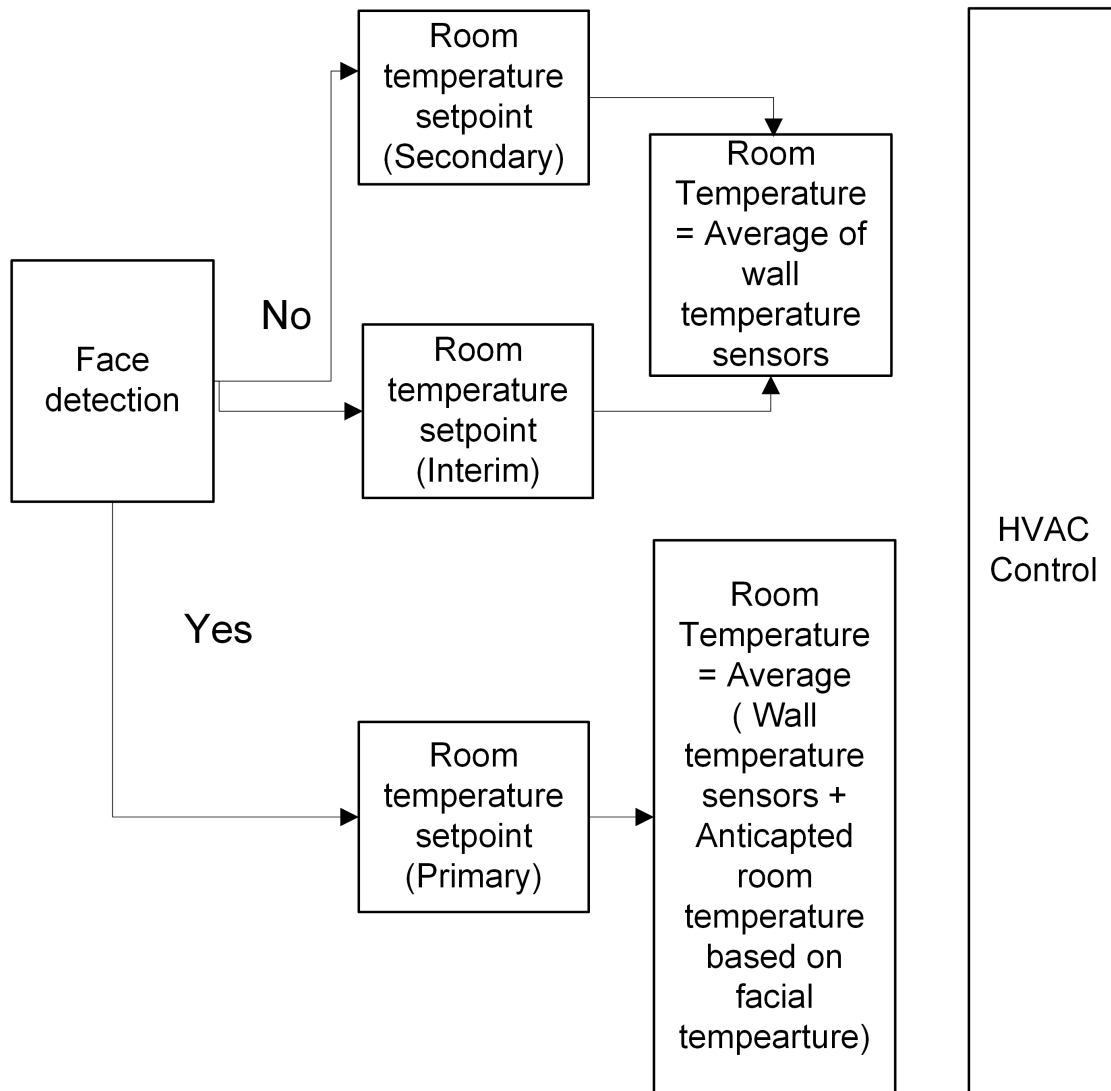


FIGURE 4.9: Adaptive HVAC control logic for average room temperature calculation.

The PPCL table function is employed to determine the primary setpoint temperature, enabling the application of piecewise linear or stepwise control strategies through interpolation between defined data points. According to the earlier equation, the anticipated room temperature is constrained between 18 °C and 27 °C. The primary setpoint temperature is further restricted to a range of 21 °C to 23 °C, in accordance with the established building control logic for the office environment.

Tables 4.5 and 4.6 summarize the adaptive HVAC control data recorded during two test days.

TABLE 4.5: Day 1 summary of adaptive HVAC control data.

Face detected	Facial temp. (°C)	Calculated room (°C)	Primary setpoint (°C)	Interim setpoint (°C)	Secondary setpoint (°C)	Avg. room (°C)	HVAC mode
Yes	34.7	25.67	21.29			23.93	Normal
Yes	33.8	23.09	21.87			23.82	Normal
Yes	34.4	24.81	21.49			23.20	Normal
Yes	33.3	21.66	22.19			22.33	Normal
Yes	33.8	23.09	21.87			22.30	Normal
No			21.87			21.98	Normal
No				21.87		20.97	Economy
No				21.87		20.85	Economy
No					21	20.75	Economy
No					21	20.93	Economy
No					21	21.10	Economy
No					21	21.02	Economy
Yes	33.9	23.38	21.80			22.68	Normal
Yes	33.6	22.52	22.00			22.50	Economy

TABLE 4.6: Day 2 summary of adaptive HVAC control data.

Face detected	Facial temp. (°C)	Calculated room (°C)	Primary setpoint (°C)	Interim setpoint (°C)	Secondary setpoint (°C)	Avg. room (°C)	HVAC mode
Yes	35.8	28.82	21.00			24.24	Normal
Yes	36.1	29.68	21.00			24.10	Normal
Yes	35.4	27.67	21.00			23.69	Normal
Yes	35.7	28.53	21.00			23.71	Normal
Yes			21.00			22.10	Normal
No				21.00		21.50	Normal
No				21.00		21.20	Economy
No					21.00	20.90	Economy
No	33.7	22.80	21.93		21.00	21.40	Economy
No	33.4	21.94	22.12		21.00	21.14	Economy
No	33.1	21.08	21.08		21.00	20.78	Economy
No			21.08		21.00	20.61	Economy
Yes				21.08		20.65	Economy
Yes				21.08		20.63	Economy

Implementation of the adaptive HVAC control strategy demonstrated effective regulation of office temperature in response to real-time physiological and environmental inputs. When facial temperature data were available, the system dynamically adjusted the primary setpoint temperature, maintaining room conditions within the prescribed comfort range. When the calculated primary setpoint temperature fell outside the defined range, the adaptive control logic automatically clipped the value to the nearest bound specified by the PPCL table function, ensuring compliance with building control requirements. In cases where no face was detected, the control logic transitioned to the wall-mounted room sensor.

Throughout the two-day experimental period, the HVAC system demonstrated dynamic switching between normal and economy operational modes in response to real-time inputs. The continuous adjustment of temperature setpoints based on facial temperature variations enabled the system to maintain occupant comfort during periods of detected presence, while transitioning to energy-efficient operation when no face was detected or when temperature conditions stabilized. The participant did not experience thermal discomfort, and fan speeds adjusted automatically when room temperature remained within ± 0.5 °C of the setpoint, minimizing drafts. Gradual setpoint transitions also resulted in quieter HVAC operation compared to fixed setpoint strategies.

4.5 Discussion

This study demonstrates the successful implementation of an adaptive HVAC control strategy that leverages real-time facial temperature measurements to regulate office temperature dynamically. The system maintained room conditions within the prescribed comfort range of 21 °C to 23 °C by continuously adjusting setpoints based on physiological feedback, as determined by a linear regression model. When facial temperature data were unavailable, control reverted to wall-mounted sensors, enabling energy-saving “Economy” mode operation.

Experimental validation in a representative office environment confirmed the system’s responsiveness and reliability, with dynamic switching between normal and economy modes according to occupancy and physiological indicators. The adaptive control logic, implemented via a BACnet-enabled Raspberry Pi, provided robust BACnet

communication, and real-time monitoring, ensuring operational transparency and stability.

Results highlight the limitations of static setpoint approaches and underscore the need for dynamic comfort models that respond to real-time occupant feedback. The integration of facial temperature data enabled more precise and personalized thermal comfort management, directly addressing shortcomings in traditional models such as Fanger's PMV, which assume static environmental and physiological parameters.

A noteworthy observation was the difference in BACnet communication latency between the two network setups. On the localized network, the Raspberry Pi functioned as a controller. On the commercial network, it operated as a sensor. An increased delay was observed when connected to the commercial network. This was likely due to the presence of non-BMS devices sharing the same IP range. Latency test was less relevant as the experiment was conducted on HVAC controls requiring less time-sensitive updates. No significant delay was observed on the localized network. Latency measurements were performed using the YABEE tool.

Overall, the findings demonstrate that real-time physiological feedback can be effectively integrated into building management systems to enhance occupant comfort and energy efficiency. The adaptive control strategy offers a promising pathway for future development of closed-loop, occupant-centric environmental control frameworks, with significant implications for the evolution of thermal comfort modeling and smart building technologies.

4.6 Conclusion

This study demonstrates the effectiveness of an adaptive HVAC control strategy that utilizes real-time facial temperature measurements to optimize indoor comfort. The system, built on a BACnet-enabled Raspberry Pi platform, dynamically adjusts HVAC setpoints based on physiological feedback, maintaining office conditions within the optimal comfort range of 21°C to 23°C. The adaptive control logic prioritizes facial temperature data for setpoint selection, reverting to wall-mounted sensor readings and energy-saving "Economy" mode when facial data is unavailable. This closed-loop

approach overcomes the limitations of traditional static setpoint methods, providing more accurate and personalized comfort management.

A key contribution of this work is the validation of the Raspberry Pi as a low-cost, open-source BACnet device, capable of functioning both as a sensor and as a controller within building automation systems. The Raspberry Pi successfully operated as a BACnet sensor, enabling real-time acquisition and transmission of occupant thermal comfort data. While the controller functionality was verified in a simulated local network, it could not be tested on the operational office network due to security protocols and the risk of interfering with existing building automation infrastructure. This limitation highlights the importance of network safety when deploying new control technologies in live environments.

Overall, the findings highlight the potential for affordable, open-source hardware to advance adaptive control strategies and real-time comfort optimization in modern buildings. The integration of physiological sensing and BACnet communication paves the way for occupant-centric, energy-efficient building management. For future research, the development and implementation of a real-time Fanger model—incorporating dynamic physiological and environmental data—would further enhance the accuracy and responsiveness of thermal comfort prediction and control, supporting the evolution of truly intelligent building environments.

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Chapter 5

Facial Temperature Estimation Using Low-Cost Thermal Imaging and Transfer Learning for Indoor Comfort Assessment

Chapter 5 extends the sensing work from Chapter 3 by applying deep learning models, specifically MobileNetV2 with transfer learning, to experimentally collected thermal datasets. It presents comparative test results that address low resolution constraints and improve facial temperature estimation accuracy for occupant-centric comfort assessment. The BACnet enabled control capability discussed in Chapter 4 will also be achievable with MobileNetV2; however, since the conceptual control logic was already developed in Chapter 4, this chapter focuses on updating the sensing technique to suit the MobileNetV2-based framework rather than on developing the BACnet capability itself.

Abstract

Facial temperature is a key physiological indicator for assessing individual thermal comfort in indoor environments. However, traditional comfort assessment methods often rely on expensive equipment or intrusive sensors, limiting their scalability and practicality. This study presents a novel framework for real-time facial temperature

estimation using low-cost thermal imaging and transfer learning, aimed at supporting occupant centric indoor comfort assessment. Leveraging affordable thermal cameras and a MobileNetV2-based deep learning model, the system employs transfer learning to adapt pre-trained networks for accurate face detection and temperature regression on low resolution thermal data. The approach enables non-contact, continuous monitoring of facial temperature, providing a scalable solution for dynamic comfort evaluation in smart buildings. Experimental results demonstrate that the proposed method achieves high accuracy, with a root mean squared error (RMSE) of 0.37°C and a mean absolute error (MAE) of 0.29°C , within physiologically plausible temperature ranges. The integration of low-cost sensing, advanced analytics, and transfer learning offers a practical pathway for enhancing indoor environmental quality and adaptive building management.

5.1 Introduction

Thermal comfort is a critical aspect of indoor environmental quality (IEQ), directly affecting occupant health, productivity, and overall satisfaction[1, 2]. Recent years have seen a growing emphasis on individualized and dynamic comfort assessment, as traditional models often fail to capture the real-time physiological responses and diverse needs of building occupants[3, 4]. The COVID-19 pandemic has further highlighted the importance of non-contact, scalable monitoring solutions for indoor environments [5].

Infrared thermography has emerged as a powerful non-contact method for monitoring skin and facial temperatures, which are reliable indicators of thermal sensation and comfort[6, 7]. While high-end thermal cameras provide accurate measurements, their high cost and complexity limit widespread adoption in real-world building applications[8]. The advent of affordable thermal imaging devices, such as the Topdon TS001, has made it feasible to deploy large-scale, occupant centric monitoring systems, though challenges remain in calibration, resolution, and measurement accuracy [9, 10].

Deep learning, particularly convolutional neural networks (CNNs), has revolutionized image analysis and pattern recognition tasks in recent years[10]. Lightweight architectures such as MobileNetV2 are especially well-suited for deployment on resource constrained devices, enabling real-time processing of thermal images in smart building environments[11]. Transfer learning further enhances the utility of these models by

allowing pre-trained networks to be adapted to specific domains with limited labeled data, such as thermal imaging for comfort assessment[12, 13]. Recent studies have demonstrated the effectiveness of combining low-cost thermal imaging and transfer learning for accurate, real-time, non-contact comfort assessment in buildings[14, 15].

Despite these advances, several research gaps persist. Issues related to sensor calibration, data quality, and the generalizability of deep learning models in diverse, real-time environments remain unresolved[10, 16]. Moreover, the integration of affordable thermal sensors and advanced analytics into building management systems is still in its infancy, requiring further research to ensure scalability, reliability, and user acceptance[17].

This study aims to address these gaps by investigating the feasibility and accuracy of facial temperature estimation using low-cost thermal imaging and transfer learning, supporting the development of adaptive, occupant centric building environments.

The novelty of this work is the integration of low-cost thermal imaging devices with transfer learning and lightweight deep learning architectures for real-time, non-contact facial temperature estimation in indoor comfort assessment. In contrast to previous approaches that rely on expensive sensors or generic models, this study demonstrates the adaptation of MobileNetV2 via transfer learning to operate effectively on low-resolution thermal data, thereby enabling scalable and occupant centric monitoring in practical building environments. The proposed framework bridges the gap between affordable sensing technology and advanced analytics, offering a robust, adaptive solution for individualized comfort evaluation and smart building management.

Taken together with the preceding work, this stage adds robust and coherent evidence by improving facial accuracy and temperature measurement, further supporting the thesis-level research goal.

5.2 Related Work

5.2.1 Thermal Comfort and Indoor Environmental Quality

Thermal comfort is a cornerstone of indoor environmental quality (IEQ), directly influencing occupant health, productivity, and satisfaction [1, 2]. Fanger's Predicted

Mean Vote (PMV) model [3] and adaptive comfort models [4] have been widely used, but both have limitations in real-time, individualized comfort assessment [5, 6].

5.2.2 Non-Contact Temperature Sensing and Thermal Imaging

Infrared thermography and non-contact temperature sensing are established tools for building diagnostics and envelope performance [7, 8]. High end thermal cameras offer accurate surface temperature mapping but are often cost-prohibitive [9]. The emergence of low-cost thermal sensors, such as the Topdon, has enabled new applications in comfort monitoring, though challenges remain in calibration and resolution [10].

5.2.3 Physiological Sensing for Comfort Assessment

Physiological parameters, especially skin and facial temperature, are increasingly recognized as reliable indicators of thermal sensation [11, 12]. Facial thermal imaging provides a non-invasive method for comfort assessment, but most prior work has relied on wearables or subjective surveys [13, 14]. The use of facial thermal imaging for real-time comfort assessment is an emerging research area [15].

5.2.4 MobileNetV2 for Thermal Imaging

MobileNetV2 is a lightweight convolutional neural network (CNN) architecture designed for efficient image classification and regression tasks, particularly on resource-constrained devices [16]. It utilizes depthwise separable convolutions and inverted residuals with linear bottlenecks, significantly reducing computational cost and model size while maintaining high accuracy [17]. These features make MobileNetV2 especially suitable for deployment on embedded systems and edge devices, such as Raspberry Pi or similar platforms used with low-cost thermal cameras [18].

Recent studies have demonstrated the effectiveness of MobileNetV2 for thermal image analysis, including applications in medical thermography, industrial inspection, and human detection [19, 20]. Its ability to extract meaningful features from low-resolution thermal images makes it a strong candidate for occupant comfort assessment using affordable sensors like the Topdon [21]. Transfer learning further enhances its performance,

allowing pre-trained MobileNetV2 models to be fine-tuned for specific thermal imaging tasks with limited labeled data [22]. This approach enables accurate, real-time facial temperature estimation and comfort prediction in smart building environments.

5.2.5 Low-Cost Sensors and Practical Deployment

Affordable thermal cameras, such as the Topdon, present new opportunities for scalable comfort monitoring [23]. However, their lower resolution and calibration challenges require advanced data processing and robust models [24]. Integrating these sensors with AI-driven control strategies remains an open research area [25].

5.2.6 Identified Gaps and Research Motivation

Despite significant progress in the fields of sensing technology and artificial intelligence, several critical gaps remain in the literature concerning occupant comfort assessment in buildings. Most existing studies on thermal comfort rely on either high-cost thermal imaging systems or intrusive wearable sensors, both of which present barriers to widespread adoption in real-time building environments [9, 13]. Furthermore, while deep learning models have demonstrated strong performance in image-based tasks, their application to low-resolution, low-cost thermal imaging data for occupant comfort assessment is still in its infancy [19, 21].

A particularly underexplored area is the integration of lightweight convolutional neural networks, such as MobileNetV2, with affordable thermal cameras for real-time, non-contact monitoring of occupant physiological states. Although MobileNetV2 has been successfully applied in other domains for efficient image analysis on resource-constrained devices [16, 17], its potential for processing thermal images from low-cost sensors like Topdon in the context of building comfort has not been fully realized. Additionally, the use of transfer learning to adapt pre-trained models to the unique characteristics of thermal imaging data in buildings remains largely unaddressed in the literature [22].

Another gap is the lack of scalable, occupant centric solutions that can be seamlessly integrated with building management systems (BMS) to enable adaptive, real-time control of indoor environments. Most current BMS implementations still rely on static setpoints and environmental averages, failing to account for the dynamic and

individualized nature of occupant comfort [5, 6]. There is a pressing need for methods that can provide accurate, real-time comfort assessment without requiring direct occupant input or expensive infrastructure.

Motivated by these gaps, this research aims to develop a novel framework that leverages low-cost thermal imaging, MobileNetV2, and transfer learning to deliver a scalable, accurate, and accessible solution for smart building management. By enabling real-time, non-contact assessment of occupant comfort, the proposed approach seeks to bridge the divide between advanced AI techniques and practical, deployable solutions for occupant well-being and energy-efficient building operation.

5.3 Materials and Methods

5.3.1 Thermal Imaging System and Data Acquisition

Thermal data were collected using the Topdon TS001 thermal camera, which captures frames at a native resolution of 256×192 pixels. Each frame consists of two channels a high byte and a low byte that together encode the raw thermal signal for each pixel, preserving the full dynamic range of the sensor for accurate temperature extraction. To ensure all temperature information was retained, training images were acquired at the full 256×192 resolution, allowing the use of all hi and lo values for temperature computation. The camera was calibrated using a blackbody reference to ensure temperature accuracy across the field of view. For deep learning model training and face detection, images were resized to 224×224 pixels to match the input requirements of the MobileNetV2 architecture. Temperature measurement and extraction were performed at the original 256×192 resolution, while face detection and model training were conducted on images resized to 224×224 . Data acquisition was performed in a controlled indoor environment to minimize the influence of ambient temperature fluctuations and reflective surfaces.

5.3.2 Frame Settings and Preprocessing

The integrity of thermal data is highly dependent on frame settings, including exposure, gain, and environmental conditions. Each frame was split into its high and low byte

components, and the raw value for each pixel was reconstructed as follows:

$$\text{raw} = (\text{hi} \ll 8) + \text{lo} \quad (5.1)$$

where hi and lo are the high and low bytes, respectively. The temperature in degrees Celsius was then computed using the sensor’s calibration formula:

$$\text{temp} = \frac{\text{raw}}{64.0} - 273.15 \quad (5.2)$$

This conversion is critical, as any error in raw data interpretation directly impacts the accuracy of temperature estimation. The resulting temperature maps were normalized to the range $[0, 255]$ and resized to 224×224 pixels. Data augmentation techniques, including random horizontal flips, rotations, and intensity scaling, were applied to improve model generalization.

5.3.3 Challenges in Face Temperature Measurement

Measuring face temperature in thermal imagery is inherently challenging due to several factors:

- **Physiological Variability:** Skin emissivity, perspiration, and blood flow can cause local temperature variations, making it difficult to identify a single representative temperature for the face.
- **Environmental Influences:** Airflow, ambient temperature, and reflective surfaces can introduce artifacts or obscure true facial temperature.
- **Sensor Limitations:** Low spatial resolution and sensor noise can degrade the quality of facial features, complicating both detection and temperature regression.
- **Occlusions and Pose:** Glasses, masks, and head pose variations can obscure key facial regions, leading to missed detections or inaccurate readings.

To address these challenges, our system employs a region-based approach, focusing on the largest contiguous area within a physiologically plausible temperature range (30–37°C), which is likely to correspond to exposed facial skin.

5.3.4 Face Detection and Blob Analysis

Traditional face detection methods, such as Haar cascades or HOG-based detectors, are ill-suited to thermal imagery due to the lack of texture and contrast. Instead, we employ a deep convolutional neural network (CNN) based on MobileNetV2, trained to output a face confidence score for each frame. When the face confidence exceeds a threshold (0.5), we apply connected component analysis to the temperature map, identifying all contiguous regions (blobs) within the 30–37°C range. The largest blob is assumed to correspond to the face, and its centroid is used as the reference point for temperature estimation. This approach is robust to spurious hot objects in the background, as it leverages both the spatial extent and physiological plausibility of the detected region.

5.3.5 Model Architecture: MobileNetV2 MultiTask

The core of our system is a multitask MobileNetV2 architecture, chosen for its balance of computational efficiency and representational power. The model is initialized with ImageNet-pretrained weights and modified as follows:

- The final classification layer is replaced with two parallel heads:
 - **Face Classification Head:** A fully connected layer outputs a single logit, passed through a sigmoid to yield the probability of face presence.
 - **Temperature Regression Head:** A fully connected layer outputs a single value, representing the estimated temperature at the face centroid.
- The backbone processes 224×224 grayscale (replicated to 3 channels) thermal images, with normalization parameters $\mu = 0.5$, $\sigma = 0.5$.

The multitask design enables the model to learn shared representations for both detection and regression, improving generalization and robustness.

5.3.6 Training Procedure

The model was trained on a dataset of 80 thermal frames, with ground truth annotations for face presence and temperature. The training pipeline included:

- **Data Augmentation:** To enhance the model's generalization capability and robustness to real-world variations, extensive data augmentation techniques were employed during training. These included random horizontal flips, random rotations within a specified angle range, and intensity scaling to simulate sensor variability. Augmentation was applied in real time to each mini-batch, ensuring a diverse set of training samples.
- **Loss Functions:** The model was trained in a multi-task setting, jointly optimizing for face detection and temperature estimation. Binary cross-entropy (BCE) loss was used for the face classification branch, while mean squared error (MSE) loss was employed for the temperature regression branch. The total loss was computed as a weighted sum of the two objectives, allowing the model to balance classification and regression performance.
- **Optimization:** Model parameters were optimized using the Adam optimizer, with an initial learning rate of 1×10^{-4} and a weight decay regularization term of 1×10^{-5} . The learning rate was optionally reduced on plateau based on validation loss to facilitate convergence.
- **Batch Size and Training Epochs:** Training was conducted with a batch size of 32, for a total of 20 epochs. Early stopping was implemented, monitoring the validation loss to halt training when no improvement was observed over a predefined patience period, thereby mitigating overfitting.
- **Validation Strategy:** The dataset was partitioned into training and validation subsets, with 80% of the data allocated for training and 20% reserved for validation. The split was performed at the video sequence level to ensure that frames from the same sequence did not appear in both subsets, thus preserving the integrity of the evaluation and preventing information leakage.
- **Implementation Details:** All experiments were conducted using the PyTorch deep learning framework. Model checkpoints were saved based on the lowest observed validation loss, and the best-performing model was selected for subsequent inference and evaluation.

Care was taken to ensure that frames from the same video sequence were not split between training and validation sets, to prevent data leakage.

5.3.7 Inference Pipeline

Model Inference: The preprocessed frame is passed through a MobileNetV2-based multi-task neural network, implemented in PyTorch. The model outputs a face confidence logit, which is converted to a probability via the sigmoid function. This value represents the likelihood that the current frame contains a human face.

Face Region Segmentation: If the face confidence exceeds a threshold of 0.8, the temperature map is thresholded to create a binary mask corresponding to the physiological range of human skin temperature (30°C to 35°C). Connected component analysis is performed on this mask using an 8-connectivity criterion to identify contiguous regions (blobs) that may correspond to faces.

Centroid Localization and Temperature Extraction: Among the detected blobs, the largest (excluding the background) is selected as the most probable face region. The centroid of this region is computed, and the temperature at the centroid is extracted from the original temperature map. This value is reported as the estimated facial temperature for the frame.

Visualization and User Feedback: The processed frame is overlaid with visual cues to enhance interpretability. If a face is detected, a circle is drawn at the centroid location, and the estimated temperature is displayed in a compact text box. An additional overlay indicates the face detection status (“Face detected: Yes/No”) to provide immediate feedback to the user. All overlays are rendered using OpenCV’s drawing functions to ensure clarity and readability.

Real-Time Performance: The entire pipeline is optimized for real-time operation, achieving frame rates in the range of [9 to 10 FPS] frames per second on a standard CPU or GPU. This enables seamless integration into live monitoring systems and supports interactive data collection workflows.

5.4 Results

5.4.1 Calibration of the Topdon TS001

Before conducting the experiment, the Topdon TS001 thermal camera was evaluated for temperature measurement accuracy. Calibration was carried out using a Sentry TS663 infrared temperature sensor (Sentry Optronics Corp., Ban-Ciao, Taipei, Taiwan, R.O.C.) and the Hierarchical Linear-Polynomial Mapping (HLPM) technique. All measurements were traceable to the International System of Units (SI) through the Measurement Standards Laboratory (MSL) in New Zealand. A blackbody source with a 35 mm aperture, operating over a 0–90 °C range, was used for reference, with ambient conditions maintained at 20 ± 2 °C and an instrument readability of 1 °C. For calibration, both the TS001 and TS663 recorded temperatures at five setpoints between 30 °C and 35 °C, positioned 0.5 m from the blackbody, with a measurement resolution of 0.5 °C. The results showed that all recorded values were within a ± 1 °C margin of error.

5.4.2 Setup – Training and Testing

During data collection, the participant was seated at a fixed distance of 0.8 m from the thermal camera. All measurements were conducted in a controlled indoor environment, where the ambient room temperature was maintained at 22 °C. This setup ensured consistent environmental conditions and minimized external influences on the thermal measurements.

For model training, data were collected from a single participant. Images for face detection were acquired using the thermal camera positioned at distances ranging from 0.5 m to 1 m. A total of 40 images containing faces and 40 images without faces were captured within this distance range, providing a balanced dataset for training and evaluating the face detection model.

5.4.3 Quantitative Evaluation of Temperature Estimation

The performance of the proposed MobileNetV2-based system for face temperature estimation was rigorously evaluated using standard regression metrics, including Root Mean

Squared Error (RMSE), Mean Absolute Error (MAE), and the observed temperature range. These metrics provide a comprehensive assessment of the model's predictive accuracy and reliability in real-world thermal imaging scenarios.

5.4.3.1 Root Mean Squared Error (RMSE)

The RMSE quantifies the average magnitude of the error between predicted and ground truth temperatures. For the validation set, the RMSE was calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (5.3)$$

where y_i is the ground truth temperature, $\hat{y}_i$

$\hat{y}_i$ is the predicted temperature, and N is the number of samples. In this study, the RMSE was found to be **0.37,°C**, indicating high predictive accuracy.

5.4.3.2 Mean Absolute Error (MAE)

The MAE provides an alternative perspective by measuring the average absolute difference between predicted and actual temperatures:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (5.4)$$

The MAE for the validation set was **0.29,°C**, further confirming the model's ability to consistently provide temperature estimates close to the actual values.

5.4.3.3 Temperature Range

The observed temperature range for detected face regions in the validation set was **29.35,°C** to **33.10,°C**. This range is physiologically plausible for human skin temperature and demonstrates that the model maintains predictions within realistic intervals, minimizing the risk of false alarms or missed detections.

5.4.3.4 Summary of Results

Table 5.1 summarizes the key quantitative metrics for temperature estimation.

TABLE 5.1: Quantitative Results for Face Temperature Estimation

Metric	Value	Interpretation
RMSE (°C)	0.37	High accuracy
MAE (°C)	0.29	Low average error
Temperature Range (°C)	29.35–33.10	Physiologically plausible

5.4.4 Interpretation and Significance

The combination of low RMSE and MAE values, along with a realistic temperature range, highlights the effectiveness of the proposed approach. The model’s high precision is attributable to the use of raw thermal data, careful preprocessing, and blob-based region selection, which focuses on the most probable facial area. These results suggest that the system can be reliably used in real-time applications where both accuracy and speed are essential.

5.4.5 Visualization of Error Distribution

To further illustrate the model’s performance, we present a histogram of the absolute errors between predicted and ground truth face temperatures across the validation set (see Figure 5.1). The ground truth temperature for each frame was established through a systematic annotation process during dataset preparation. Specifically, each thermal frame was manually reviewed, and frames containing a visible face were annotated by marking the face region. The centroid of the annotated face region was computed, and the corresponding pixel value in the raw thermal data was extracted. This value was then converted to temperature using the sensor’s calibration formula:

$$T = \frac{(\text{hi} \ll 8) + \text{lo}}{64.0} - 273.15 \quad (5.5)$$

where `hi` and `lo` represent the high and low bytes of the thermal sensor output, respectively. The resulting temperature at the centroid was designated as the ground truth face temperature for that frame. This approach ensures that the reference

temperature values are both spatially precise and physically meaningful, providing a robust basis for evaluating the model’s predictive performance.

As shown in Figure 5.1, the majority of errors are clustered below 0.5 °C, with very few instances exceeding this threshold. This distribution underscores the consistency and robustness of the model’s predictions.

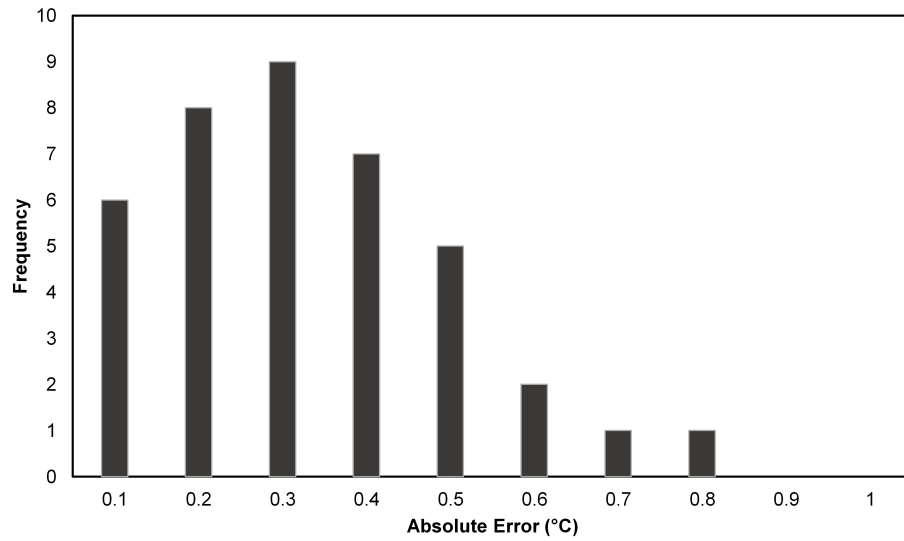


FIGURE 5.1: Histogram of absolute errors between predicted and ground truth face temperatures. Most errors are below 0.5 °C, indicating high model accuracy.

5.4.6 Sample Predictions

Table 5.2 presents a selection of predicted face temperatures and their corresponding locations, as extracted from the validation set.

TABLE 5.2: Sample Predicted Face Temperatures

Frame	Centroid (x, y)	Predicted Temp (°C)
1	(123, 120)	33.23
2	(127, 121)	32.54
3	(135, 121)	32.85
4	(139, 120)	33.66
5	(140, 121)	32.66
6	(136, 121)	32.60
7	no face	no face
8	no face	no face
9	no face	no face
10	no face	no face

5.4.6.1 No Face Detected

Figures 5.2 show sample frames where no face was detected by the model.



FIGURE 5.2: Sample frames with no face detected.

5.4.6.2 Face Detected

Figures 5.3 show sample frames where a face was detected, along with the predicted centroid and temperature.



FIGURE 5.3: Sample frames with face detected, showing centroid and predicted temperature.

The results demonstrate that the proposed system achieves high accuracy and reliability in face temperature estimation from thermal video data. The low error metrics and physiologically plausible temperature predictions support its suitability for real-time temperature monitoring when a face is detected.

5.5 Practical Implications

The findings of this study have significant practical implications for the deployment of occupant centric comfort monitoring systems in real-world building environments. By leveraging low-cost thermal imaging and lightweight deep learning models, it is feasible to implement scalable, non-contact facial temperature monitoring across a wide range of indoor settings, including offices, schools, and healthcare facilities. The proposed approach enables real-time assessment of occupant thermal comfort without the need for intrusive sensors or manual intervention, supporting adaptive building management strategies that can enhance both occupant well-being and energy efficiency. Furthermore, the use of transfer learning allows for rapid adaptation of the system to new environments or sensor types, reducing the need for extensive labeled data and facilitating broader adoption.

5.6 Limitations and Future Work

Despite the promising results, several limitations should be acknowledged. First, the accuracy of facial temperature estimation is inherently constrained by the resolution and calibration of low-cost thermal sensors, which may introduce measurement noise and limit the detection of fine-grained temperature variations. Second, the current model was trained and validated in a controlled indoor environment; its generalizability to diverse real-world settings with varying lighting, occupancy, and environmental conditions remains to be fully established. Third, factors such as occlusions (e.g., masks, glasses), head pose, and individual physiological differences can affect both face detection and temperature estimation accuracy.

Future work will focus on addressing these limitations by: (1) expanding the dataset to include a wider range of environments and occupant demographics; (2) integrating

additional sensor modalities (e.g., RGB cameras, environmental sensors) to improve robustness; (3) developing advanced calibration and domain adaptation techniques to enhance model transferability; and (4) exploring the integration of the system with building management platforms for closed-loop, occupant centric control of indoor environments.

5.7 Conclusion

This study demonstrates the feasibility and effectiveness of using low-cost thermal imaging and transfer learning for real-time, non-contact facial temperature estimation in indoor environments. The proposed MobileNetV2-based system achieves high accuracy, with low RMSE and MAE values and physiologically plausible temperature predictions. The approach supports scalable, occupant centric comfort assessment and has the potential to inform adaptive building management strategies that enhance both occupant well-being and energy efficiency. While challenges remain in sensor calibration, environmental variability, and model generalizability, the results provide a strong foundation for future research and practical deployment in smart building applications.

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Chapter 6

Conclusion and Recommendations

6.0.1 Conclusion

This research addressed the critical need for accurate and real-time thermal comfort sensing in modern indoor environments. It focused on developing occupant centric solutions that incorporate adaptive control strategies. The study delivered a smart, aware, and adaptable solution that fuses AI based sensing with adaptive control strategies for modern building controls. The research began with a comprehensive review of existing thermal comfort models and technologies, highlighting the limitations of traditional approaches such as Fanger’s Predicted Mean Vote (PMV) and the reliance on static, population-averaged parameters and subjective feedback. These conventional methods often fail to capture the dynamic and individualized nature of occupant comfort, leading to suboptimal building management and energy inefficiency.

To overcome these challenges, a low cost, non contact facial temperature monitoring system was developed, using an RGB-T camera integrated with embedded hardware. The system employed advanced facial detection techniques using DLib to enable robust and automated region-of-interest extraction, focusing on the forehead as a key site for temperature measurement. This approach allowed for reliable, continuous monitoring of occupant skin temperature, providing a direct and objective indicator of thermal sensation.

The research further advanced the integration of physiological data into building management by implementing adaptive control strategies. A BACnet enabled Raspberry Pi platform was used to facilitate real-time communication between the sensing system and building management systems, enabling dynamic HVAC setpoint adjustment based on real-time occupant state. This adaptive approach addressed the shortcomings of fixed setpoints and environmental proxies, supporting more responsive and energy-efficient indoor climate control.

The final system employed a multitask MobileNetV2 deep learning architecture, fine-tuned via transfer learning, to jointly perform face detection and temperature regression directly on thermal images. This unified approach eliminated the need for external face detection libraries and enabled robust, real-time estimation of facial temperature using only low cost thermal sensors. Quantitative evaluation demonstrated high accuracy, with low RMSE and MAE values and physiologically plausible temperature predictions. The system's real-time performance and reliability highlight its suitability for occupant centric comfort assessment and adaptive building management. By bridging affordable sensing technology with advanced analytics, this research provides a scalable foundation for future smart building applications, supporting both occupant wellbeing and energy efficiency.

6.0.2 Identified Gaps and Solutions

- **Gap:** Existing thermal comfort models and building management systems rely on static parameters, subjective feedback, and environmental proxies, failing to provide real-time, individualized comfort assessment and adaptation to dynamic occupant needs.

Solution: Established the need for real-time, occupant centric solutions and laid the foundation for integrating advanced sensing technologies and AI driven models to enable adaptive, personalized comfort assessment.

- **Gap:** Conventional temperature monitoring methods, such as wall-mounted sensors and infrared devices, are often inaccurate due to placement issues and environmental interference, and are not designed for direct occupant comfort assessment.

Solution: Developed a low cost, non contact RGB-T camera system with

automated facial detection and region of interest extraction, enabling reliable, continuous measurement of facial skin temperature as a direct and objective indicator of occupant comfort.

- **Gap:** Traditional building management systems operate with fixed setpoints and lack adaptive control, preventing dynamic response to real-time occupant needs and localized thermal conditions. High costs and complexity further limit the adoption of occupant centric adaptive controls.

Solution: Implemented an adaptive control strategy by integrating real-time physiological data (facial temperature) into a BACnet enabled Raspberry Pi platform, enabling dynamic HVAC control that continuously adjusts environmental conditions based on actual occupant state.

- **Gap:** low cost thermal sensors present challenges in resolution and accuracy, and there is limited application of advanced deep learning models for robust, real-time temperature estimation and comfort prediction in practical building environments.

Solution: Applied and validated deep learning techniques, specifically MobileNetV2 with transfer learning, to achieve accurate facial temperature estimation from affordable thermal images, supporting scalable, occupant centric comfort prediction and demonstrating the potential for integrating AI driven analytics into smart building management.

6.0.3 Significance

This research makes significant contributions to both academia and industry. From an academic perspective, it provides a validated, interdisciplinary framework that bridges the gap between traditional thermal comfort models and modern AI driven, sensor-based approaches. By integrating affordable thermal imaging, advanced facial detection, and deep learning, the study offers a new paradigm for occupant centric comfort assessment that warrants further exploration and refinement in future research. The methodology and findings provide a foundation for subsequent studies in adaptive environmental control, physiological sensing, and intelligent building management, thereby encouraging cross-disciplinary collaboration among fields such as building science, computer vision, and artificial intelligence.

For industry, the proposed solution demonstrates a scalable and cost-effective pathway to enhance occupant comfort and energy efficiency in buildings. The use of low cost hardware, open-source software, and embedded platforms makes the system accessible for widespread adoption, even in resource-constrained settings. By enabling real-time, non contact monitoring and adaptive HVAC control, the research supports the deployment of intelligent, responsive building management systems that can improve occupant wellbeing, reduce energy consumption, and lower operational costs. The practical implications extend to commercial, residential, and institutional buildings, offering a roadmap for the next generation of innovative, sustainable indoor environments.

6.0.4 Limitations

A key limitation of this study is the use of a single participant for experimental validation. While this restricts the generalizability of the findings to broader populations, it also presents a unique advantage. The single-participant approach ensured high consistency and control across all experimental phases, minimizing inter-individual variability and allowing for precise calibration, algorithm development, and system evaluation. This level of experimental control enabled a robust assessment of the technical feasibility and accuracy of the proposed framework. Moreover, the Topdon TS001 provides a thermal frame resolution of 256×192 pixels, with an effective field coverage of approximately $0.78 \text{ m} \times 0.44 \text{ m}$ at the experimental distance between 0.5 m to 0.8 m . This spatial coverage and resolution were sufficient for single-face ROI extraction. The sensing framework and BACnet capability for integration with building controllers is technically extensible to multi-occupant applications. Robust multi-participant detection and thermal tracking were not practical under the current optical coverage and spatial resolution constraints of the hardware setup.

Another significant limitation is the time constraint associated with completing the research within the allocated timeframe. The limited duration necessitated a focused experimental design, thereby restricting the scope of participant recruitment and long-term field trials. As a result, the study prioritized depth and technical rigor in system development and validation over broader population sampling and extended real world deployment.

However, the results may not fully capture the diversity of physiological responses and comfort preferences present in larger, more heterogeneous populations. Future studies should address these limitations by including a wider range of participants, longer observation periods, and more varied environmental conditions to validate and refine the system for broader application.

Finally, the affordable sensing setup worked well as a sensor on a commercial building management system network, the affordable BACnet controller has so far only been tested in a local BACnet network environment. This represents a limitation, as testing solely in a local network may not fully capture the operational challenges, interoperability requirements, and adaptability needed for deployment in real commercial BMS networks. Therefore, future work should focus on validating the BACnet controller's performance, scalability, and integration capabilities within actual commercial BMS infrastructures to more rigorously assess its practical utility and ensure its suitability for widespread adoption in real-world building environments.

6.0.5 Recommendations

To further enhance the accuracy and robustness of the proposed system, future research should consider integrating advanced artificial intelligence models, such as transformer architectures and attention based networks. These state of the art approaches are highly effective at discerning complex patterns, enabling the system to focus on the most relevant facial features for temperature estimation. Thereby improving performance even when utilizing low cost, lower-resolution imaging devices.

Moreover, expanding the analysis to include temperature measurements from multiple facial regions, rather than relying on a single point, can provide a more comprehensive and physiologically meaningful assessment of occupant thermal comfort. By capturing and synthesizing heat distribution data across various anatomical sites, the system's predictive capability and reliability can be significantly improved.

Appendix A - DRC16 Form

DRC16 Statement of Contribution - Chapter 2

 MASSEY UNIVERSITY TE KUNENGA KI PŪREHUROA UNIVERSITY OF NEW ZEALAND		GRADUATE RESEARCH SCHOOL	
STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS			
We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.			
Student name:	Mozammil Ahsan		
Name and title of main supervisor:	Dr Wajiha Shahzad		
In which chapter is the manuscript/published work?	Chapter 2		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: ¹ Conceptualization, methodology, investigation - Mozammil Ahsan (Lead), Wajiha Shahzad, and Khalid Mahmood Arif Original draft preparation & visualization - Mozammil Ahsan Review and editing - Mozammil Ahsan, Wajiha Shahzad, and Khalid Mahmood Arif			
Please select one of the following three options:			
☒	The manuscript/published work is published or in press Please provide the full reference of the research output: Ahsan, M., Shahzad, W., & Arif, K. M. (2024). AI-Based Controls for Thermal Comfort in Adaptable Buildings: A Review. Buildings, 14(11), 3519. https://doi.org/10.3390/buildings14113519		
☐	The manuscript is currently under review for publication Please provide the name of the journal:		
☐	It is intended that the manuscript will be published, but it has not yet been submitted to a journal		
Student's signature:	Mozammil Ahsan Digitally signed by Mozammil Ahsan DN: cn=Mozammil Ahsan, email=m.ahsan@massey.ac.nz, c=US Date: 2025.12.11 19:22:39 +1300 Adobe Acrobat Reader version: 2025.001.20957	Main supervisor's signature:	Wajiha Shahzad Digitally signed by Wajiha Shahzad Date: 2026.01.07 13:46:31 +13'00'
<i>This form should be placed at the beginning of each relevant thesis chapter.</i>			

¹ Refer to the Massey University Publishing and Authorship guidelines ([OneMassey for staff](#), [Stream for students](#)) and/ or [Contributor Roles Taxonomy \(CRediT\) guidelines](#) for guidance.

FIGURE 1: DRC16 Statement of Contribution for Chapter 2

DRC16 Statement of Contribution - Chapter 3

 MASSEY UNIVERSITY TE KUNENGA KI PŪREHUROA UNIVERSITY OF NEW ZEALAND		GRADUATE RESEARCH SCHOOL	
STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS			
We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.			
Student name:	Mozammil Ahsan		
Name and title of main supervisor:	Dr Wajiha Shahzad		
In which chapter is the manuscript/published work?	Chapter 3		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: ¹			
Conceptualization, methodology, investigation - Mozammil Ahsan (Lead) and Khalid Mahmood Arif Original draft preparation & visualization - Mozammil Ahsan Review and editing - Mozammil Ahsan, Wajiha Shahzad, and Khalid Mahmood Arif			
Please select one of the following three options:			
☒ The manuscript/published work is published or in press Please provide the full reference of the research output: Ahsan, M., Shahzad, W., & Arif, K. M. (2025). Accurate Facial Temperature Measurement Using Low-Cost Thermal Camera for Indoor Thermal Comfort Applications. Buildings, 15(22), 4050. https://doi.org/10.3390/buildings15224050			
☐ The manuscript is currently under review for publication Please provide the name of the journal:			
☐ It is intended that the manuscript will be published, but it has not yet been submitted to a journal			
Student's signature:	Mozammil Ahsan Digitally signed by Mozammil Ahsan DN: cn=Mozammil Ahsan, email=mazammil.ahsan@hotmail.com, c=US Date: 2025.12.11 21:07:34 +1300 Adobe Acrobat Reader version: 2025.001.20907	Main supervisor's signature:	Wajiha Shahzad Digitally signed by Wajiha Shahzad Date: 2026.01.07 13:49:20 +13'00'
<i>This form should be placed at the beginning of each relevant thesis chapter.</i>			

¹ Refer to the Massey University Publishing and Authorship guidelines ([OneMassey for staff](#), [Stream for students](#)) and/ or [Contributor Roles Taxonomy \(CRediT\) guidelines](#) for guidance.

FIGURE 2: DRC16 Statement of Contribution for Chapter 3

DRC16 Statement of Contribution - Chapter 4

 MASSEY UNIVERSITY TE KUNENGA KI PŪREHUROA UNIVERSITY OF NEW ZEALAND		GRADUATE RESEARCH SCHOOL	
STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS			
We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.			
Student name:	Mozammil Ahsan		
Name and title of main supervisor:	Dr Wajiha Shahzad		
In which chapter is the manuscript/published work?	Chapter4		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: ¹ Conceptualization - Mozammil Ahsan Methodology and Investigation - Mozammil Ahsan and Khalid Mahmood Arif Original draft preparation and Visualization - Mozammil Ahsan Review and Editing - Mozammil Ahsan, Wajiha Shahzad and Khalid Mahmood Arif			
Please select one of the following three options:			
☐	The manuscript/published work is published or in press Please provide the full reference of the research output:		
☐	The manuscript is currently under review for publication Please provide the name of the journal:		
☒	It is intended that the manuscript will be published, but it has not yet been submitted to a journal		
Student's signature:	Mozammil Ahsan Digitally signed by Mozammil Ahsan DN: cn=Mozammil Ahsan, email=MozammilAhsan@hotmail.com, o=US Date: 2025.12.11 21:09:04 +1300 Adobe Acrobat Reader version: 2025.001.20467	Main supervisor's signature:	Wajiha Shahzad Digitally signed by Wajiha Shahzad Date: 2026.06.29 15:17:24 +12'00'
<i>This form should be placed at the beginning of each relevant thesis chapter.</i>			

FIGURE 3: DRC16 Statement of Contribution for Chapter 4

DRC16 Statement of Contribution - Chapter 5

 MASSEY UNIVERSITY TE KUNenga KI PŪREHUROA UNIVERSITY OF NEW ZEALAND		GRADUATE RESEARCH SCHOOL	
STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS			
We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.			
Student name:	Mozammil Ahsan		
Name and title of main supervisor:	Dr Wajiha Shahzad		
In which chapter is the manuscript/published work?	Chapter 5		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: ¹ Conceptualization - Mozammil Ahsan Methodology and Investigation - Mozammil Ahsan and Khalid Mahmood Arif Original draft preparation and Visualization - Mozammil Ahsan Review and Editing - Mozammil Ahsan, Wajiha Shahzad, and Khalid Mahmood Arif			
Please select one of the following three options:			
☐	The manuscript/published work is published or in press Please provide the full reference of the research output:		
☐	The manuscript is currently under review for publication Please provide the name of the journal:		
☒	It is intended that the manuscript will be published, but it has not yet been submitted to a journal		
Student's signature:	Mozammil Ahsan Digitally signed by Mozammil Ahsan DN: cn=Mozammil Ahsan, email=mazammil@icloud.com, o=UNZ Date: 2025.12.11 21:00:04 +1300' Adobe Acrobat Reader version: 2025.001.20967	Main supervisor's signature:	Wajiha Shahzad Digitally signed by Wajiha Shahzad Date: 2026.01.07 14:04:17 +13'00'
<i>This form should be placed at the beginning of each relevant thesis chapter.</i>			

¹ Refer to the Massey University Publishing and Authorship guidelines ([OneMassey for staff](#), [Stream for students](#)) and/ or [Contributor Roles Taxonomy \(CRediT\) guidelines](#) for guidance.

FIGURE 4: DRC16 Statement of Contribution for Chapter 5

Appendix B: Ethics Approval



Ethics Application

Application ID :	4000031158
Application Title :	Smart, Aware and Adaptable Buildings
Date of Submission :	19/08/2025
Primary Investigator :	Mohammed Ahsan (Applicant)
Other Personnel :	Dr Wajiha Shahzad (Applicant)

Initial Assessment**Project Detail****Human Ethics Application Risk Assessment Form**

Does your research fall within the scope of the Code? The scope includes:

- a. All research involving either the participation of human or where the research impacts on individuals, groups or communities. This includes consultancies, contract research, staff research and supervised student research.
- b. Any teaching which involves the participation of students for the demonstration of procedures or phenomena that have a potential for harm.
- c. Any evaluation of university services, organisational practices or teaching programmes where information of a personal nature may be collected, where participants may be identified, or where the performance of staff may be commented on. This does not include routine organisational quality improvement activities, e.g. academic programme evaluations or service delivery projects but does include activities which have a research component and may lead to publications.

NB: Where research involves a Massey staff researcher using their own students as participants please refer to the [Decision Chart](#) in Section 2 of the Code.

Applicant Information- PEER REVIEW

If your application is deemed to be high risk after the risk assessment questions have been answered, there will be an option for you to have your full application peer reviewed, prior to submitting it for approval. (This could be a supervisor if you are a student, or a colleague in the case of academic research). The process is as follows:

- Click on the 'Send for peer review' action.
- Follow the instructions given.

Note:

This process will send an email to your peer reviewer which contains a pdf of the application.

The peer reviewer comments by email outside of the RIMS process.

This **IS NOT** part of the approval process.

Following comment (if any) from your peer reviewer, you must **STILL** submit the final application by clicking on the "Submit" action.

- 1 Project Title:
(Please limit this to a maximum of 25 words)

Smart, Aware and Adaptable Buildings

- 2 **Recruitment / Data collection start date:**

This date must be in the future.

Data collection /recruitment cannot begin until notification of submission has been received.

20/08/2025

- 3 What date do you expect data collection and analysis activities to be completed by?

Note: this must be done within 3 years of ethics approval.

30/06/2026

- 4 **Project Type:**

☒ Postgraduate Student Research

- 5 **Aim of the project:**

Measure the Facial thermal temperature of the occupant in an indoor environment so that an algorithm can be prepared for measuring occupant comfort in real time via AI methods.

- 6 **Project Summary:**

Please outline in no more than 2000 characters in lay language (What you're doing, how you're doing it, who you're doing it with)

In my research, I am measuring face temperature using thermal imaging. The thermal images do not include any facial identification, and for the experiments, I have only used my own thermal images. I am doing the experiment under the supervision of Dr Wajiha Shahzad and Dr Khalid Arif.

- 7 **Describe the peer review process that has been used to discuss and analyse the ethical issues present in this project:**
(maximum of 4000 characters)

The following steps were taken in the process.

1) Reviewed and discussed ethical resources with the Supervisors

a. Massey University's Code of Ethical Conduct for Research, Teaching, and Evaluations Involving Human Participants to understand institutional ethical requirements.

b. The ethics application form, which provides a structured framework for addressing ethical concerns.

2) Reviewed the project scope with the supervisor in consideration of the ethical values.

3) Discussed the practical outcomes and objectives of the project in consideration of the ethical values.

4) A final detailed report summarising the ethical concerns, project scope, and objectives was prepared, which was then discussed with the supervisors.

- 8 Summarise the ethical issues considered and explain how each has been addressed:
(maximum of 2000 characters)

Ethical issue considered - Occupant privacy and risk to Massey University ethical values.
 Addressed -
 1) Use low resolution thermal camera as a result the occupant cannot be identified.
 2) Consult and Analyse data collected with the supervisors to ensure Massey University ethical values and standards are not breached.

9 With whom did you peer review the ethical aspects of your research?
 (maximum of 2000 characters)

Dr Wajjha Shahzad (Main supervisor)
 Dr Khalid Arif (co- supervisor)

Applicant

1 Applicant Department:

School of Built Environment

2 Ethics Category:

Human

3 Campus of Chief Applicant:
 (or Campus of Supervisor for Student)

☒ Albany

4 Internal Personnel:

Please add any additional team members here. For student applicants, please also add your supervisor(s) here.

1	Surname	Ahsan
	Given Name	Mohammed
	Full Name	Mohammed Ahsan
	Position	Applicant
	Primary?	Yes
	Work Number	Not Answered
	Email Address	Mohammed.Ahsan.1@uni.massey.ac.nz
	Department	Not Answered
	College	Not Answered
2	Surname	Shahzad
	Given Name	Wajjha
	Full Name	Dr Wajjha Shahzad
	Position	Applicant
	Primary?	Not Answered
	Work Number	Not Answered
	Email Address	W.M.Shahzad@massey.ac.nz
	Department	School of Built Environment
	College	College of Sciences

5 External Personnel:

Please add name of co researchers if unable to locate above

1	Full Name	Dr Khalid Arif
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Health and Disability Ethics Committee

Is Health and Disability Ethics Committee (HDEC) review required for this study?

☒ No

If you are unclear about whether approval from HDEC is required, please click on the links below.

[Operating Procedures for HDECs \(NZ Government Health and Disability Ethics Committees website\)](#)

[Find out if your study requires HDEC review \(NZ Government Health and Disability Ethics Committees website\)](#)

Please click on 'Save' to continue, then click on the blue button that says "Next Page: Risk Assessment Questions".

Risk Assessment Questions

Does your research include:

Note: all of the risk assessment questions are mandatory

- a) **Situations where the researcher may be at risk of harm.**
☒ No
- b) **Use of a questionnaire or interview, whether or not it is anonymous, which might reasonably be expected to cause discomfort, embarrassment or psychological or spiritual harm to the participants.**
☒ No
- c) **Processes that are potentially disadvantageous to a person or group, such as the collection of information which may expose a person / group to discrimination.**
☒ No
- d) **Collection of information of illegal behavior(s) gained during the research which could place the participants at risk of criminal or civil liability or be damaging to their financial standing, employability, professional or personal relationships.**
☒ No
- e) **Collection of blood, body fluid, tissue samples or other samples.**
☒ No
- f) **Any form of exercise regime or manipulation (e.g. sleep pattern or dietary).**
☒ No
- g) **Any form of physical examination (e.g. physical, radiation, ultrasound).**
☒ No
- h) **The administration of any form of drug (including alcohol), medicine (other than in the course of standard medical procedure), or placebo.**
☒ No
- i) **Physical pain, beyond mild discomfort.**
☒ No
- j) **Any Massey University teaching which involves the participation of Massey University students for a demonstration of procedures or phenomena which have potential for harm.**
☒ No
- k) **Participants whose identities are known to the researcher giving oral consent, rather than written consent, other than for cultural reasons.**
☒ No
- l) **Participants who are unable to give informed consent.**
☒ No
- m) **Research on your own students / pupils. For Massey Staff - refer to the Decision Chart in section 2 of the Code.**
[Code of Ethical Conduct - Decision Chart](#)
☒ No
- n) **The participation of children (seven (7) years old or younger).**
☒ No
- o) **The participation of children under sixteen (16) years old where active parental consent is not being sought.**
☒ No
- p) **Participants who are in a dependent situation, such as nursing home or prison, or patients highly dependent on medical care.**
☒ No
- q) **Participants who are vulnerable.**
☒ No
- r) **The use of previously collected identifiable personal information or research data for which there was no explicit consent for this research.**
☒ No

- s) **The use of previously collected biological samples for which there was no explicit consent for this research.**
☐ No
- t) **Any evaluation of organisational services or practices where information of a personal nature may be collected and where participants or the organisation may be identified.**
☐ No
- u) **Deception of the participants, including concealment or covert observations.**
☐ No
- v) **Conflict of interest situation.**
[Code of Ethical Conduct - Special Relationships](#)
e.g. Is the project funded or supported in any way that might result in a conflict of interest, do any of the researchers have a financial interest in the outcome, or is there a professional or other relationship between the researcher and the participants?
☐ No
- w) **Payments or other financial inducements (other than reasonable reimbursement of travel expenses or time) to participants.**
☐ No
- x) **A requirement by an outside organisation (e.g. a funding organisation or a journal in which you wish to publish) for Massey University Human Ethics Committee approval.**
☐ No
- y) **I wish to submit a full application for Training / Education purposes.**
☐ No

Risk Level

Risk Assessment

Due to your responses to the risk assessment questions, your application has been categorized as Low Risk.

If you click on Submit, you will have access to the sign off section and submit the application for review (if applicable) in the Low Risk category. Note that you will not be able to change the Risk Assessment during that stage.

If you want to change this, please review and update the Risk Assessment section to re-evaluate the risk level.

Please click on 'Yes' to confirm and submit to continue

☒ Yes

Sign off**Applicant Sign Off**

To submit this application please select the check box below, then click on the Submit action on the right hand side of this page.

As Chief Applicant;

- I have read the Code of Ethical Conduct for Research, Teaching and Evaluation involving Human Participants.
- I understand my obligations and the rights of the participants.
- My Head of Unit knows that I am undertaking this research. (for academic staff research)
- I understand that Low Risk Notifications are audited by the Ethics Office and that breaches in complying with Low Risk conditions will be followed up.
- I agree to undertake the research as set out in the Code.

Are there any co-researchers?

☒ No

- The information in this application is to the very best of my knowledge accurate and not misleading.

☒ I have read and understood the above statements

Your supervisor will have to approve this application before it can be processed.
Click on the Review Group button in the toolbar on the right. Search for your supervisor by searching for their surname only. Click on the entry that has a six digit ID code, as this is their staff ID rather than their student ID.

Approver Signoff

Comments for researcher.

The application has been reviewed by supervisory team and deemed as low risk.

Once you have completed the comments section you must submit the form. To do this click on the Submit button on the right hand side.

- I have read the Code of Ethical Conduct for Research, Teaching and Evaluation involving Human Participants.
- I understand my obligations and the rights of the participants.
- I understand that Low Risk Notifications are audited by the Ethics Office and that breaches in complying with Low Risk conditions will be followed up.
- I agree to undertake the research as set out in the Code.