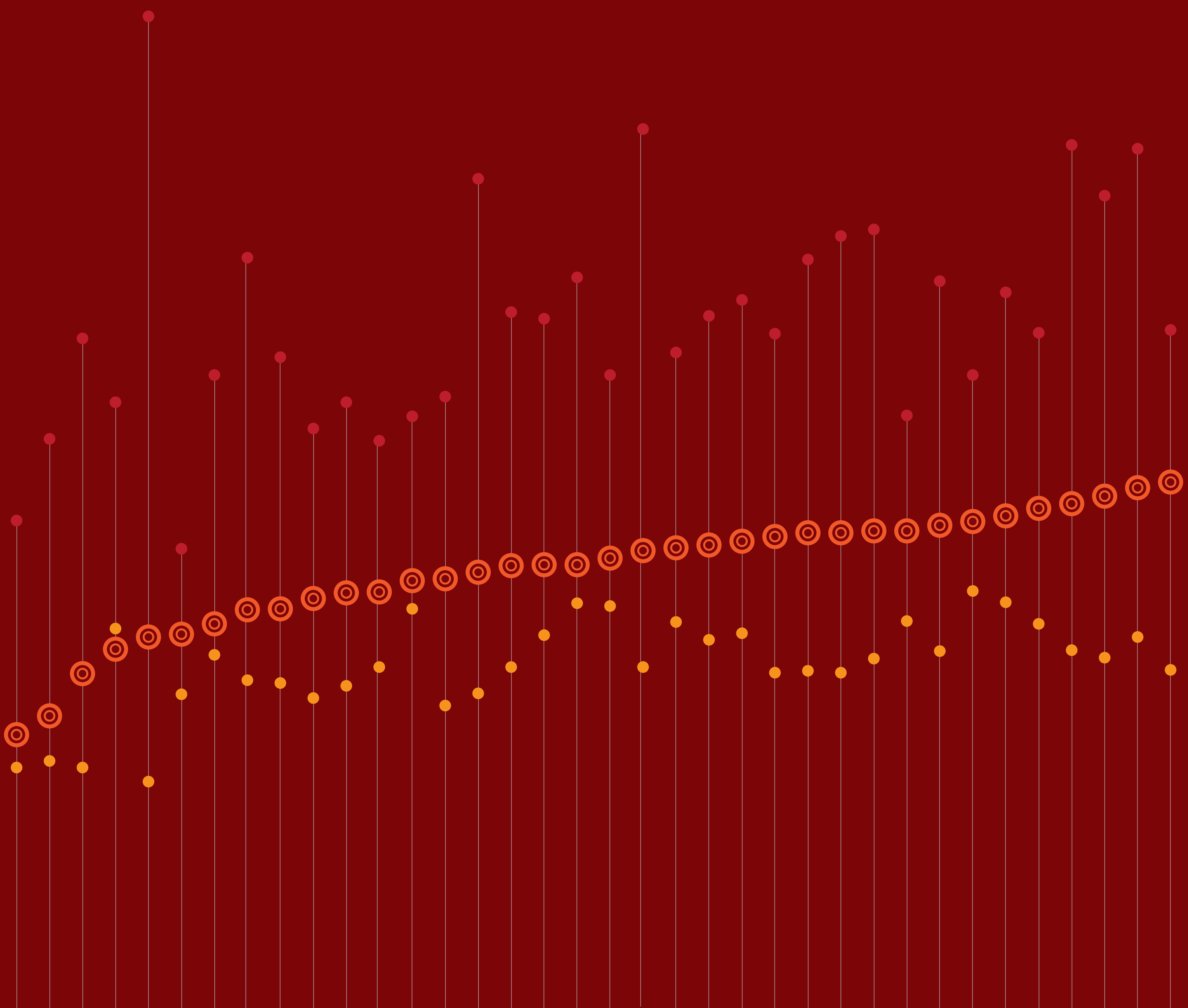
Understanding thermal comfort and wellbeing of older South Australians using occupant-centric models

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

Larissa Arakawa Martins

School of Architecture and Built Environment
Faculty of Engineering, Computer and Mathematical Sciences
The University of Adelaide



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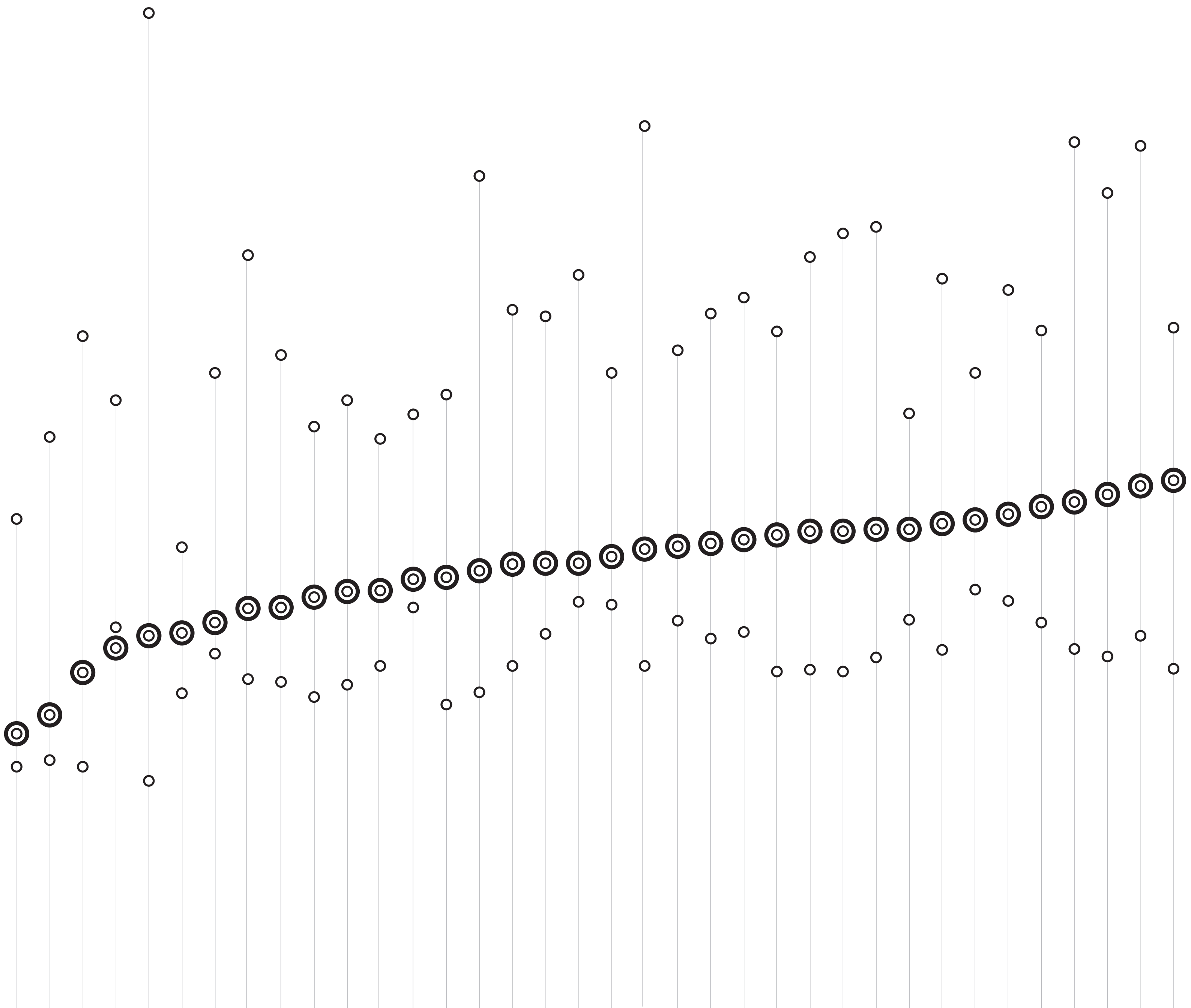

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List of abbreviations and nomenclature

(except for those only present in published chapters)

Acc - Accuracy

ANN – Artificial Neural Network

AUC – Area Under the Receiver Operating Characteristic Curve

AVA – Arteriovenous Anastomoses

BMI – Body Mass Index

BMR – Basal Metabolic Rate

CO_2 – Carbon Dioxide

COP – Coefficient of Performance

EER – Energy Efficiency Ratio

EMS – Energy Management System

FOV – Field of View

HVAC – Heating, Ventilation and Air Conditioning

IoT – Internet of Things

max – maximum

min – minimum

MRES - Modified Reported Edmonton Scale

PCM – Personal Comfort Model

PCS – Personal Comfort System

PMV_c – Converted Predicted Mean Vote

PMV – Predicted Mean Vote

PPD – Predicted Percentage of Dissatisfied

ReLU - Rectified Linear Unit activation function

ROC – Receiver Operating Characteristic

TPV – Thermal preference vote

TSV – Thermal sensation vote

VIF – Variance Inflation Factor

VOC – Volatile Organic Compound

WLS – Weighted Least Squares

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Included publications, associated publications, presentations and awards

Journal publications included in this thesis

Arakawa Martins, L., Soebarto, V., Williamson, T. (2022) "A systematic review of personal thermal comfort models", Building and Environment, Vol. 207, Part A, https://doi.org/10.1016/j.buildenv.2021.108502

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Arakawa Martins, L., Soebarto, V., Williamson, T. (2022) "Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables", Journal of Building Engineering, Vol. 51, https://doi.org/10.1016/j.jobe.2022.104357

Associated publications

Williamson, T., Soebarto, V., Bennetts, H., **Arakawa Martins, L.**, Pisaniello, D., Hansen, A., Visvanathan, R., Carre, A., van Hoof, J. (2022) "Chapter 7: Assessing human resilience: A study of thermal comfort, wellbeing and health of older people", in Nicol, F., Rijal, H.B., & Roaf, S. (Eds.). Routledge Handbook of Resilient Thermal Comfort (1st ed.), Routledge. https://doi.org/10.4324/9781003244929

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Arakawa Martins, L., Williamson, T. J., Pisaniello, D., Soebarto, V. (2020) "A deep learning approach to personal thermal comfort models for an ageing population", Imaginable Futures: Design Thinking, and the Scientific Method: 54th International Conference of the Architectural Science Association (ANZAScA) 2020, 27 November 2020, online.

Arakawa Martins, L., Bennetts, H., Williamson, T., Hansen, A., Pisaniello, D., van Hoof, J., Zuo, J., Visvanathan, R., Soebarto, V. (2020) "Understanding the Thermal Quality of the Living Environment of Older South Australians", 53rd Australian Association of Gerontology Conference, 19 November 2020, online.

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Arakawa Martins, L., Williamson, T., Soebarto, V. (2019) "Towards an understanding of comfort and wellbeing of older people using occupant centric models.", XV Encontro Nacional de Conforto no Ambiente Construído ENCAC, 18 September 2019, João Pessoa, Brazil.

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Awards

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HDR Thesis Declaration

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In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Larissa Arakawa Martins

March, 2022

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Abstract

The proportion of older people (i.e., those aged 65 or over) in the world's population is increasing due to historically low fertility rates combined with increased life expectancy. In order to respond to these demographic trends, a growing body of policy and research over the last decades has accepted that ageing-in-place is most beneficial in the interests of older people's independence, health and wellbeing, as well as to reduce the economic burden on governments and society for the provision of aged care facilities. While there are several guidelines that provide information about designing dwellings to suit ageing-in-place, information to aid older people's thermal comfort and related wellbeing is not always considered. This thesis addresses the current knowledge on thermal comfort of older people in order to provide environments that meet their individual requirements and help improve their overall wellbeing.

Traditionally, thermal comfort standards adopt aggregate modelling approaches as the bases on which to establish the requirements for human occupancy in the built environment. Aggregate models explain thermal comfort at a population level, which can result in limitations in real scenarios as individual thermal perceptions can vary significantly. In recent years, a growing number of studies have been conducted to address these limitations by developing 'personal comfort models'. Instead of an average response from a large population, personalised models predict individuals' thermal comfort by using a single person's direct feedback. Nonetheless, up until the research presented in this thesis, studies on personal comfort models have focused on younger adults, generally in office environments. This presents a critical research gap because intergroup heterogeneity in personal capabilities and needs tends to be greater among older people, causing the use of aggregate models for older adults to result in even more frequent exposure to unacceptable thermal environments. These, in turn, can interact with multiple comorbidities, leading to adverse health outcomes and possibly premature institutional care. Thus, personalising models hold the promise of a more accurate way to predict older people's thermal comfort and to manage their thermal environments better.

Considering the issues and opportunity presented above, the goal of this research is to advance the current knowledge on the use of personal thermal comfort models by focusing on older people in their home environments. The research aims to achieve this goal by: (1) reviewing the present understandings of personal comfort models, (2) investigating older people's' thermal environment, behaviours and preferences; (3) developing personal comfort models for older people and comparing the results with the

predictions by established aggregate models; and (4) investigating the application of personal comfort models in managing the thermal environment of older people.

Two indoor environmental monitoring field studies and related point-in-time thermal comfort surveys were conducted to collect datasets for the analyses. The first dataset was collected from 71 older adults in 57 households located in South Australia across 9 months. This was followed by the application of deep learning (i.e., a class of machine learning) to develop personal comfort models for 28 out of these 71 participants using different combinations of the collected series of indoor environmental measurements, along with behavioural and health/wellbeing survey answers. The second dataset was collected during shorter 2-week periods involving 11 of the original 71 participants, during which, in addition to measuring the indoor environmental parameters and collecting behavioural and health/wellbeing survey answers, the participants' hand skin temperatures were measured. The development of personal models for 4 of these participants was then conducted, including skin temperatures as an additional modelling input. Several performance indicators, including average accuracy, Cohen's Kappa Coefficient and Area Under the Receiver Operating Characteristic Curve (AUC) were employed to assess the skill of the developed individual models. All models' performance indicators were then compared with a 'version' of the Predicted Mean Vote (PMV) model, termed, in this thesis, the PMVc.

The results showed that the 28 personal thermal comfort models for older adults that used environmental, behavioural and health/wellbeing perception as input variables presented an average accuracy of 74%, an average Cohen's Kappa Coefficient of 61% and an average (AUC) of 0.83. This represented a significant improvement in predictive performance when compared with the generalised PMVc model, which presented an average accuracy of 50%, an average Cohen's Kappa Coefficient of 24%, and an average AUC of 0.62. Similarly, the exploration with the 4 personal comfort models adding skin temperature measurements to the abovementioned input variables, and excluding health/wellbeing perception − which yielded slightly lower performance when included −, resulted in an average accuracy of 67%, an average Cohen's Kappa Coefficient of 50% and an average AUC of 0.77. This also represented a superior predictive performance of the individualised models when compared with the PMVc model.

In order to investigate the applications of the personal comfort models in operation, two participants were selected as case studies and their respective personal models were tested for their ability to estimate personal heating and cooling temperature set points, using calibrated building performance simulation models. The simulated energy loads derived from the use of personal set points were compared with simulated energy loads using 21°C as the heating set point and 24°C as the cooling set point, which represented the common averaged set points used in building simulation studies. The results show that, using the personal set points, good agreement between the actual and simulated heating and cooling energy loads was achieved. When comparing the error ratios with the ones resulting from simulations assuming a 21°C set point for heating and a 24°C for cooling, the study also showed that the personal set points significantly outperformed these traditional assumptions.

Finally, as a secondary application exploration, one selected participant's personal model was converted to a smart phone Application (App) format to examine the opportunity to use the model as a web-based smart phone tool to aid designers and caregivers to manage the thermal environments of older people by considering individual requirements. This conversion also proved to be successful, allowing the automatic calculation of thermal preference for the selected participant, thereby demonstrating its potential to aid designers and caregivers.

The novelty and therefore the contributions of this research lay in different areas. Whilst the literature on personal comfort models has focussed solely on younger adults in office environments, this research has explored a methodology for predicting thermal comfort of older people in their dwellings. Additionally, it has introduced health/wellbeing perception as a predictor of thermal preference – a variable often overlooked in architectural sciences and building engineering. Finally, the research indicates that, compared with aggregated models, personal models provide superior utility in predicting an individual's preferred thermal environment, which therefore offers the potential for more accurate tools to design and improve older people's living environments so that wellbeing is optimised, healthy ageing is fostered and autonomy while ageing is prolonged.

The research recommends a range of topics for future investigation, such as the models' misclassification costs and the integration among wearable sensors, predictors and actuators in the context of older people. In addition, the development of standard protocols necessary for the models' deployment in real scenarios is prescribed.

In conclusion, the research demonstrates that, as a concept, personal comfort models have the ability to absorb people's diversity in the context of their environmental conditions, and may therefore represent an important step towards providing knowledge aimed at enhancing wellbeing and improving the overall resilience of the built environment.

Chapter 1. Introduction

1.1. Overview of the research background

As stated by the United Nations Department of Economic and Social Affairs, Population Division, the number of older people[1] is increasing as a proportion of the world's population due to historically low levels of fertility combined with increased life expectancy. As seen in **Figure 1-1** and described by the United Nations' report, "*In 2018, for the first time in history, persons aged 65 years or over worldwide outnumbered children under age five. Projections indicate that by 2050 there will be more than twice as many persons above 65 as children under five. By 2050, the number of persons aged 65 years or over globally will also surpass the number of adolescents and youth aged 15 to 24 years*" (United Nations Department of Economic and Social Affairs Population Division, 2019a).

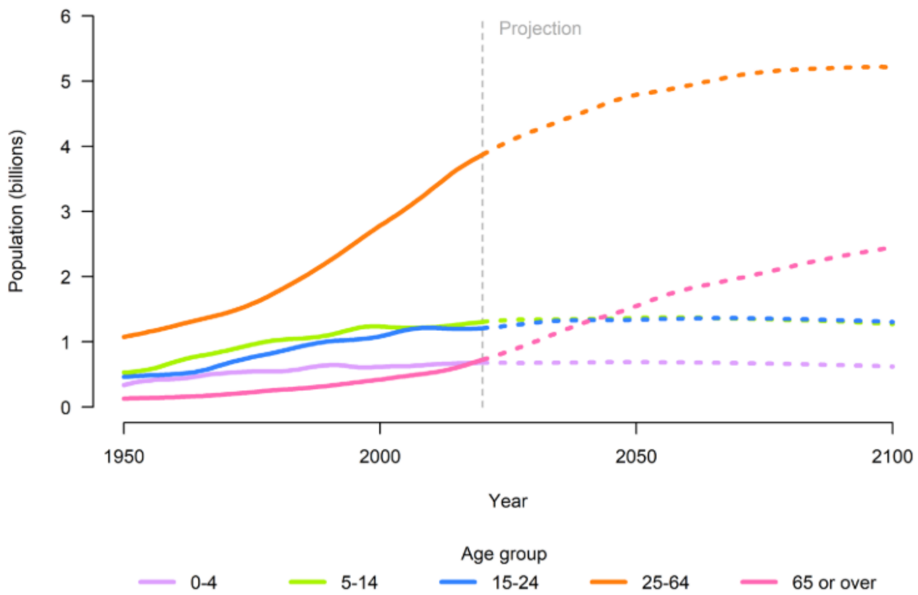

Figure 1-1 - Estimated and projected global population by broad age group, 1950-2100, according to the medium-variant projection. Source: United Nations Department of Economic and Social Affairs Population Division (2019a).

Furthermore, the OECD (Organisation for Economic Co-operation and Development) highlighted that the average old-age (65 years or over) to working-age (24 to 64 years) ratio will almost double in the

[1] Throughout this thesis, older people are defined as aged 65 years old or over, following Australian standard practice.

next 40 years among the OECD countries, as depicted in **Figure 1-2**. By 2060, South Korea, Spain and Japan will be the countries with the highest proportion of older people compared with younger adults' populations. In fact, South Korea will go from having 2.4 older people to every 10 working age people in 2020, to having 9 older people to every 10 working age people in 2060, configuring the fastest demographic change among the OECD members.

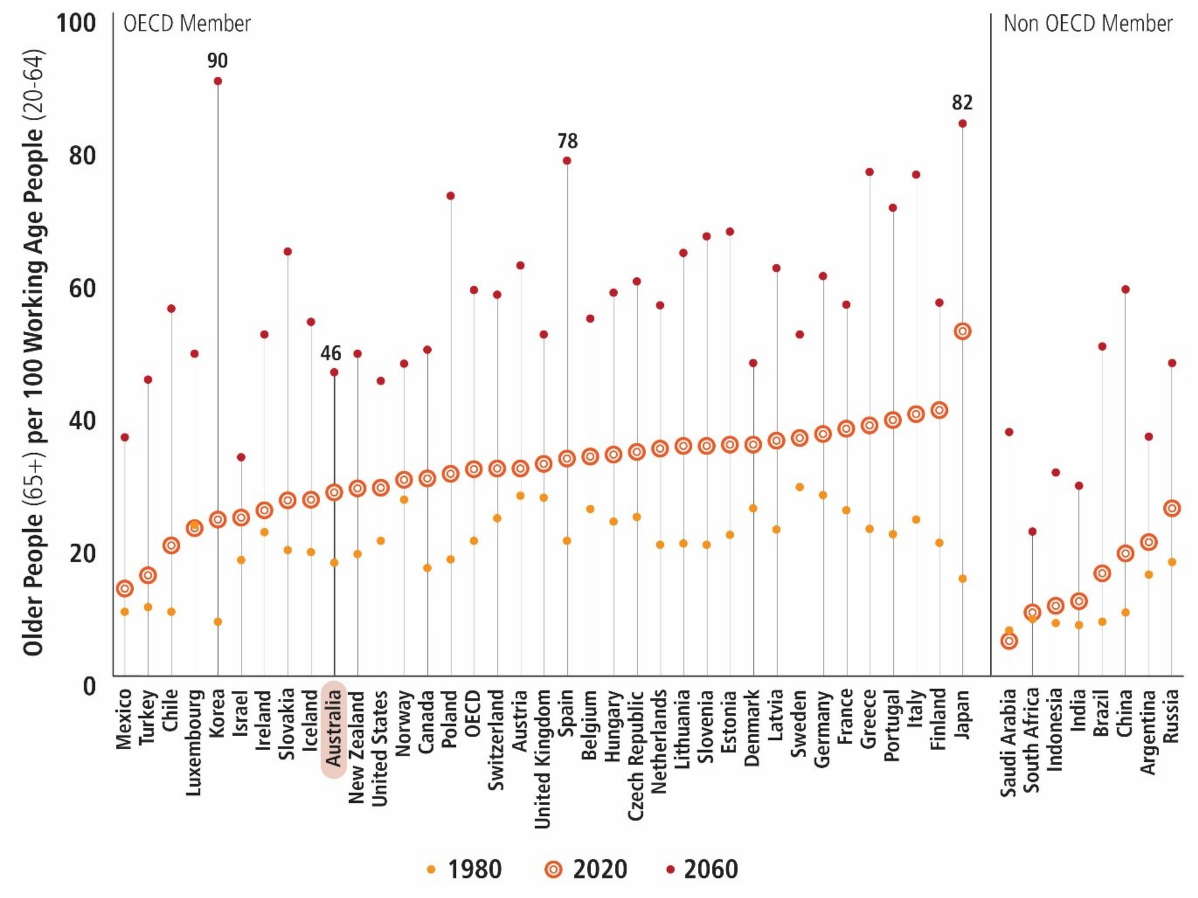

Figure 1-2 - Number of people older than 65 years per 100 people of working age (20-64), 1980-2060, based on data from OECD (2019) and United Nations Department of Economic and Social Affairs Population Division (2019b)

Like the rest of the world, Australia is going through the same demographic changes. According to the latest National, State and Territory Population Statistics, in December 2020, 16.4% of Australians were aged 65 and over (Australian Bureau of Statistics, 2021a). By 2066, it is projected that 20.7%[2] of Australia's population will be aged 65 or over (Australian Bureau of Statistics, 2018). Consequently, this ageing phenomenon has been acknowledged by the Australian Department of Treasury since the early

[2] Under high fertility, mortality and net overseas migration assumptions, using 2017 as the base year.

2000s as having important effects on public policies, especially in areas such as health and housing (Australian Government Department of Treasury, 2010).

In order to respond to these demographic trends, a growing body of policy, research and program developments over the last decades have accepted that ageing-in-place[3] is beneficial in the interests of older people's independence, health[4] and wellbeing[5], as well as reducing the economic burden on governments for the provision of aged care facilities. Judd et al. (2010) confirmed that not only do older Australian homeowners want to remain in their own homes and neighbourhoods for as long as possible, but they also greatly recognise the importance of the design of the dwelling in order to remain independent and able to participate in the community throughout their ageing course.

While there are several design guidelines that provide information about modifying, building or managing dwellings to suit ageing-in-place (Carnemolla and Bridge, 2018), modifications to aid thermal comfort and related wellbeing are not always considered. Therefore, this thesis addresses the current knowledge on thermal comfort of older people in order to provide environments that meet their ***individual thermal comfort requirements*** and help improve their overall wellbeing.

Overall, physical ageing is commonly associated with changes on the body's thermoregulation processes that can compromise the efficiency of thermal defence mechanisms and the ability to respond effectively to temperature fluctuations, upsetting the homeostatic balance of health in some. As people age, unavoidable physiological changes such as structural skin modification and metabolic alterations affect their thermal perception, sensitivity and regulation (Blatteis, 2012; Dufour and Candas, 2007). As thermoregulation plays a vital part in human survival (Shibasaki et al., 2013), older people can become more vulnerable at temperature extremes in their environment, therefore demanding special attention be paid to their thermal requirements.

This is particularly important because it is hypothesised that extreme weather events may increase not only in number, but also in intensity and overall duration (Intergovernmental Panel on Climate Change, 2014; World Health Organization, 2015a). Based on comprehensive research that analysed a wide body of observations and modelling studies of the world climate systems, as well as the plausibility of future projections across all commonly used scenarios, the detailed report from the Intergovernmental

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[3] Ageing-in-place: the ability to live in one's own home for as long as confidently and comfortably possible (Judd et al., 2010).

[4] Health: commonly defined by practitioners, policy makers, and scholars as a resource for everyday life (Williamson and Carr, 2009).

[5] Wellbeing: a multidimensional concept involving physical, emotional, psychological, social, spiritual, intellectual, and economic wellness (White, 2008; Wellbeing People, 2018)

Panel on Climate Change (2014) points to the increase in the number of warm days and nights on the global scale and to the increase in the frequency of heatwaves in large parts of Europe, Asia and Oceania.

Likewise, Australia is reported as one of the world's regions that is particularly susceptible to heat waves and drought conditions, according to the 2011-2015 report from the World Meteorological Organization (2016). In the summers of 2012/2013 and 2013/2014, for instance, the country experienced records for persistent heat in many cities, including four consecutive days above 41 °C in Melbourne, Victoria. The 2020 report from the same organisation also reported extreme temperatures such as 2020 Penrith's (western Sydney, New South Wales) 48.9°C − the highest temperature observed in an Australian metropolitan area −, and Canberra's (Australian Capital Territory) 44.0°C on the same day (World Meteorological Organization, 2021). Adelaide, South Australia, also records regular heatwaves and extreme heat events, during which total ambulance call-outs and total mortality tend to escalate (Faunt et al., 1995; Nitschke et al., 2011). Therefore, as lowered heat tolerance can make older people more vulnerable to heatwaves as well as to cold spells (Hansen et al., 2011; Stafoggia et al., 2006), understanding older people's thermal needs and preferences to improve the thermal conditions of their environment becomes an important consideration.

Many international studies have addressed thermal comfort and adaptation for the ageing population (Jiao et al., 2017; Taylor et al., 1995; van Hoof and Hensen, 2006; Yang et al., 2016; Wang et al., 2020). While consistent progress has been made from diverse perspectives, other topics still benefit from further investigation, such as the geographical differences in older people's thermal perception, the effects of thermal disturbances on older adults' health and smart home technologies for enhancing thermal comfort (van Hoof et al., 2017b).

Furthermore, thermal comfort studies investigating the differences and similarities between older and younger adults regarding thermal comfort are still inconclusive. Wang et al. (2018) conducted a literature review on both climate chamber studies and field studies, concluding no significant differences between the comfort temperatures of young and older people once clothing, metabolic, and anthropometric differences were taken into account. Other studies, however, reported contradicting differences between cohorts, such as that older people preferred higher (Schellen et al., 2010) or lower (Tartarini et al., 2017) temperatures than younger cohorts, and that their comfort range was narrower (Hwang and Chen, 2010) or wider (Yang et al., 2016). In these cases, the distinction between how older adults and younger populations seem to perceive their thermal environments could be explained by a combination of both physical ageing and relevant behavioural differences.

Apart from intergroup variability between younger and older adults, the differences relating not only to thermal comfort and perception (Shipworth et al., 2016; Wang et al., 2018), but also to health and physical functioning (World Health Organization, 2015b), can occur among individuals inside both groups. In fact, explaining diversity in perceived thermal comfort has been an interest of many studies for decades (Wang et al., 2018). The fact that subjects might perceive and respond completely differently when exposed to the exact same thermal environment indicates that other factors and stressors than the environmental parameters should also be considered when designing or managing the built environment. These factors can range from psychological, physiological and personal characteristics to the social and environmental contexts of each individual (Bluyssen, 2019).

Nevertheless, although intragroup diversity is present in both younger and older cohorts, this heterogeneity tends to be greater in older age than in younger ages. This is because older adults have been submitted to a greater range of cumulative social, economic and environmental factors and trajectories across their individual life courses, which affect their needs and perceptions in significantly different ways (World Health Organization, 2015b). For this reason, understanding diversity in older age also becomes crucial to predict older people's needs and requirements accurately.

According to the WHO - World Health Organization (2015b), diversity is a hallmark of older age and in order to develop relevant policy that fosters healthy ageing for all older people, studying their needs at the individual level is essential. Among the different ways to achieve this, person-centred approaches are strategies highlighted by the WHO for health and long-term care settings (World Health Organization, 2020). This new approach could result in a real paradigm shift in the way global health services are managed and provided, delivering health services that respond directly to people's needs and preferences, in a flexible and consequently effective way.

Looking from the same perspective, the field of thermal comfort is also experiencing the same paradigm shift. Most studies on thermal comfort that focus on the population level, on averaged responses from a group of people and on one-size-fits-all centralised thermal management, are being called into question by much more individualised and occupant-centric alternatives (Kim et al., 2018a). This indicates that diversity in preferences and perceptions are beginning to be considered in these studies, and that occupants whose comfort perception generally deviates from averaged population means are finally being regarded as relevant.

In this context, since older people's individual differences are wide, much profit can be derived from investigating their environmental comfort from the same person-centred approach.

1.2. Problem statement

Traditionally, international thermal comfort standards (ANSI/ASHRAE, 2020; CEN, 2007; ISO, 2005) adopt aggregate modelling approaches, such as the Predicted Mean Vote (PMV) model (Fanger, 1970) and the adaptive model (de Dear and Brager, 1998; Nicol and Humphreys, 1973) as the bases for the thermal requirements for human occupancy in the built environment. Aggregate models explain human thermal comfort on a population level, mainly based on environmental parameters and/or behavioural factors. This implies that assessing building design options is based on complying with averaged thermal comfort conditions, disregarding occupants whose comfort perceptions deviate from the population mean.

However, predicting thermal comfort at the population level might result in limitations for these two methods when used to predict occupants' comfort in real case scenarios. These limitations include the models' poor predictive performance when applied to different individuals and the inability of the models to be calibrated with diverse feedback or to incorporate addition personal input variables that may be significant (e.g., age, health status, body composition) (Kim et al., 2018a). In addition, the standards' models have been developed based on data mainly from office buildings, with fewer studies focused on behaviours in dwellings. This can also be limiting when considering the diversity of thermal conditions that residential settings generally provide in comparison with controlled office environments.

To address these limitations, recent studies have shown an increasing number of strategies to develop 'personal thermal comfort models' as an alternative to the conventional approaches. Instead of relying on an average response from a large population, personalised models are designed to predict individuals' thermal comfort responses using a single person's direct feedback and/or personal characteristics as calibration inputs. In addition, with the rapid development of the IoT (Internet of Things) and smart sensors, investigating individuals' thermal comfort requirements, predicting their needs directly from data collected in their everyday environment, and acting upon these predictions has become substantially easier.

Nevertheless, although increasingly researched, personal comfort models' studies have maintained the trend to focus on office environments and younger adults. Studies on personal comfort models that focus on older people and dwellings are still insufficiently researched in the current literature. This thesis aims, therefore, to address this methodological research need.

1.3. Research questions

Considering the issues presented above, the main question to be addressed by this research is:

Can personal thermal comfort models be developed and used to predict older people's thermal preferences in a more accurate way than traditional thermal comfort models used in the field today?

To answer this main question, this research proposes to answer the following sub-questions:

A. What thermal conditions exist in the houses occupied by the older people participating in the study, and what are their thermal preferences and sensations?

B. What variables are significant in explaining the thermal preferences and sensations of the older people participating in the study?

C. How will the accuracy of personal thermal comfort models be affected by individuals' particular variables?

D. How can the use of personal thermal comfort models lead to a more accurate prediction of older people's thermal preferences, in comparison with the prediction by a generalised model such as PMV?

E. Can personal comfort models for older people be used to determine heating and cooling set points more accurately?

F. How can personal comfort models for older people be used to aid the control and adaptation of older people's environments to increase comfort and health and wellbeing?

1.4. Aim and objectives

The main aim of this research project is to advance the current knowledge of the use of personal thermal comfort models for older people's living environments. Considering this and the research questions highlighted above, this research has the following objectives:

(1) Investigate older South Australians' thermal environment, thermal preferences, behaviours, and physiological responses during hot and cold weather (related to research questions A and B).

(2) Develop personal thermal comfort models for older people from the data collected, considering their personal and behavioural characteristics, as well as the conditions of their thermal environments, and compare the results with the predictions by established models such as the PMV model (related to research questions C and D).

(3) Investigate the application of personal thermal comfort models in managing the thermal environment of older people's dwellings and the health and wellbeing of older people in general (related to research questions E and F).

1.5. Research methodology

This study was conducted within a quantitative research framework and methodology. In order to answer the research questions, the following phases/methods were conducted, corresponding to each of the 3 research objectives highlighted above. A brief description of each method is presented below; however, overall details of these methods will be presented in **Chapters 4 to 8**.

1.5.1. Methods to achieve Objective (1)

Objective (1) *To investigate older South Australians' thermal environment, thermal preferences, behaviours, and physiological responses during hot and cold weather.*

Two environmental monitoring studies were conducted to collect datasets for statistical analysis. The first dataset used in this study was collected in the Australian Research Council Discovery Project (ARCDP180102019) entitled "*Improving thermal conditions in housing for older Australians*", in which the candidate acted as a research assistant. The project collected data from 71 participants from 57 households located in 3 climate zones in South Australia, across a period of 9 months (from January 2019 to September 2019), providing a range of variations in the environmental conditions necessary for a comprehensive analysis.

This data collection process involved:

(a) A questionnaire about individual socio-economic information, as well behaviours and responses during hot and cold weather, collected by the project team.

(b) An open-ended interview about the house details (directed by a checklist), including the collection of energy bills, plans, elevations, and photos, collected and processed by the candidate.

(c) Environmental monitoring of each house's main living room and bedroom, every 30 minutes for 9 months, collected by the project team and processed by the candidate. Weather data at 30-minute intervals was also collected from the Australian Bureau of Meteorology station closest to each house.

(d) Thermal comfort surveys about participants' preferences and sensations, answered by participants 3 to 4 times a week for 9 months, collected by the project team and processed by the candidate.

(e) A body composition assessment, collected and processed by the candidate.

(f) An additional questionnaire to assess participants' frailty status, as well as their use of outdoor spaces, conducted and processed by the candidate.

All data collection tools were designed to collect a wide range of variables and factors that were relevant in the context of architectural science, gerontology and public health fields of study to influence and affect thermal comfort, sensation and preference. Details of this specific methodology are described in **Chapters 4, 5 and 6**.

Note that, while the ARC project analysed the dataset collected at the climate zone level and cluster level, this thesis extended the research by looking at the individual level through personal thermal comfort modelling, which yielded a more granular and occupant-centric analysis.

The second dataset used in this study was collected by the author from a subset of the original cohort of participants. In order to collect additional data on skin temperature, consecutive 2-week data collection periods were conducted with 11 of the original 71 participants. Apart from monitoring the environmental conditions inside the dwelling and conducting daily indoor environment surveys, this data collection process also involved the measurement of the hand skin temperature of the participants involved. Details of this specific methodology are described in **Chapters 4, 5 and 7**. Statistical analysis was then used to investigate the most significant factors influencing the cohort's thermal sensations and preferences.

1.5.2. Methods to achieve Objective (2)

Objective (2) *To develop personal thermal comfort models for older people from the data collected, considering their personal and behavioural characteristics as well as the conditions of their thermal environments, and compare the results with the predictions by established models such as the PMV model.*

The framework that guided the modelling process of this study is based on the work of Kim et al. (2018a) on personal comfort models and the work of Raschka (2018) on machine learning modelling. By correlating daily environmental measurements and a series of thermal preference, behavioural and wellbeing related survey answers, the study applied machine learning algorithms – more specifically *deep learning* (Goodfellow et al., 2016) − to develop personalised comfort models for a subset of the participants involved in the monitoring study.

The models were developed to perform a multiclass classification task of occupants' thermal preference (TPV) on a 3-point-scale ("preferring to be cooler", "preferring no change" or "preferring to be warmer"), and according to up to 8 environmental and personal input features collected and chosen according to the outcomes of *Objective (1)*.

The survey's TPV was used as the ground truth to train the models and later verify the predicted values. Instead of the thermal sensation vote (TSV) scale — which is commonly used in thermal comfort studies —, the thermal preference scale (TPV) was used because not only does it represent a measure of what ideal conditions would be for each person, but it also suggests in which direction the change is desired (Kim, 2018a). This is particularly relevant when considering the use of these models for the control of Heating, Ventilation, and Air Conditioning (HVAC) systems. In addition, using TPV rather than TSV avoids the assumption of associating comfort with neutral thermal sensation, which may not always be true (Humphreys and Hancock, 2007).

The modelling process involved the following stages:

(1) Participant dataset and input selection.

(2) Dataset pre-processing.

(3) Model tuning and selection.

(4) Model evaluation.

The models' performance indicators were later compared with PMV predictions. Details of this specific methodology are described in **Chapters 4, 6 and 7**.

1.5.3. Methods to achieve Objective (3)

Objective (3) *To investigate the application of personal thermal comfort models in managing the thermal environment of older people's dwellings and the health and wellbeing of older people in general.*

In order to investigate the application of the personal thermal comfort models − derived from *Objective (2)* − in managing the thermal environment of older people's dwellings, a building performance simulation technique was adopted. Two case buildings were modelled based on two participants' house details, house operation trends and other relevant information. The models were calibrated using measured data from the monitoring period derived from Objective (1).

Following this, the personal comfort models from each participant were used to derive the indoor temperature limits in which they had a predominant thermal preference for 'no change', which were considered to be the best representations of heating and cooling temperature set points. The personal set points were then input in building performance simulation models of these participants' real dwellings, and the energy loads errors were calculated between the simulated heating and cooling energy loads and the "actual" heating and cooling energy loads, obtained from disaggregating the participant's energy use records. Weather data from three different years were used, to cover the corresponding energy use records available. This comparison was intended to test the accuracy of the personal comfort models and evaluate their use for heating and cooling set point configuration and possible automation.

As a secondary application option, one selected participant's personal comfort model was converted to a smart device application format, to examine the opportunity to use the individual models as a personalised web-based tools to aid care givers to manage thermal environments, considering individual and personalised requirements.

Details of these specific methodologies are described in **Chapters 4 and 8**.

1.6. Thesis structure

This thesis is structured in 9 chapters, in a combination of conventional and publication formats, in accordance with the "Specifications for Thesis 2022" of The University of Adelaide. **Figure 1-3** and the following breakdown of chapters explain how the thesis is organised.

Chapter 1. Introduction

Includes an overview of the research background, main motivations and significance, as well as the research questions, aims and objectives and the summary of the methodology applied.

Chapter 2. Background on thermal comfort for older people and generalised thermal comfort modelling

Underlines the current literature divided into 2 sections: (1) thermal comfort and older people and (2) generalised thermal comfort modelling.

Chapter 3. Systematic literature review of personal thermal comfort models

Presents a systematic review of the literature of personal thermal comfort models. This chapter presents a published work:

Arakawa Martins, L., Soebarto, V., Williamson, T. (2022) "A systematic review of personal thermal comfort models", Building and Environment, Vol. 207, Part A, https://doi.org/10.1016/j.buildenv.2021.108502

Chapter 4. Research methodology

Presents an overall description of the research methodologies chosen to address the 3 main research aims of this thesis, including the data collection phases, modelling phases, building performance simulation process and the smart device app development.

Chapter 5. Field study and initial analysis of factors associated with older people's thermal comfort

Presents the outcomes corresponding to research *Objective (1)*, using statistical analysis to investigate the older South Australians involved in the study and their thermal environments, thermal preferences, behaviours, and physiological responses during hot and cold weather. The chapter also determines the most significant factors to be used as inputs for the personal comfort models developed in the next chapters.

Chapter 6. Personal thermal comfort models for older people using environmental, behavioural and health variables

Presents the outcomes corresponding to research *Objective (2)*, evaluating the performance of the personal comfort models developed for older people using environmental, behavioural and health variables, and comparing them with the PMV individual predictions. This chapter presents a published work:

Arakawa Martins, L., Soebarto, V., Williamson, T., Pisaniello, D. (2022) "Personal thermal comfort models: a deep learning approach for predicting older people's thermal preference", Smart and Sustainable Built Environment, Vol. ahead-of-print, No. ahead-of-print, https://doi.org/10.1108/SASBE-08-2021-0144

Chapter 7. Personal thermal comfort models for older people using skin temperature and environmental, behavioural and health variables

Presents the further outcomes corresponding to the research *Objective (2)*, evaluating the performance of the personal comfort models developed for older people, adding skin temperature as one of the input variables, and comparing them with the generalised model's predictions. This chapter presents a published work:

Arakawa Martins, L., Soebarto, V., Williamson, T. (2022) "Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables", Journal of Building Engineering, Vol. 51, https://doi.org/10.1016/j.jobe.2022.104357

Chapter 8. Applications of personal thermal comfort models for older people

Draws on the results of the personal comfort models to test possible applications using building performance simulation and an experimental smart device application, corresponding to research *Objective (3)*.

Chapter 9. Main findings and conclusions

Presents a final overview of the thesis, the key findings, the contributions and limitations, as well as recommendations regarding personal comfort models for older people.

References and relevant appendices, including the original versions of the included publications, are presented at the end of this thesis. A complete list of abbreviations, figures and tables can be found on pages vii-xiv.

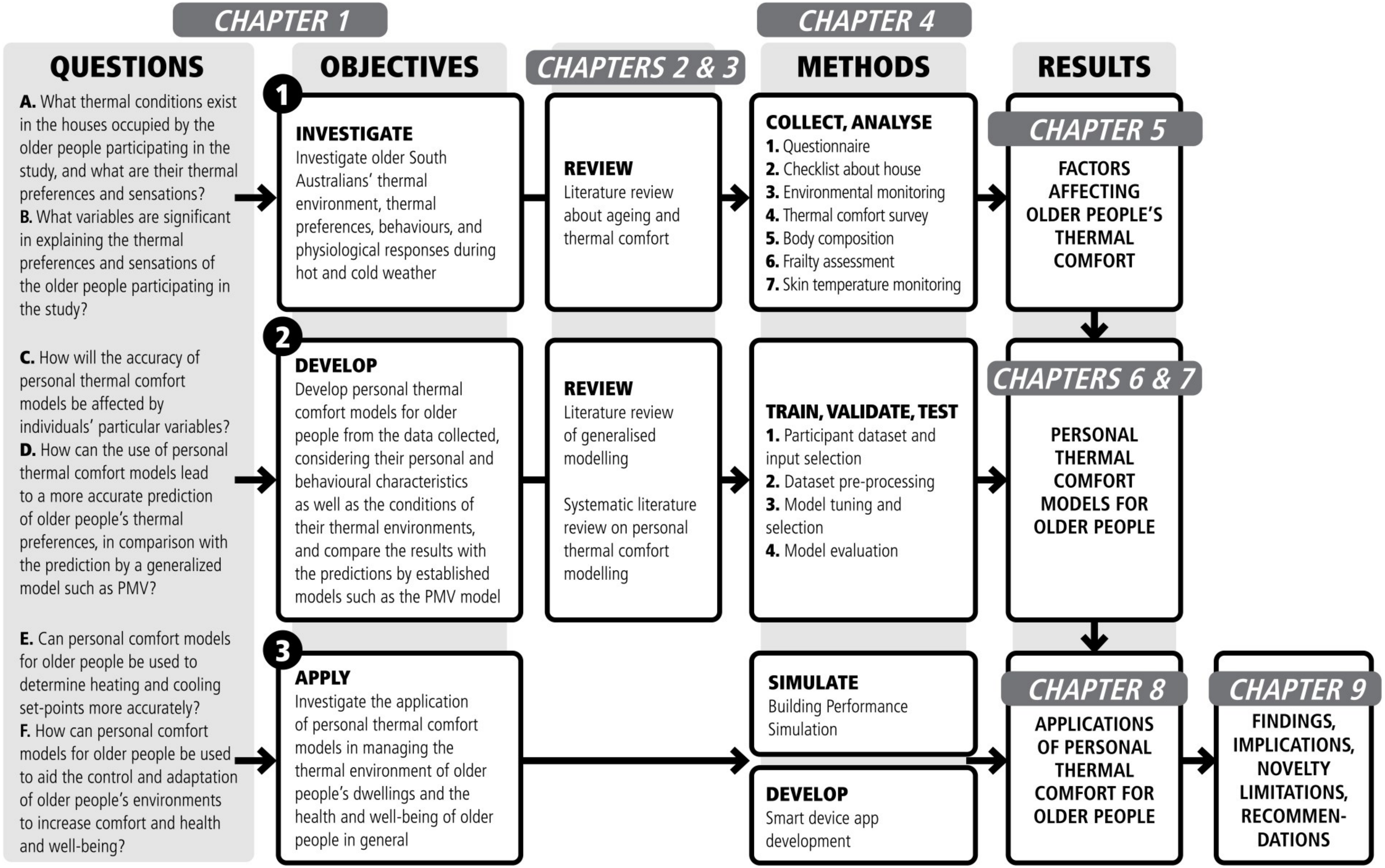

Figure 1-3 - Thesis structure

Chapter 2. Background on thermal comfort for older people and generalised thermal comfort modelling

The following literature review aims to establish the overall background and current context for the research presented in this thesis. It also presents relevant issues that have been considered to become the basis for the methodology chosen for the research.

The first section investigates the important relationships between ageing, the built environment and human diversity, making the case for the development of a much more individualised way to study, plan and design thermal environments targeted to older people's needs. The second section explores the conventional approaches towards thermal comfort modelling, and how their inherited generalising methods present important barriers to addressing the heterogeneity of the thermal comfort requirements of older people living in their dwellings. The chapter concludes with a summary of the current thermal comfort modelling limitations, leveraging the personal thermal comfort modelling alternative, discussed in more detail in **Chapter 3**.

2.1. Thermal comfort and older people

2.1.1. Environmental influences on physical and psychological health for older people

Investigations regarding the potential environmental effects on overall health and wellbeing have been increasing in the past two decades. According to the extensive work by Golembiewski (2017) on health promotion theories and salutogenesis, there is a considerable amount of evidence that explains how architecture and the built environment provide a context that affects a person's behaviour, neural and endocrine systems, thus directly influencing health. Moreover, there is a substantial body of research that focuses on building designs that not only improve recovery from diseases but also augment and promote people's physical and psychological faculties, making them feel better and perform their activities more effectively. In this sense, a recent study by Peters (2017) argues that architecture can do more than just provide basic needs or minimise harmful conditions. For the author, appropriate and sustainable design can offer measurable and integrated positive co-benefits for human health and wellbeing.

With a specific focus on older people, recent literature has also established the links between the built environment and overall health and wellbeing. Annear et al. (2014), for example, through an extensive systematic review process, have highlighted relevant correlations between physical and mental health among older adults and the quality of environmental features around them. These features range from proximity to, and density of, public open spaces, to micro-scale architectural details that promote visibility (such as housing oriented to provide visual oversight of public areas). Likewise, a further study by Yen et al. (2014) found strong correlations between the built environment and mobility levels for older populations by synthesising more than 120 articles on the subject. The authors concluded that aesthetics, land use and connectivity are the three interrelated factors that strongly influence older adults' decisions about their mobility, which may consequently affect physical activity frequency and ageing-in-place. The study also highlights that environmental components influence decisions about mobility through one central mechanism: the perception of safety. This means that older adults need to perceive that their environment is safe for them to be more mobile and active.

In a more practical approach, the work of the Women's Design Service and University of the West of England (2009) analysed 10 case studies of existing buildings designed for older people in England. The studies show extensive evidence of how appropriate and comfortable built environments have provided homes where people feel safe, respected and part of the community. This emphasises the important social effects that the built environment can have.

Considering the above-mentioned, many aspects should be acknowledged when planning, designing, adapting or building the living environments for older people. These range beyond accessibility aspects, incorporating everything that may affect the physical and/or psychological integrity of older people. As highlighted by van Hoof and Hensen (2006), health should always be a key design factor for any built environment. Therefore, thermal comfort is introduced in this context, as it plays an important but insufficiently researched role in guaranteeing health and wellbeing for older populations.

2.1.2. Age-associated changes in thermoregulation

As people age, physiological changes affect their thermal sensitivity and regulation. As detailed by Shibasaki et al. (2013), advancing age is undoubtedly associated with the attenuation of thermoregulatory responses in the skin, possibly resulting from "reduced skin sympathetic nerve activity, decreased release of primary neurotransmitters and cotransmitters, and impaired end-organ responsiveness" (Shibasaki et al., 2013). Building on this idea, Dufour and Candas (2007), confirmed a significantly reduced sweat output with age, associated with a local origin (i.e., skin changes) rather than central alterations (i.e., in the hypothalamus). The researchers also indicated a relevant correlation between thermal sensitivity and local sweat rate in older and middle-aged subjects, which was not observed in young adults.

Furthermore, a literature review by Blatteis (2012) confirmed that, as ageing progresses, in addition to the decrease in the number of sweat glands activated by heat, dehydration is a contributing factor to the risk of hyperthermia for older people in hot environments, as the production of sweat depends on an adequate supply of blood (i.e., the source of its liquid). Blatteis (2012) also added that age-related cardiac or pulmonary dysfunctions, as well as endocrine deficiencies, could impair people’s ability to produce sufficient extra heat in cold environments. These studies indicated, therefore, that alterations occurring with advancing age could compromise the efficiency of people’s thermal defence mechanisms and the ability to respond effectively to temperature fluctuations in their environments, upsetting the homeostatic balance of health in some.

2.1.3. Age-associated differences in thermal comfort

Many studies have addressed age-associated differences in thermal comfort, preference and response in the built environment. While consistent progress has been made from diverse perspectives, the studies’ results, however, remain inconclusive.

Wang et al. (2018), for instance, conducted an extensive literature review and analysis of both climate chamber studies and field studies, concluding that there is no difference in thermal comfort temperatures between young and older adults, especially once clothing, metabolic and anthropometric differences were considered. Other studies, on the other hand, reported differences between younger and older cohorts. Schellen et al. (2010), for example, conducted experiments in a climate chamber with eight young adults, aged 22 to 25, and eight older adults, aged 67 to 73, measuring both physical and physiological (i.e., skin temperature) parameters continuously, in both steady temperature settings and transient conditions. They concluded that the thermal sensation of older people was, in general, 0.5 scale units lower in comparison with their younger counterparts. In addition, during a constant temperature level and equal clothing level, the older cohort preferred a higher temperature in comparison with younger adults. Tartarini et al. (2017), however, indicated that older adults with dementia preferred lower temperatures than those recommended by thermal comfort standards. In their study, subjective perception of the thermal environment was gathered from field studies in six nursing homes, involving 157 residents, 31 family members and 64 staff. The study also indicated that the residents of nursing homes were more tolerant to the same thermal environments than non-residents. Likewise, Bills (2019), through a field study of 18 houses and 22 older participants, reported a consistent trend toward a preference for cooler conditions than predicted by current thermal comfort standards.

Hwang and Chen (2010) conducted a field study with eighty-seven older adults, comparing the results with their previous study with younger counterparts. They concluded that, compared with the range of temperature acceptable to 80% of the younger adults in the summer (23.0–28.6°C), the range of temperatures acceptable to the older participants in this study in the summer was narrower (23.2–27.1°C). Yang et al. (2016), on the contrary, through an extensive field study in twenty-six aged care facilities involving hundreds of older adults in different seasons, concluded that older adults preferred a wider range of temperatures than expected from thermal comfort standards.

Although no consensus can be drawn from these studies regarding the preferred conditions of older adults, the distinction between how they and their younger counterparts seem to perceive their thermal environments could be explained by a combination of both physical ageing and relevant behavioural differences (van Hoof and Hensen, 2006).

Apart from intergroup variability between younger and older adults, the differences relating to thermal comfort and perception can occur among individuals inside both groups. In fact, explaining individual diversity in perceived thermal comfort has been an interest of many studies for decades. The fact that individuals might perceive and respond differently when exposed to the same thermal environment indicates that other factors and stressors than the environmental parameters should also be considered when designing or managing the built environment.

Shipworth et al. (2016), for instance, developed a theoretical model to explain inter-individual diversity drivers. According to the authors, these drivers range from physiological factors, such as body composition (e.g., body size, age, sex, lean and fat mass), to people's contextual characteristics and thermal experiences, including climatic, cultural and personal levels of differences. In addition, psychological drivers are highlighted as the model's third pillar, of which the impacts on thermal comfort are, however, still under-researched. The model further distinguished between short-term 'states', and longer-term 'properties' of both environment and individuals that shape people's perception of thermal comfort.

Likewise, Bluyssen (2019) proposes an integrated analysis approach for assessing not only thermal comfort, but also indoor environmental quality (IEQ) in general, through the lens of multiple environmental stressors and individual differences in needs, preferences and behaviours. Apart from an environment model that indicates patterns of stressors that should be considered in the assessment, the authors introduce a human model, which leads to preferences and needs (profiles) of the occupant for which the assessment is performed. The human model included the interactions among physical and psycho-social stressors; confounders such as genes, sex, and age; effects of diseases and disorders; and previous exposures. The environment model comprised of not only physical stressors such as noise, odour, temperature, and light, but also their changes over time, occupants' behaviour and their psycho-social stressors such as working time, control and expectations. By including all interactions for both the environment and the occupant, the approach could be used to understand occupants' preferences and needs and assess if their profile matches the environment in question, and ultimately identify the negative and positive stressors of concern to improve this environment.

In this context, it is undeniable that intragroup diversity is present in both younger and older cohorts. This heterogeneity, however, tends to be greater in older age, because older adults have been submitted to a greater range of cumulative social, economic and environmental factors and trajectories across their individual life courses, which affect their needs and perceptions in significantly different ways (World Health Organization, 2015b). For this reason, understanding diversity drivers, specifically in older age, also becomes crucial to target their needs and requirements more accurately.

2.1.4. Diversity in older age

As above-mentioned, the ageing process is deeply influenced by complex changes affecting not only the biological but also the physiological layers of the individual. However, these changes are mostly independent from chronological age − the total number of years a person has lived −, and, although largely inevitable, they cannot be considered linear, as they can happen in different stages, speeds and intensities throughout older age (World Health Organization, 2015b). For this reason, it is very common to observe older people with the same chronological age having completely different functional capabilities. This means that, while some older people with a certain chronological age may be frail or lack the capacity to meet their basic needs and undertake basic activities, other older individuals with the same chronological age may retain full physical and mental functioning, not requiring any external support.

According to the World Report on Ageing and Health, developed by the World Health Organization (2015b), this diversity in older age happens firstly because the mechanisms of ageing are extremely random. Secondly, it is believed that environmental and behavioural elements also play a relevant part in the trajectories of ageing. According to the report, older people's heterogeneity drivers go beyond genetic inheritance, or the deliberate choices made during their lives. For the researchers involved in the report, the physical and social environments that people inhabit can affect health both directly and indirectly.

As an example of the wide range of physical functioning experienced in older age, the report used data from the Australian Longitudinal Study on Women's Health. Illustrating the different trajectories of physical capacity across life, it is possible to observe that the range of physical functioning is far greater in older age than in younger ages, as seen in **Figure 2-1**.

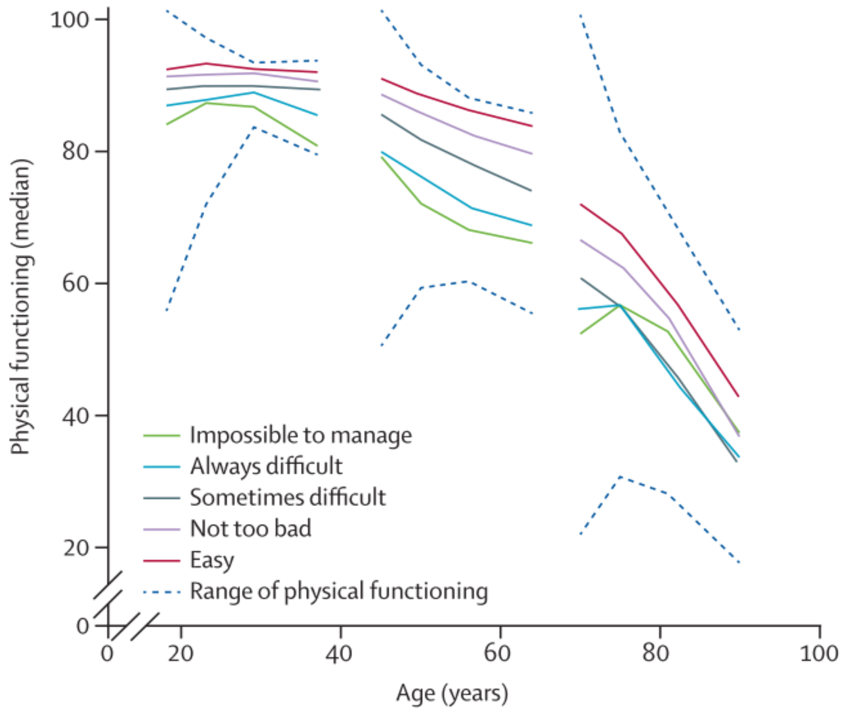

Figure 2-1 - Physical functioning across the life course, stratified by ability to manage on current income. Source: World Health Organization (2015b)

The World Health Organization report also highlighted that "Healthy Ageing" can only be reached when older people are able to achieve the things that they have reason to value. In order to do so, developing functional ability is essential. Functional ability, on the other hand, comprehends the "intrinsic capacity" of each individual and the multiple interactions between this person and the diverse "environmental characteristics" to each he/she is exposed to.

"Intrinsic capacity" is considered to be the combination of all the physical and mental capacities of an individual, including personal characteristics and genetic inheritance. "Environments" (or "environmental characteristics") are all the elements in the external world that shape the context of an individual's life, including the built environment, health and social policies, and the systems and services that support them. **Figure 2-2** illustrates these concepts.

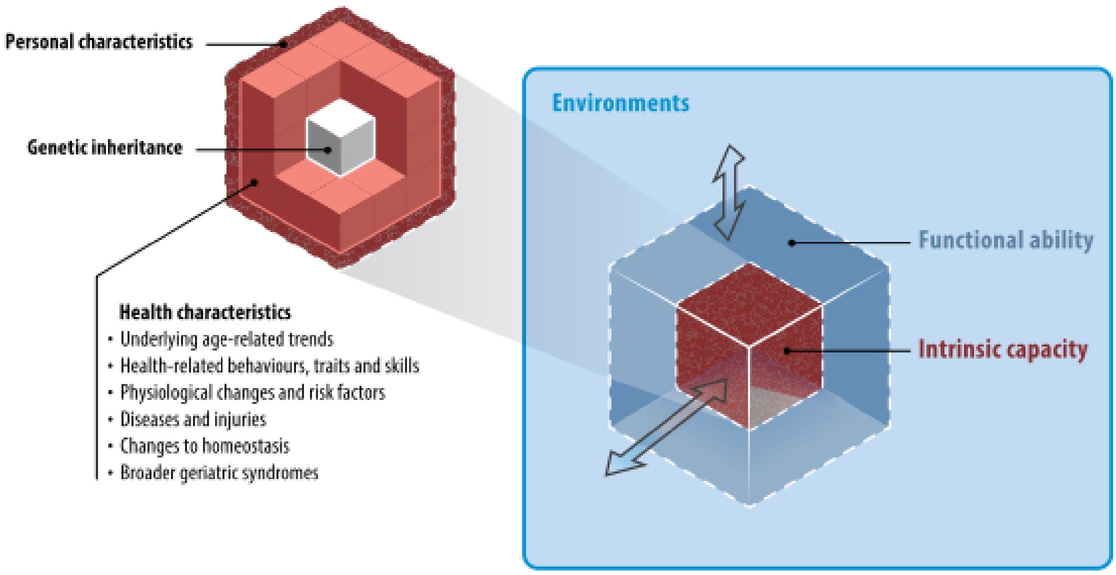

Figure 2-2 - Elements that define healthy ageing. Source: World Health Organization (2015b)

Therefore, whether older people can achieve the things that they have reason to value — and consequently experience healthy ageing — will be determined not only by their individual capacity but also by the interactions with the environments they are surrounded by at a certain point in time. This means that two older people with the same limitations in their physical capacity can have opposite mobility outcomes if, for example, they have access or not to an assistive device or accessible public transportation. In other words, the final combination of the individual and their environments, and the interaction between them, is the individual's functional ability - the most relevant determinant of healthy ageing.

In its conclusion, the World Report on Ageing and Health emphasised the need to better understand the diverse needs of older populations in order to develop relevant policy that fosters healthy ageing. Among the different ways to achieve this better understanding, the report stressed person-centred approaches as strategies already in use that could be applied by the WHO for health and long-term care settings. According to the report, this new approach could result in a real paradigm shift in the way global health services are managed and provided, delivering health services that respond directly to people's needs and preferences, in a safe and effective way.

Looking from the same perspective, the field of thermal comfort is also experiencing the same paradigm shift. Most studies on thermal comfort today focus at the population level, and they are now being called into question by much more individualised and occupant-centric alternatives (Kim et al., 2018a; Wang et al., 2018). This indicates that diversity in preferences and perceptions is beginning to be taken into account in thermal comfort modelling and management. In this context, since older people's individual needs are excessively broad, much could be profited by investigating their environmental comfort from the same occupant-centric approach.

2.2. Generalised thermal comfort models

Before discussing the current state of research on individualised and occupant centric approaches towards thermal comfort modelling and their potential to address the diversity observed in people in general and in older people specifically, it becomes essential to first introduce a review on thermal comfort modelling from the generalised perspective to provide contextual information for this current paradigm shift.

Generalised thermal comfort models are termed as such in this thesis as models designed to predict the average thermal comfort of large populations. Also called "aggregate models", these models are explored in this section to allow a clear understanding of the current paradigm shift from generalised to personal thermal comfort modelling techniques, which are the basis for the later chapters. The literature on generalised thermal comfort approaches used today can be divided into studies based on thermal comfort indices (**Section 2.2.1**.) and research into the adaptive comfort approach (**Section 2.2.2**). Both methods and applications are detailed below.

2.2.1. Thermal comfort indices

Multiple thermal comfort indices have been developed over the years, ranging from single-variable correlations between air temperatures and comfort votes, to more complex heat-balance indices, such as the PMV and SET* (Epstein and Moran, 2006). One of the earliest studies to indicate the use of a single index to explain thermal comfort was developed in 1905 by Haldane (Haldane, 1905). Through a series of experiments in both field and controlled scenarios, the study pointed to the use of wet-bulb temperature as an important measure to express heat stress. In 1916, the kata-thermometer, which allowed the measurement of both dry and wet temperatures, was introduced by Hill (Hill et al., 1916) and marked a pivotal empirical basis to describe the body's cooling rate and heat loss and measure the warmth of the environment as perceived by a human being.

Later in the 1920s, Yaglou, Houghten and Miller (Houghten and Yaglou, 1923; Yaglou and Miller, 1925) developed the Effective Temperature (ET), an empirical index based on the relationship between thermal sensation and both air temperature and humidity in conditioned environments (Olesen, 2020;

Blazejczyk et al., 2012), followed later by adaptations from Vernon and Warner (Vernon and Warner, 1932) and Missenard (Missenard, 1933), which introduced the influence of air speed.

In 1932, Dufton published his work on the Eupatheoscope, a device that measured what he called the Equivalent Temperature of an environment, combining the effects of the air temperature, thermal radiation and air movement into a single number (Dufton, 1933; Dufton, 1932). The 1930s also marked the classic thermal comfort field studies by Bedford. Published in 1936, his study looked into the thermal environment of factory workers in England (Bedford, 1936). Due to the large scale and innovative statistical approach of his research project at the time, Bedford is today considered a pioneer of the systematic thermal comfort field study. He compared the agreement of 11 different environmental measurements and several other indices (including Hill's kata-thermometer, Yaglou's ET and Dufton' eupatheoscope) with thermal comfort votes from participants. Surprisingly, none of the other indices performed significantly better than the simple air temperature or the mean radiant temperature. Building on this analysis, Bedford later used multiple regression to develop a revised version of Dufton's Equivalent Temperature and published a new index of subjective warmth, with air temperature, mean radiant temperature, water vapour pressure and air speed as predictors (Humphreys et al., 2016).

During the 1940s and 50s, Webb identified a need for research similar to Bedford's, but for an equatorial climate such as Singapore's, where he was based at the time (Webb, 1959; Webb, 1960; Webb, 1964). Webb collected longitudinal data and supervised the development of a multiple regression-based model to build a thermal comfort index for the tropics called the Singapore Index. In addition, Webb was able to quantify considerable differences among the participants' comfort preferences. He later conducted further studies on tropical scenarios in India and Iraq, with the objective of updating Bedford's Equivalent Temperature using the statistical methods developed for his Singapore Index (Humphreys et al., 2016).

In 1966, Stolwijk and Hardy provided the first convincing attempt to develop a comprehensive 'comfort' index based on a "rational" physical and physiological basis (Stolwijk and Hardy, 1966). From this proposal a new effective temperature scale (ET*) was developed based on a two-node model of thermophysiology (Gagge et al., 1971). This effective temperature describes the dry bulb temperature of a uniform sea level environment at 50% relative humidity (RH), which is thermally equivalent to the actual environment. By adopting a standard set of conditions, e.g., air speed, clothing, and activity, a standard effective temperature (SET*) is defined and explained further in this section.

Later in the 1960s and 70s, the work of Rohles and Nevins (Nevins et al., 1966; Rohles, 1974; Olesen, 2020) continued to contribute to a better understanding of population-level thermal comfort modelling. It was in their test facility at Kansas State University that Fanger undertook analysis that later resulted in the basis for his notable Predicted Mean Vote - Predicted Percentage of Dissatisfied (PMV/PPD) index (Olesen, 2020), described below in more detail.

PMV/PPD and ePMV

The PMV (Predicted Mean Vote), originally developed in the second half of the 1960s by Fanger, is an index that represents the mean value of the thermal sensation votes of a group of people occupying a specific environment, on a 7-point thermal sensation scale from -3 (cold) to 3 (hot). Based on data obtained through American and European climate chamber studies and involving over a thousand heathy adults, the model calculates thermal comfort sensations according to the heat dynamics occurring between the body and the environment (Fanger, 1970). The calculation of the index, presented by Fanger (1970) and later adapted in ISO (2005), comprises of the following equations:

$$PMV = (0.303e^{-0.036 \cdot M} + 0.028) \cdot [(M - W) - H_{skin} - H_{sweat} - H_{latent\,respiration} - H_{dry\,respiration} - H_{radiation} - H_{convection}] \quad (1)$$

where heat loss by each process is defined by:

$$H_{skin} = 3.05 \cdot 10^{-3} \cdot [5733 - 6.99 \cdot (M - W) - p_a] \quad (2)$$

$$H_{sweat} = 0.42 \cdot [(M - W) - 58.15] \quad (3)$$

$$H_{latent\,respiration} = 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - p_a) \quad (4)$$

$$H_{dry\,respiration} = 0.0014 \cdot M \cdot (34 - t_a) \quad (5)$$

$$H_{radiation} = 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (t_r + 273)^4] \quad (6)$$

$$H_{convection} = f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \quad (7)$$

and:

M is the metabolic rate in W/m^2;

W is the external work, or effective mechanical power in W/m^2;

p_a is the water vapor partial pressure, in Pa;

t_a is the air temperature, in °C;

t_r is the mean radiant temperature, in °C;

I_{cl} is the clothing thermal insulation, in m²K/W;

f_{cl} is the clothing surface area factor, calculated by:

$$f_{cl} = \begin{cases} 1 + 1.29 \cdot I_{cl} & for \quad I_{cl} \leq 0.078 \\ 1.05 + 0.645 \cdot I_{cl} & for \quad I_{cl} > 0.078 \end{cases} \tag{8}$$

t_{cl} is the clothing surface temperature, in °C, calculated through an iterative process, using the following equation:

$$t_{cl} = t_{skin} - I_{cl} \cdot 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (\bar{t_r} + 273)^4] - I_{cl} \cdot f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \tag{9}$$

t_{skin} is the skin temperature, in °C, calculated by:

$$t_{skin} = 35.7 - 0.028\,(M - W) \tag{10}$$

h_c is the heat transfer coefficient, in W/m²K, calculated by:

$$h_c = \begin{cases} 2.38 \cdot |\, t_{cl} - t_a|^{0.25} & for\ 2.38 \cdot |\, t_{cl} - t_a|^{0.25} > 12.1 \cdot \sqrt{v_{ar}} \\ 12.1 \cdot \sqrt{v_{ar}} & for\ 2.38 \cdot |\, t_{cl} - t_a|^{0.25} < 12.1 \cdot \sqrt{v_{ar}} \end{cases} \tag{11}$$

v_{ar} is the relative air velocity, in m/s.

The model defines the optimum condition (or the thermal neutral condition) as the condition wherein a person does not feel either hot or cold in his/her environment.

Furthermore, the PPD (Predicted Percentage of Dissatisfied) index quantifies the expected percentage of thermally dissatisfied people in an environment and is calculated as a function of the PMV index:

$$PPD = 100 - 95 \cdot e^{-(0.03353 \cdot PMV^4 + 0.2179 \cdot PMV^2)} \tag{12}$$

The standards (ANSI/ASHRAE, 2020; ISO, 2005) recommend that the optimal indoor temperature is defined when PPD is lower than 10%, which corresponds to a PMV index between -0.5 and 0.5, as seen in **Figure 2-3**.

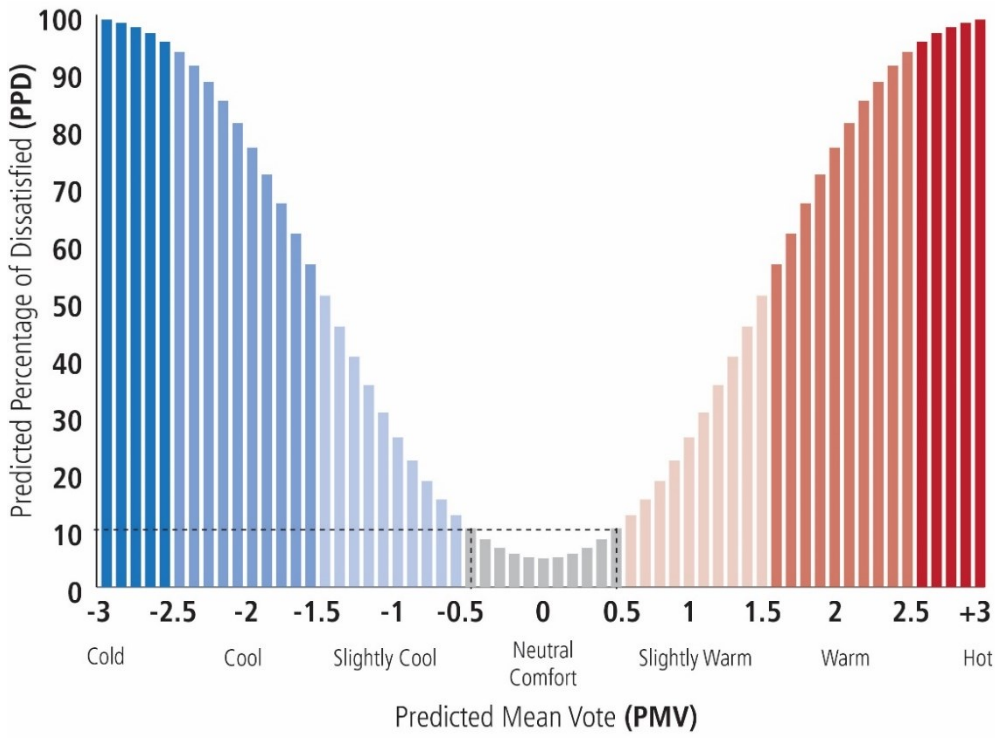

Figure 2-3 - Predicted Percentage of Dissatisfied (PPD) versus Predicted Mean Vote (PMV)

The PMV and PPD indexes are considered official tools to evaluate thermal comfort in buildings, being adopted by several international standards worldwide (ANSI/ASHRAE, 2020; CEN, 2007; ISO, 2005). However, as it is mainly based on data from healthy adults, it cannot be applied to children, older adults (people aged 65 years and over) or people with diseases or disabilities, without adequate modelling adaptations (van Hoof, 2008). In addition, although used worldwide for all building types, the model is recommended for application in environments with heating, ventilation, and air-conditioning (HVAC) systems, situated in cold, temperate and warm climates. The model performs poorly when applied to non-air-conditioned buildings in warm climates (Humphreys, 1978; Brager and de Dear, 1998; Humphreys et al., 2016), where occupants may sense the warmth as being less severe than the PMV model predicts due to occupants' lower thermal expectations and possibly due to metabolic rate estimations higher than expected in warmer environments (Fanger and Toftum, 2002).

For this reason, Fanger and Toftum (2002) later introduced the ePMV model, extending the suitability of the calculations for buildings without HVAC systems, in warm and humid climates, by adding adaptive factors to the original index. This updated model considers an expectancy factor, *e*, to be multiplied with PMV to reach the mean thermal sensation vote of occupants of actual non-air-conditioned buildings in a warm climate.

The *e* factor ranges between 0.5 and 1, where 1 is the factor for buildings with HVAC systems. According to the authors, for buildings without HVAC systems, the correction factor depends on the duration of the period of warm weather during the year, and if the building can be compared with many buildings from the region where HVAC systems are used. Therefore:

> "*if the weather is warm all year or most of the year and there are no or few other air-conditioned buildings, e may be 0.5, while it may be 0.7 if there are many other buildings with air conditioning. For non-air-conditioned buildings in regions where the weather is warm only during the summer and no or few buildings have air-conditioning, the expectancy factor may be 0.7±0.8, while it may be 0.8±0.9 where there are many air-conditioned buildings. In regions with only brief periods of warm weather during the summer, the expectancy factor may be 0.9±1*" (Fanger and Toftum, 2002).

Validating the ePMV model with global datasets from field experiments, the authors demonstrated that the extended PMV model agrees well with available quality field studies in non-air-conditioned buildings in warm climates of three continents.

SET*

The Standard Effective Temperature (SET*), presented by Gagge et al. (1986) and later adapted for use in ANSI/ASHRAE (2020), is another well-known index used to evaluate human thermal environments. It was developed to account for the fact that people's tolerance for high or low air temperatures can vary depending on humidity and other physical factors. It is defined by the equivalent dry bulb temperature of an isothermal environment at 50% relative humidity, in which an occupant, wearing clothing standardised for the activity concerned, would have the same heat exchange at skin surface and the same thermoregulatory strain (represented by skin wettedness or sweat) as in the actual test environment (Gagge et al., 1986). It satisfies the two-node heat balance equation involving the physical factors describing the environment, the standardised clothing insulation worn in relation to the activity, the standardised heat transfer coefficients for both clothing and effective air movement, and the resulting skin temperature and wettedness.

The SET* index has the advantage of allowing direct comparisons between environments at any combination of physical input variables, as it represents the thermal strain experienced by a "standard" person in a "standard" environment (Enescu, 2019). However, the requirement for a "standard" occupant might also represent the index's main disadvantage, especially when considering diverse groups of building users.

Although both PMV and SET* indices are based on essentially the same heat balance equations, the methods to calculate the physiological variables used in each model differ substantially. In the SET* calculations, a "two-node" thermoregulation model − where the human body is partitioned into an external region formed by the skin and a connected internal core – uses a *finite difference procedure* to estimate the physiological parameters (i.e., surface skin temperature and surface skin wettedness). The heat transfer between the environment, the skin and the core are simulated at one-minute intervals by the model, updating the physiological variables until the specified exposure time (i.e., the number of iterations) is reached. These variables are later used to calculate the index (Doherty and Arens, 1988; Fountain and Huizenga, 1996). For the PMV calculation, on the other hand, physiological parameters (i.e., skin temperature and heat loss due to sweating) are not estimated and rather directly calculated based on metabolic rate (Doherty and Arens, 1988), as presented in Equations 3 and 10.

Other indices

Apart from SET* (Gagge et al., 1973), the two-node model is the basis of other, currently less used, thermal indices such as DISC (Predicted Thermal Discomfort) and TSENS (Predicted Thermal Sensation) (Fountain and Huizenga, 1996; Doherty and Arens, 1988). These indices, in addition to PMV/PPD, are categorised as **rational indices**, as they are derived from heat balance equations and mathematical models involving the thermal physics and physiology that describe the behaviour of the human body in thermal environments (Parsons, 2000; Humphreys et al., 2016).

Furthermore, other indices, also currently less used, such as the PD (Predicted Percentage of Dissatisfied due to Draft) by Fanger et al. (1988), PS (Percentage of Satisfied) by Fountain et al. (1994) and TS (Thermal Sensation) by Rohles (1973) have been developed and categorised as **empirical indices**, since they derived from experiments, relying in the direct relationship between two or more variables that dominate the phenomena (Parsons, 2000; Fountain and Huizenga, 1997).

Finally, a third category of indices, named **direct or derived indices**, are the ones based on measurements taken on a simple instrument that directly responds to factors in the thermal environment, which also affect people (Parsons, 2000). The Wet Globe Temperature (WGT), for instance, can be considered a derived index as the instrument used to measure it responds to thermal radiation, air temperature, relative humidity and air velocity and can be employed to provide an indication of environmental heat stress.

2.2.2. Adaptive thermal comfort approach

While a certain level of behavioural adaption is accounted for in the thermal comfort indices such as PMV and SET* (e.g., clothing), numerous research studies on thermal comfort have highlighted the lack of considerations to other dimensions of thermal adaptation, such as psychological, cultural, climatic and social contexts (Brager and de Dear, 2001). In addition, the expectation that people would be universally satisfied within a centrally controlled environment was called into question. According to these studies, non-neutral thermal preferences are experimentally common (Williamson et al., 1995), questioning the thermal neutrality proposed as the only optimal thermal condition for people. In addition, very low and very high PMV values do not always represent a state of discomfort for a relevant number of people (van Hoof et al., 2017b; van Hoof and Hensen, 2006; van Hoof, 2008).

The adaptive thermal comfort approach argued that people cannot be considered as passive recipients of the environment, and that they constantly interact with it through several strategies to optimise their conditions and achieve thermal comfort. For Humphreys et al. (2016), this meant that thermal comfort "*is not to be seen primarily as a matter of the physiology of heat regulation and the science of clothing, but rather as a wide-ranging and intelligent adaptive behavioural response to climate*." The authors pointed out, however, that both rational and adaptive models could be considered theoretically complementary, since heat exchange between a person and the environment is still an integral component of the adaptive model (Humphreys et al., 2016). The fundamental distinction between the rational and adaptive models lies, therefore, in what is considered the cause for the shift in comfort temperatures. While rational models only account for behavioural adjustments (personal/technological) to heat balance variables such as clothing or air velocity, the adaptive models add physiological (i.e., acclimatisation) and psychological (i.e., expectations/habituation) drivers (de Dear et al., 1997). Likewise, while rational models account for thermal comfort in terms of the microclimate immediately affecting the heat exchanges of the individual, the adaptive approach predicts comfort from broad-scale contextual factors (de Dear and Brager, 2002).

In order to evaluate adaptive actions in everyday living, the main principle of the adaptive approach was to reintroduce field-studies, particularly in naturally ventilated buildings, such as Bedford's pioneer studies in the 1930s (Bedford, 1936), to explore thermal comfort. Therefore, through extensive explorations with field data and a resulting empirical model that correlated both outdoor and indoor temperatures and people's temperature acceptability, researchers confirmed that the indoor temperature considered to be the most comfortable increases significantly in warmer climate zones and decreases in colder contexts. This reinforced the idea that people have an intrinsic ability to adapt to seasonal variations in environment conditions, thus revealing that satisfaction towards the thermal environment does not necessarily result in an environment restrained at an invariable indoor temperature (Humphreys et al., 2016; Kim et al., 2018a; van Hoof et al., 2017b; van Hoof, 2008).

One of the foundation documents for the adaptive model was the work of Humphreys (1975), which applied an in-depth analysis of thermal comfort field surveys conducted between 1930 and 1975. This was later complemented by Auliciems (1981), who updated the model by adding new data and cleaning data considered to be of lower quality (Humphreys et al., 2007). Later in the 1990s, a new adaptive relation was formalised by de Dear and Brager (1998), derived from the extensive compilation of the ASHRAE RP-884 database of thermal comfort surveys in 160 buildings from 9 countries (de Dear et al., 1997).

According to de Dear and Brager (1998), after statistically analysing the raw data collected in each of the buildings, the authors conducted a meta-analysis of how human subjective thermal response interacted with indoor, contextual (i.e., buildings with or without HVAC) and outdoor meteorological factors. First, the study used weighted linear regression analysis to quantify the relationship between the thermal sensation vote and the indoor operative temperature in each building, retaining only those regressions that were significant at the 95% confidence level, as seen in **Table 2-1**. The resulting regression equations for each building were then solved for thermal sensation vote = 0, to find the operative temperature corresponding to indoor thermal neutrality.

Table 2-1 - Summary of the weighted linear regression of mean thermal sensation on indoor operative temperature, reproduced from de Dear and Brager (1998)

	Centrally Heated/Air-Conditioned Buildings	**Naturally Ventilated Buildings**
Number of Buildings	109 (2 missing values)	44 (1 missing value)
Number of Buildings with regression Models Achieving 95% Significance	63 (57.8% of total)	36 (81.8% of total)
Mean (±stdev) Model Constant (a = y-intercept)	-11.96 (±5.839)	-6.65 (±3.572)
Mean (±stdev) Model Gradient (b)	0.51 (±0.248)	0.27 (±0.134)

To explain the tendency for indoor neutrality to increase as the outdoor climate becomes warmer, and the fact that this relationship is stronger in naturally ventilated buildings, the study statistically tested the relationship between the mean outdoor daily effect temperature (ET^*_{out}) and the neutral indoor operative temperatures (i.e., indoor thermal neutrality). The resulting models are presented in **Figure 2-4**.

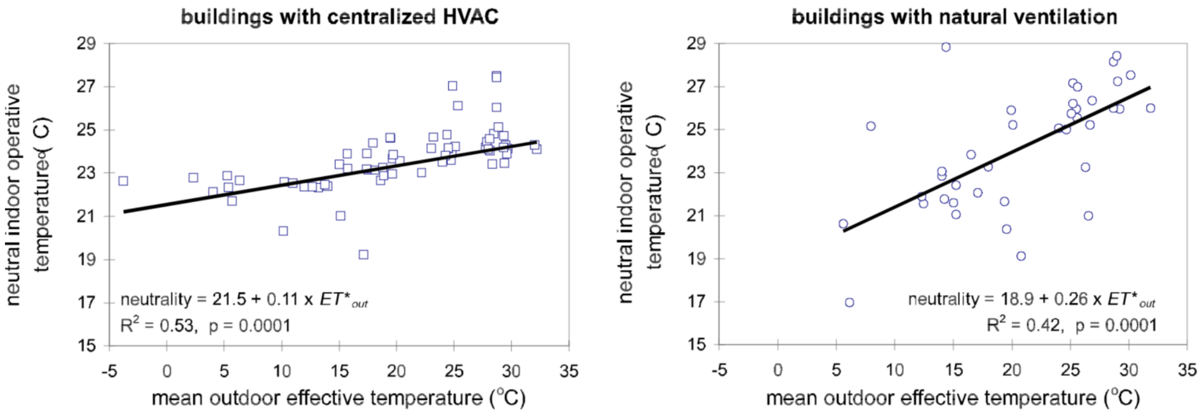

Figure 2-4 - Dependence of indoor thermal neutrality on mean temperature recorded outdoors during each building survey. Source: de Dear and Brager (1998)

80% and 90% thermal acceptability criteria for general thermal comfort were then estimated for each building as the range of operative temperatures falling between mean thermal sensations of ±0.85 and ±0.5, respectively, as presented in **Table 2-2**.

Table 2-2 - Range of Acceptable Operative Temperatures, reproduced from de Dear and Brager (1998)

	Centrally Heated/Air-Conditioned Buildings	**Naturally Ventilated Buildings**
Number of Buildings	108 (3 missing values)	41 (4 missing values)
Number of Buildings with regression Models Achieving 95% Significance	62 (57% of total)	33 (75% of total)
80% Acceptability Criterion, Mean (±stdev)	4.1K (±1.91)	6.9K (±2.79)
90% Acceptability Criterion, Mean (±stdev)	2.4K (±1.12)	4.9K (±3.27)

These calculations were later updated by the same authors (de Dear and Brager, 2002) to incorporate the adaptive model to the ASHRAE Standard 55 (ANSI/ASHRAE, 2020), which recommends the following adaptive comfort equation for naturally ventilated buildings:

$$T_{comf} = 17.8 + 0.31 \cdot T_{pma(out)} \qquad (13)$$

where T_{comf} is the acceptable operative temperature and $T_{pma(out)}$ is the prevailing mean outdoor air temperature, calculated as the arithmetic mean of all the mean daily outdoor air temperatures of the 7 to 30 sequential days prior to the day in question.

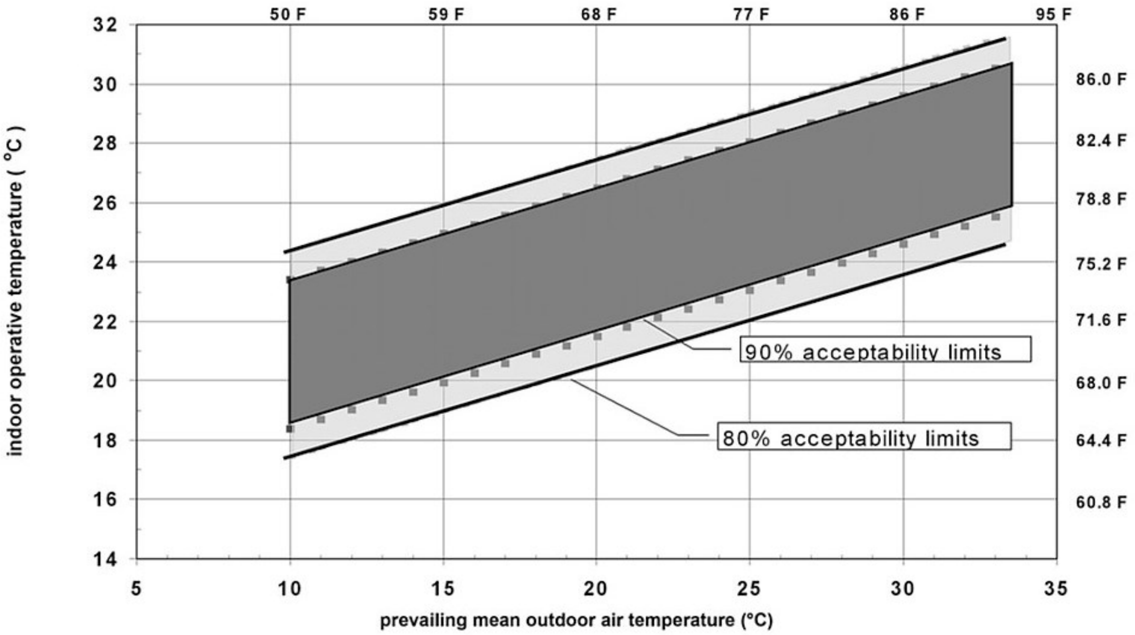

Figure 2-5 - Acceptable operative temperature ranges for naturally conditioned spaces, according to the adaptive model. Source: ANSI/ASHRAE (2020)

From 1997 and 2000, extensive field data from Europe was collected and analysed by Nicol and McCartney (2001) through the Smart Controls and Thermal Comfort project (SCATs project) in response to a European Union call for research regarding 'smart controls' for building energy use saving. One of the main parts of the project was the exploration of further adaptive relationships between climate and comfort indoors, applicable for the diverse climates of European countries.

Through the use of the Griffiths method (Griffiths, 1990), the comfort temperatures were estimated from the collected data in order to extract the relationship between the climate and thermal comfort indoors. The values of the running mean of the outdoor temperature (T_{rm}) were calculated using the exponentially weighted running mean with a weighting-constant α of 0.8. In this approach, the comfort temperature (T_c) was found constant below an outdoor temperature of 10◦C, while increasing with outdoor temperatures above 10◦C (Humphreys et al., 2016). Therefore, the study suggested the following adaptive model for conditioned buildings:

$$T_c = 22.9 + 0.09 \cdot T_{rm} \tag{14}$$

and the following for free-running buildings, with outdoor running mean temperature above 10◦C:

$$T_c = 18.8 + 0.33 \cdot T_{rm} \tag{15}$$

European Standard 15251 (CEN, 2007) uses Equation 15 as the basis of the adaptive approach for buildings operating in the free-running mode.

Recently, a series of new adaptive models were developed for other specific contexts. Among several studies, extensive work has been undertaken by Nguyen et al. (2012) for hot humid South-East Asia, Manu et al. (2016) for five different Indian climate zones, Barbadilla-Martín et al. (2017) for the southwestern area of Spain, Rupp et al. (2018) for the southern region Brazil, Pérez-Fargallo et al. (2018) for the central-south region of Chile, de Dear et al. (2018) for the humid subtropical climate in Sydney, Australia, and Williamson and Daniel (2020) for temperate climates in Australia.

2.2.3. Thermal comfort scales

Regardless of the approach used to assess thermal environments, detailed above, the use of occupants' subjective responses captured through thermal comfort scales is overall predominant in all methods. In these cases, occupants are asked to rate their thermal perception, sensation, comfort, preference, dis/satisfaction or acceptability on a descriptive linear scale, in which phrases or category labels (descriptors) are associated with specific ordinal numbers. Most scales' categories are arranged symmetrically in relation to a "neutral" or "comfortable" category (Andamon, 2005; Humphreys et al., 2016). In addition, the intervals between the categories are commonly assumed as equally spaced, hence the predominant use of statistical methods such as linear regression on thermal comfort studies (Schweiker et al., 2016).

Three main scales are commonly used today: the 7-point Bedford scale for thermal sensation/comfort, the 7-point ASHRAE scale for thermal sensation and the 3-point McIntyre scale for thermal preference (Table **2-3**). Variations of these scales, such as increasing the number of points/categories or minor modifications in the terms used, are also used depending on the study's goals and assumptions.

Table 2-3 - Bedford, ASHRAE and McIntyre scales

Thermal sensation/comfort		**Thermal sensation**		**Thermal preference**	
Bedford		**ASHRAE**		**McIntyre**	
7-point scale		**7-point scale**		**3-point scale**	
1	Much too cool	-3	Cold		
2	Too cool	-2	Cool		
3	Comfortably cool	-1	Slightly cool	1	Warmer
4	Comfortable	0	Neutral	2	No change
5	Comfortably warm	1	Slightly warm	3	Cooler
6	Too warm	2	Warm		
7	Much too warm	3	Hot		

The numbering systems used for each scale can vary. Depending on the kind of numerical and statistical analysis involved, it might be convenient to avoid negative numbers. Certain programming languages, for instance, might also require that lists of categories or labels (i.e., array numbering) begin with the number 0 instead of negative values or the number 1. In addition, thermal comfort researchers also recommend to number the scale in such way that warm extremes (e.g., Bedford's "much too warm" or McIntyre's "prefer to be cooler") have the higher numbers, since it seems more natural to associate warmer sensations with higher values (Humphreys et al., 2016).

Bedford scale

Bedford (1936), during a thermal comfort field study with factory workers, used a structured interview to ask participants about their responses, which were later converted to a 7-point scale for analysis. Known today as the Bedford scale, this scale is a combined estimate of warmth and comfort, used often in field studies in countries of greater British influence. Each category does not represent a thermal sensation, but a combination of the sensation and its respective evaluation as comfortable or not. However, the relationship between the estimates of warmth and comfort is not always considered constant (Humphreys et al., 2016), which can compromise the use of the scale in general.

ASHARE scale

The ASHRAE thermal sensation scale is the most frequently used scale to record occupants' responses and assess their environments. Originally used in American research, this scale is used worldwide today. Although it does not contain any explicit references to thermal comfort in its categories, the scale is commonly assumed to have the three central categories as indicators of thermal comfort. This assumption is clear in the adoption of a PPD lower than 10% (i.e., PMV between -0.5 and 0.5) as the recommended thermal performance of built environments in standards (ISO, 2005; ANSI/ASHRAE, 2020).

When extreme thermal conditions are being explored, it is common to extend the range of the 7-point ASHRAE thermal sensation scale to a 9-category form, adding labels "very cold" and "very hot" (Humphreys et al., 2016). Nevertheless, psychology experiments such as the work by Miller (1994) recommend limiting questionnaire response options to 5 and 7, due to the fact that people's ability to process information and make judgments significantly decreases when presented with more than 7 alternatives simultaneously (Kim et al., 2018a).

McIntyre scale

As explained in **Section 2.2.2**, the preference for non-neutral thermal sensations is experimentally common, and low and high thermal sensation values do not always represent a state of discomfort for a relevant number of people. Therefore, in order to estimate occupants' desired thermal sensation with more precision, researchers proposed to supplement the ASHRAE thermal sensation scale with a scale of thermal preference. The 3-point thermal preference scale, attributed to the work of McIntyre (1980), is the most commonly used scale to account for the desire for thermal change and explore environments' acceptability among occupants. A 5-point category variation of this preference scale, known as the Nicol scale, is also used, presenting the categories: "much warmer", "a bit warmer", "no change", "a bit cooler" and "much cooler". The thermal preference scale is especially effective when the objective of its use is for the control of HVAC systems, since the scale not only suggests the desire for change, but also a direction for the change (Kim et al., 2018a).

The use of these scales in general, however, has several points of concern in the field. Schweiker et al. (2016), for instance, argued that the common assumption of equidistance between scales' categories (e.g., the difference between "warm" and "hot" being equal to that between "warm" and "slightly warm") is one of the main questionable aspects of the scales. This observation was built around the analysis by Lantz (2013) on Likert-type[6] data, which had already confirmed that the way verbal anchors (i.e., category labels) are used in a Likert-type scale significantly influence the perceived distance between the scale's points. The author stated that:

> "*Anchors only at the end points create a relatively larger perceived distance between points near the ends of the scale than in the middle (end-of-scale effect), while anchors at all points create a larger perceived distance between points in the middle of the scale (middle-of-scale effect). Hence, Likert-type scales are generally not perceived as equidistant by subjects*" (Lantz, 2013).

Further work by Schweiker et al. (2020), using a large international collaborative questionnaire study conducted in 26 countries, confirmed that the assumption of equidistance was agreed by only a subset of the responses acquired. Likewise, Fuchs et al. (2018) indicated the existence of different conceptions concerning the relationships between the labels of scales. The study involved 63 participants who first assessed the relative distances between labels of the ASHRAE thermal sensation scale and their distribution along different dimensions (sensation, preference, comfort, pleasantness, acceptability,

[6] A type of psychometric response scale in which responders are asked to choose one out of five possible degrees of agreement, ranging from "strongly agree" to "strongly disagree" (Lantz, 2013).

and tolerability), and later were asked to rate office rooms at cool, neutral, and warm conditions in terms of the same dimensions. The analysis revealed multiple subgroups (or clusters) of people with different conceptions of scales, whose rates of room temperatures differed considerably.

Furthermore, Humphreys and Hancock (2007) indicated, by comparing 868 actual and desired thermal sensations, that categories on the ASHRAE scale have more than one meaning for respondents. According to the authors, thermal sensations votes could indicate both thermal satisfaction and heat-discomfort depending on the occasion and on different people. This exploration highlighted the importance of using not only thermal sensation scales, but also thermal preference scales, to have a better understanding of the data collected. In addition, the meaning associated with sensory information also changes through generations and cultures, and evolves as a culture changes over time (Humphreys et al., 2016).

Finally, the absence of thermal comfort votes in the end categories is also a common issue when applying scales, especially when studying isolated summer or winter conditions, or when analysing highly stable environments. When using the 3-point McIntyre preference scale, for instance, the “prefer warmer” option might hardly be chosen by participants located in hot climates in summer, rendering it impossible to model preferences and calculate a preferred condition. Likewise, studies in cold climates in winter might have no “prefer cooler” option recorded. A possible solution, in these cases, could be to divide the scale range more finely, using 5 or 7-point versions of this scale (Humphreys et al., 2016), such as the Nicol scale for thermal preference.

The correct choice of scale used in thermal comfort studies, therefore, requires a deep understanding of not only the barriers of semantics and interpretations, but also the final application envisaged for the data collected (i.e., whether it will be used for predictive modelling applied for building assessment, or for preferred condition calculation or for HVAC system optimisation).

2.2.4. Generalised models’ limitations and the personal thermal comfort model alternative

Despite the PMV/PPD and the adaptive approach being successfully adopted and accepted in international standards, these two different methods have several limitations. According to the pivotal work of authors Kim et al. (2018a), these limitations include:

(1) the difficult and costly attainment of input variables, especially considering metabolic rate and clothing levels,

(2) the models’ poor predictive performance when applied to individuals,

(3) the inability of the models to be calibrated, adapting to feedback and re-learning,

(4) and the inability of the models to incorporate new relevant input variables (such as age, health status, body mass index) beyond their pre-defined factors.

In addition, these standard models have been developed based on data mainly from office buildings and considerably fewer studies have focused on residential environments. This can also be limiting when considering the diversity of thermal conditions houses generally provide in comparison with more controlled office environments. Likewise, while in offices, the activity level and clothing tend to be constant throughout the year but may change frequently in living spaces, which again provide more diverse thermal conditions (Daum et al., 2011).

When considering older people's heterogeneous characteristics and thermal preferences, these models' disadvantages become even more critical. Hence the need to better investigate thermal comfort for older people on the individual level, enhancing the model's predictive performance and incorporating older people's diverse individual differences.

Personal thermal comfort models are alternatives to overcome these limitations. Instead of an average response calculated from the data of a group of people, a personalised model is based solely on thermal data from one single person. Analysing individual datasets enables a better understanding of specific comfort needs, requirements and issues, aiding the decision-making process involved in designing and optimising thermal environments. Addressing the issue of individual differences in an innovative way and empowered by the rapid developments in the Internet of Things (IoT) and Artificial Intelligence (AI), this change of approach can provide relevant comfort and energy related benefits (Wang et al., 2018) and allow more dynamic and flexible possibilities to absorb individual thermal comfort diversity and enhance model reliability (Rupp et al., 2015). Therefore, to capture the current state of research on this topic, a comprehensive systematic literature review on personal thermal comfort modelling is presented in the following **Chapter 3**.

Chapter 3. Systematic literature review of personal thermal comfort models

Personal comfort models were created to overcome most of the restrictions that generalised models such as the PMV and adaptive model present. Aiming for a more targeted approach and higher predictive performance, this alternative model uses the individual as the unit of analysis, predicting individuals' thermal comfort responses, instead of an average response from a large population. Relying on robust probabilistic programming tools, this new approach is fully data-driven, minimizing bias and avoiding anecdotal evidence, and is usefully flexible when testing different modelling methods and input variables.

In recent years, the development of personal thermal comfort models has been addressed using multiple frameworks, including different modelling architecture, diverse input variables and distinct data collection approaches. Although advances in the field are undeniable, there is still a lack of a thorough and critical review of the current state of the research in the field that maps the similarities and discrepancies across the research.

Therefore, this Chapter presents a systematic review of studies on personal thermal comfort models based on the literature published in the last two decades. By examining the final reviewed articles, research on personal comfort models has been critically analysed based on: (1) the data collection approach and sample size, (2) number and type of participants involved, (3) climate, seasons and type of building involved, (4) model input and output variables, (5) modelling algorithm used, (6) performance indicator used, and (7) model final application.

This systematic literature review provides key information about the development of personal comfort models for older people, presented in later chapters, while also contributing to demonstrate the significance of the findings of this thesis.

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The paper is presented here in a reformatted version for consistency of the thesis presentation. The accepted manuscript can be found in **Appendix A**. Note that this paper is published in written American English.

Statement of Authorship

Title of Paper	A systematic review of personal thermal comfort models
Publication Status	■ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
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Principal Author

Name of Principal Author (Candidate)	Larissa Arakawa Martins		
Contribution to the Paper	Study design and concept, database search (data acquisition), data analysis and interpretation, manuscript preparation, manuscript editing, and corresponding author		
Overall percentage (%)	90%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	24/02/2022

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Veronica Soebarto		
Contribution to the Paper	Study design and concept, data interpretation, manuscript editing		
Signature		Date	24/02/2022

Name of Co-Author	Terence Williamson		
Contribution to the Paper	Study design and concept, data interpretation, manuscript editing		
Signature		Date	24/02/2022

A systematic review of personal thermal comfort models

Authors names and affiliations:

Larissa Arakawa Martins[a], Veronica Soebarto[a], Terence Williamson[a]

[a] School of Architecture and Built Environment, The University of Adelaide, South Australia, 5005, Australia

Abstract: Personal comfort models have shown to predict specific thermal comfort requirements more accurately than aggregate models, increasing occupant acceptability and associated energy benefits in both shared and single-occupant built environment. Although advances in the field of personal thermal comfort models are undeniable, there is still a lack of thorough and critical reviews of the current state of research in this field, especially considering the details of the predictive modeling process involved. This study has systematically reviewed 37 papers from over 100 academic publications on personal comfort models from the last two decades, and examined: (1) the data collection approach and dataset size, (2) number and type of participants involved, (3) climate, seasons and type of building involved, (4) model input and output variables, (5) modeling algorithm used, (6) performance indicator used, and (7) model final application. The review has identified a lack of diversity in building types, climates zones, seasons and participants involved in developing personal comfort models. It has also highlighted a lack of a unified and systematic framework for modeling development and evaluation, which currently hinders comparisons between studies. With most of the studies using machine learning techniques, the review has pointed to the challenges of "black box" models in the field. Finally, the review has indicated that personal input features using physiological sensing technologies can be further explored, especially considering the rapid advances seen today in wearable sensor technologies.

Keywords: personal comfort model; thermal comfort; thermal sensation; thermal preference; machine learning; probabilistic models

3.1. Introduction

International standards (ANSI/ASHRAE, 2020; CEN, 2007; ISO, 2005) adopt the PMV (Predicted Mean Vote) model (Fanger, 1970) and the adaptive model (de Dear and Brager, 1998; Humphreys et al., 2016) as the basis from which to establish the thermal requirements for human occupancy in the built environment. The PMV model, originally developed in the second half of the 1960s by Fanger, is an index that represents the mean value of the thermal sensation votes of a group of people occupying a specific environment, on a 7-point thermal sensation scale from -3 (cold) to 3 (hot). Based on data obtained through climate chamber studies and a selection of heathy adults, the model calculates thermal comfort sensations according to the heat dynamics occurring between the body and the environment. The model defines the thermal neutrality as the condition wherein a group of people does not feel either hot or cold in an environment. Furthermore, the PPD (Predicted Percentage of Dissatisfied) index, calculated as a function of the PMV index, quantifies the expected percentage of thermally dissatisfied people in an environment. The standards recommend that the optimal indoor temperature is defined when PPD is lower than 10%, which corresponds to a PMV index between -0.5 and 0.5. Hence, the application of this model results in the maintenance of a single optimal constant indoor temperature without any variations throughout an entire day or season.

Nevertheless, numerous studies on thermal comfort have considered it unreasonable to expect everyone to be satisfied within a centrally controlled environment. Non-neutral thermal preferences are common, questioning the thermal neutrality proposed as the only optimal thermal condition for people. In addition, very low and very high PMV values do not always represent a state of discomfort (van Hoof et al., 2017b; van Hoof and Hensen, 2006; van Hoof, 2008).

The adaptive comfort approach, developed by Humphreys et al. (2016) and de Dear and Brager (1998), analyzed field-study data from naturally-ventilated buildings. Through empirical models that correlate the comfortable indoor temperatures and the outdoor temperatures, they discovered that indoor temperatures considered to be most comfortable increased significantly in warmer climates and decreased in colder contexts. This indicates that people have an intrinsic ability to adapt to seasonal variations in environmental conditions, thus revealing that satisfaction with the thermal environment does not necessarily result in an environment restrained to an invariable indoor temperature (Humphreys et al., 2016; Kim et al., 2018a; van Hoof et al., 2017b; van Hoof, 2008).

Nonetheless, both PMV and the adaptive models are aggregate models, which means they are designed to predict the average thermal comfort of large populations. Other researchers have argued that predicting comfort at the population level presents limitations in real case scenarios. In fact, many studies have already pointed out to the high levels of thermal dissatisfaction among occupants in office buildings where the standard prescriptions are used for heating and air conditioning set point controls (Aryal and Becerik-Gerber, 2018; Karmann et al., 2018; Huizenga et al., 2006; Li et al., 2017). In addition, according to the pivotal work of authors Kim et al. (2018a), these aggregate models are also limited by (1) the difficult and costly attainment of input variables, (2) their inability to be calibrated, i.e., adapting to feedback and re-learning, and (3) their inability to incorporate new, relevant, input variables (such as age, health status, body mass index and contextual features) beyond their pre-defined factors.

"Personal comfort models" were created to overcome most of the restrictions that the PMV and adaptive models present. Instead of an average response calculated from the data of a group of people, a personalized model is based solely on thermal data from one single person. By analyzing individual datasets, this approach helps to unmask and quantify the differences between individuals in an environment, enabling a better understanding of specific comfort needs and requirements and collecting diagnostic information to identify problems (Kim et al., 2018a). This information, in turn, aids the decision-making process involved in designing and optimizing thermal environments to improve comfort satisfaction and energy efficiency. When HVAC (Heating, Ventilation and Air Conditioning) systems are used in shared spaces and an individual HVAC control is not possible, personal comfort models can be used as the basis for (1) consensus-based solutions (Jazizadeh et al., 2014b; Jazizadeh et al., 2014a; Gupta and Kar, 2018), (2) personal comfort system's control automation (Katić et al., 2020; Kim et al., 2018b) or (3) development of thermal comfort profiles (or personas) for general use (as conceptually indicated by Kim et al. (2018a)). In single-occupant spaces where individual control is possible, personal comfort models can be used to automate, with high precision, any type of conditioning systems. Although different levels of control automation can benefit all individuals (Chen et al., 2019; Gupta and Kar, 2018; Aryal et al., 2021), personal comfort models can be especially relevant as assistive tools for people with lower thermal sensitivity, such as older people, or for those with more limitations to thermal management and adaptation, such as people with disabilities (van Hoof et al., 2017a). Furthermore, these models can be calibrated and adapted according to new feedback and accommodate different types of variables depending on each person's specific comfort-driving characteristics. Addressing the issue of individual differences in an innovative way and empowered by the rapid developments in technology, this change of approach provides relevant comfort and energy related benefits (Wang et al., 2018) and allows more dynamic and flexible possibilities to absorb individual thermal comfort diversity and enhance model reliability (Rupp et al., 2015).

The development of personal comfort models has been addressed using multiple frameworks, including different modeling architectures, diverse input variables and distinct data collection approaches. Nevertheless, although advances in the field are undeniable, a thorough and critical review to map the similarities and discrepancies between the predictive modeling details involved is still lacking. A structured review and compilation of the gaps and limitations will help facilitate and guide future investigations in the field.

This paper presents a systematic review on personal comfort models based on the literature published in the last two decades. It aims to provide a complete and unified overview of personal thermal comfort models, focusing specifically on the predictive modeling details. To the best of the authors' knowledge, there has not been a comprehensive, systematic and critical review specifically targeted at the predictive modeling specifics of personal thermal comfort models that rely solely on individuals as the unit of model analysis. A review by Čulić et al. (2021), for instance, focused specifically on the smart technologies for data collection, drawing insights on sensing tools used and variables measured rather than modeling processes. Zhang and Tzempelikos (2021), on the other hand, focused on the final stages of the process, namely the application or integration of personalized models into building control system. Xie et al. (2020) brought forth a more comprehensive overview than the aforementioned studies but remained non-specific when addressing modeling details, disregarding the differences in models' dataset sizes, the experimental settings used (i.e., climate chambers or field studies) and the benefits of different modeling performance indicators. Similarly, Lee and Karava (2020) provided a general overview of the topic without discussing details such as type of participants, climates, seasons and building settings involved, which can all affect modeling in different degrees. André et al. (2020) targeted the details of personal comfort systems (PCS), i.e., the hardware effecting the comfort control, but not modeling details. Finally, although the pivotal work of Kim et al. (2018a) exposes 14 relevant papers on the subject, it does not constitute a systematic review.

This chapter discusses research to date on personal comfort models and critically reviews: (1) the data collection approach and dataset size, (2) number and type of participants involved, (3) climate, seasons and type of building involved, (4) model input and output variables, including comfort scales used, (5) modeling algorithm used, (6) performance indicators used, and (7) model final application (when available).

The structure of this review is organized as follows. **Section 3.2** discusses the research methodology. **Section 3.3** presents the review results, highlighting the different aspects of the current efforts regarding personal comfort models' development. **Section 3.4** discusses the gaps of knowledge and future research directions, and **Section 3.5** concludes this review.

3.2. Research Methodology

The selection process of academic publications in this study draws on the methodology adopted in manuals such as the *JBI Manual for Evidence Synthesis* (Lockwood et al., 2020). The commonly adopted literature selection processes involve several steps: (1) scope delimiting, (2) identification of alternative terminology and creation of a logic grid, (3) defining the literature database, search rules and screening criteria, (4) database search, (5) final screening.

3.2.1. Scope delimiting

The main purpose of the review is to investigate the current state of research into personal thermal comfort prediction for the establishment of thermal requirements for human occupancy in buildings. Therefore, this review will focus on:

(a) buildings, excluding other built environments such as outdoor spaces or vehicles (e.g., cars or aircrafts);

(b) thermal comfort in buildings, excluding other forms of comfort, such as visual, acoustic or ergonomic comfort;

(c) predictive modeling of thermal comfort in buildings, excluding studies that only present descriptive statistical analysis, such as general distributions, dispersions, means, medians, variances, etc., of the data;

(d) and personal predictive modeling of thermal comfort in buildings, excluding aggregate or population-based prediction approaches.

Predictive modeling, in this paper, is termed as "the process of developing a mathematical tool or model that generates an accurate prediction", as defined by Kuhn and Johnson (2013).

Figure 3-1 illustrates the scope delimiting steps.

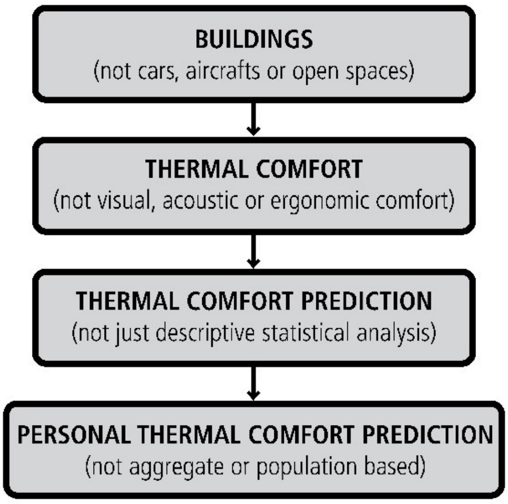

Figure 3-1 - Review's scope delimiting steps

3.2.2. Identification of alternative terminology and creation of a logic grid

After delimiting the scope, a logic grid of key words was created. **Table 3-1** presents the logic grid, highlighting the main key words, followed by the respective alternative terms. The logic grid was formatted considering basic search boolean operators (e.g., OR) and modifiers (e.g., asterisks for truncation, when different forms of the word are valid, and quotation marks, indicating when to keep phrases together).

Table 3-1 - Logic grid of keywords

PERSONAL	THERMAL COMFORT	MODEL
personal* OR individual* OR occupant-cent* OR human-cent* OR customi* OR occupant-aware OR occupant-driven	"thermal comfort" OR "thermal discomfort" OR "thermal sensation" OR "thermal preference" OR "thermal behavior" OR "thermal behaviour" OR "thermal control" OR "thermal management" OR "thermal acceptability" OR "thermal satisfaction" OR "thermal complaint" OR "thermal dissatisfaction"	model* OR predict* OR data-driven OR smart OR "machine learning"

3.2.3. Defining the literature databases, search rules and screening criteria

Scopus®, Web of Science® and Compendex® were the databases used in this study, as they cover architecture, engineering and computer science literature and allow a robust search of topics and fields. In terms of search rules, this study only reviewed literature published in peer-reviewed academic journals, as these were considered to be of higher quality than grey literature and conference papers. In addition, only publications written in English from 2000 to 2021 were included to filter the most recent studies on personal comfort models.

To select papers that strictly address personal comfort models, this systematic review only includes studies that:

(a) focus on individual occupants as a unit of model analysis;

(b) use real (non-synthetic) feedback from individuals;

(c) propose models that predict either thermal preference, sensation, acceptability, discomfort or dis/satisfaction; and

(d) present details on the development of the models.

3.2.4. Database search

The database search was conducted between January 2020 and September 2021. Using the keywords from the logic grid in titles, keyword lists and abstracts of publications, 1115 papers were initially identified in Scopus®, 1276 in Web of Science®, and 783 in Compendex®. These results, however, included duplicates, which were subsequently removed. Using the screening criteria mentioned in **Section 3.2.3**, all abstracts from the search results were read and selected for full-text screening if they met the criteria above. This process resulted in 109 papers chosen.

3.2.5. Final screening

Full-text screening involved a thorough analysis of the entire content of these 109 publications (i.e., not only title, keywords and abstract, but also the full content of the papers), filtering papers once again according to the screening criteria mentioned in **Section 3.2.3**. This process removed the papers that, although appearing to have the inclusion criteria in the titles, keywords and abstracts, upon a further analysis of the entire content, presented evidence for exclusion. This process also involved a second search through the selected publications' reference lists, to identify related papers that had not appeared in the first database search. This resulted in 7 papers being added to the list for full-text screening.

The final full-text screening resulted in 37 publications selected, which are described and analyzed in the next sections. **Figure 3-2** illustrates the research procedure of this study.

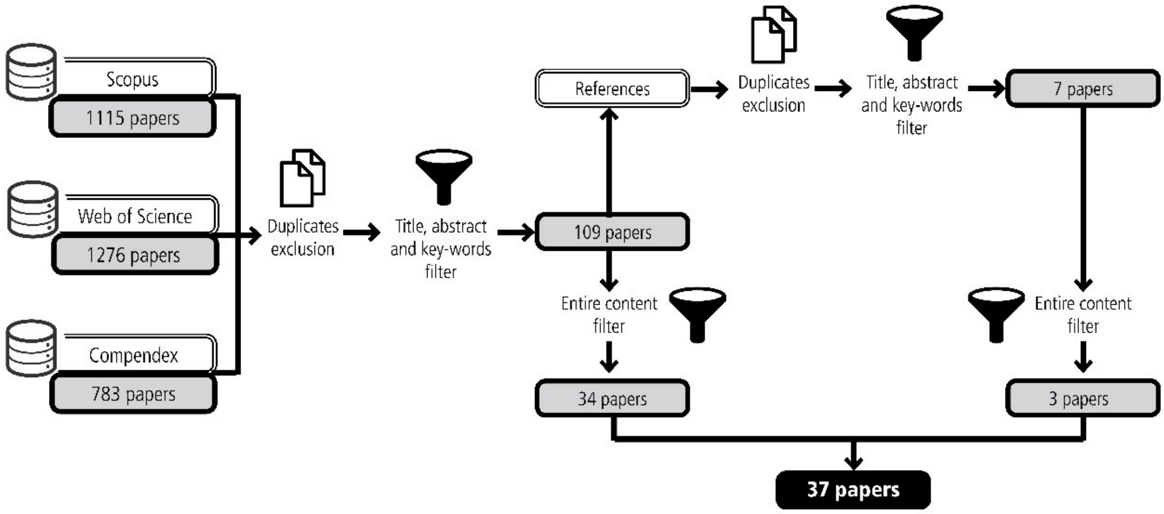

Figure 3-2 - Research procedure of this study

3.3. Results

Table 3-2 summarizes the 37 studies on personal comfort models reviewed for this paper.

Table 3-2 - Studies on personal comfort models and their characteristics

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
Aguilera et al. (2019)	Denmark	Denmark	465 (assumed from graph in study)	50 to 110	7	Office	3 weeks, March - April 2018	FC	not mentioned	0	Ti	Thermal preference	29% of occupants' thermal comfort improved with occupant-driven HVAC control
Aryal and Becerik-Gerber (2020)	USA	USA	1276	85 (average)	15	Office[6]	July - August 2019	RF, KNN, SVM, DT	5-fold cross-validation	STemp (wrist, forehead, nose, left cheek, and right cheek) [7]	Ti, RH, ASp, mTr, Heater state, Fan state [5]	Thermal sensation and thermal satisfaction	Average accuracy across participants: Thermal sensation: 72-90%[8] Thermal satisfaction: 69-94%
Aryal and Becerik-Gerber (2019)	USA	USA	543	27 (approx.)	20	Office[4]	June - August 2018	RF, SVM, KNN, Subspace KNN, Subspace LDA	5-fold cross-validation	STemp (wrist and 4 points in face) [9]	Ti [6]	Thermal comfort, thermal satisfaction and combination of both	Average accuracy across participants: Thermal sensation: 72-85%8 Thermal satisfaction: 85%–94% Combination thermal sensation and satisfaction: 62-76%
Aryal et al. (2021)	USA	USA	not mentioned	125.1 average (phase 1) and 224.8 average (phase 2)	14	Office	15 weeks, October - March 2020	RF, KNN	5-fold cross-validation	Clo	Ti, RH, Tr, To, Rho, ApT [10], Time, Heater state, Fan state	Thermal sensation and thermal satisfaction	Average accuracy across participants: Thermal sensation: 74-77%8 Thermal satisfaction: 81-86%
Auffenberg et al. (2018)	UK	Pakistan, Greece, USA, UK	not mentioned	5 to 150	576	Office and residential	from 5 to 60 days	BI	Cross-validation mentioned but not detailed, increasing training observations in steps of 1	Seasonal adaptation	To, OpT, RH	Optimal comfort temperature, Thermal preference (desired change), Thermal sensation, Thermal sensitivity	Average accuracy gains, across participants: Compared to PMV: 25.8% Compared to adaptive model: 13.2%
Daum et al. (2011)	Switzerland	Switzerland	6851	not mentioned	28	Office	2006 to 2009	MLR	not mentioned	0	Ti	Thermal sensation	not mentioned
Fay et al. (2017)	UK/Ireland	Ireland	477	5 to 227	78	Office	4 to 306 days per user	GPM	5 data points for testing, randomly repeated 50 times	0	Ti, RH, To	Thermal sensation	Average RMSE across participants: 0.71 Standard deviation of RMSE across participants: 0.28 Average PSE across participants: 34.1
Ghahramani et al. (2015b)	USA	USA	2393	19 to 202	33	Office	several months in 2012, 2013 and 2014, different seasons, 5 – 90 days per person	BI	not mentioned	0	Ti	Thermal sensation	Average accuracy across participants: 70.14% Average specificity across participants: 76.74%

Guenther and Sawodny (2019)	Germany/Singapore	Singapore	not mentioned	not mentioned	18	Office	10 months	GPM and Polynomial Basis Function	Cross-validation mentioned but not detailed	0	Ti, Supply T at the outlet of the fan coil units, Fan level, To, GSR, Time, Day of week, Variation of each parameter (except for day and time)	Thermal sensation	Average RMSE across participants: 0.68 Median RMSE across participants: 0.58 Right tendency across participants: 74%
Jayathissa et al. (2020)	Singapore	Singapore	4378	416 average	30	Office	2 weeks	RF	60-40 split	NBTemp, HR, PrefH, Room	Time, Lighting, Noise, Ti, RH	Thermal, visual and aural comfort preference	Average F1-micro-score across participants, for thermal preference: 0.60-0.668
Jazizadeh et al. (2014a)	USA	USA	328	61 to 114	4	Office[4]	3 weeks, autumn	FC	10-fold cross-validation for different numbers of fuzzy sets between 1 and 100, increasing training observations in steps of 10	0	Ti	Thermal sensation	Average[11] error between true and predicted temperatures associated with each thermal sensation, across participants: 1.165°C
Jazizadeh et al. (2014b)	USA	USA	not mentioned	not mentioned	6	Office	October - December 2012 and April and June 2013	FC	not mentioned	0	Ti	Thermal sensation	Average thermal comfort rating after using personalized HVAC control, across participants: 8.4 on 1-10 scale (10 being most comfortable)
Jiang and Yao (2016)	UK	China	1199	38 to 63	20	Climate chamber	Summer, 2008 to 2010	SVM	50-50 split 5-fold cross-validation	MET, Clo	Ti, MTr, aSp, RH	Thermal sensation	Average accuracy across participants: 89.82%
Jung and Jazizadeh (2019a)	USA	USA and Switzerland	not mentioned	not mentioned	6	Office	Varies, depending on the dataset	BI	not mentioned	0	Ti	Thermal sensation	not mentioned
Jung et al. (2019)	USA	USA	not mentioned	not mentioned	18	Climate chamber	not mentioned	RF, SVM, LR	3 scenarios for train-test split[12]	Heat flux, STemp (wrist)	Ti	Thermal preference	Median accuracy across participants: Scenario 1: 42.6-61.2%8 Scenario 2: 44.8-72.9% Scenario 3: 68.7-97%
Katić et al. (2020)	The Netherlands/ Denmark	The Netherlands	476	238	2	Climate chamber	January - February and November - December 2017	SVM, DT Ensembles (Bagged trees, Boosted trees and RUSBoosted trees)	5-fold cross-validation	PCS Control Intensity, STemp (mean and hand)	Time, Ti, RH, MTr	Thermal sensation	Average accuracy across participants11: Approach 1[13]: 59.45-95.6%8 Approach 2: 62.4-85.55% Average ROC AUC, across participants: Approach 1: 0.5-0.848 Approach 2: 0.645-0.8

Kim et al. (2018b)	USA	USA	4743	123 (average)	34	Office	April - October 2016	DT, GPM, GB, SVM, RF, Regularized LR	2-fold cross-validation, repeated 150 times	PCS Control Intensity, PCS Heating/cooling Location, PCS Occupancy Status, PCS Occupancy Frequency, Ratio of PCS Control Duration over Occupancy Duration, PCS Control Frequency, Clo	Ti, OpT, RH, Ti slope, HVAC control settings, HVAC Thermostat reading (TI, aSp, Damper position, Heating output, Discharge T), To, Sky Cover, Weighted Mean Monthly T, Precip, Day of week, Hour of day	Thermal preference	Average ROC AUC across participants: 0.61-0.718
Kim (2018b)	South Korea	Not mentioned for first data set and USA	2480	26 to 133	24	Office	March - August 2017 and July 2012 - August 2013	ANN	not mentioned	0	Time, Ti, To	Thermal discomfort	Average[11] MSE across participants: 0.002975
Konis and Annavaram (2017)	USA	USA	1490	8 to 80	45	Office	2 weeks	LR	not mentioned	0	Ti	Thermal satisfaction separated for heating and for cooling	Percentage of incorrect predictions <10%: met for 16 of 16 heating models and for 19 of 21 cooling models
Lee and Ham (2020)	USA	USA	953	63 to 115	10	Office	4 weeks, August - September 2019	KNN, GB, LVQ, SVM, RF	10-fold cross-validation	STemp, SCond, HR, MET	Ti, RH	Thermal sensation	Average11 accuracy across participants: 71-77%8 Average Cohen's Kappa across participants: 0.216-0.4418
Lee et al. (2017)	USA	North America	1712 - first phase, not mentioned - last phase	from 10	11	Office	not mentioned	BI	8 data points for training and remaining for testing	MET, Clo	Ti, MTr, ASp, RH	Thermal preference	Logistic loss of -28.5 when compared to -30 from another study (assumed from graph in study)
Lee et al. (2019)	USA	not mentioned	432	48	9	Office[4]	8 days in October and November 2017	Variational BI	2 to 8-fold cross-validation, increasing training dataset in steps of 6	MET, Clo	Ti, mTr, RH, ASp	Thermal preference	ROC AUC of approx. 0.8 (assumed from graph in paper)
Lee et al. (2020)	USA	USA	not mentioned	48 (assumed for requested phase), not mentioned (for participatory phase)	5	Office[4]	March - April 2019	Linear OP, BI	not mentioned	0	Ti	Thermal preference	Median Expected Squared Error, for each participant[14]: approx. 10-308
Li et al. (2017)	USA	USA	271 - first case study, 362 - second case study	31 to 57	3 and 7	Office and residential	June - July 2016 and 3 weeks in November - December 2016	RF	10-fold cross-validation	Act, Clo, HR, STemp	Ti, RH, Window State, To, RHo	Thermal preference	Average11 accuracy across participants: First case study, mechanical ventilation: 62.5-80.2%8 First case study, natural ventilation: 53.3-78.4% Second case study: 54-81.8%
Li et al. (2018)	USA	USA	720 (assumed according to vote frequency)	60 (assumed according to vote frequency)	12	Office[4]	December 2017 - February 2018	RF	10-fold cross-validation	STemp max. measurement of face[15], STemp gradient (forehead, nose, cheeks, ears, mouth, and neck)	0	Thermal preference, for cooling, heating and both phases	Average accuracy across participants: Cooling phase: 91.6% Heating phase: 92.7% Both phases: 85.0%

Li et al. (2020)	USA	USA	1800	180	10	Office[4]	December 2017 - February 2018	LR	10-fold cross-validation	STemp (cheeks)	0	Thermal comfort	Average[11] accuracy across participants: 67.4%
Liu et al. (2019)	USA	USA	3848	275 (average)	14	Anywhere, indoor and outdoor	2 to 4 weeks, March to May 2017 and November to December 2016	LDA, LR, ANN, SVM, KNN, NB, CART, J48, DT, RBC, C5.0, Bagged DT, RF, RF by Randomization, GB	80-20 split, 5-fold cross-validation, repeated 20 times	STemp (wrist and ankle), NBTemp, HR, Wrist Acc [16]	To, RH, ASp, SR	Thermal preference	Average[11] accuracy across participants: 64.7-72.9%[8] Cohen's Kappa across participants: 0.16-0.278 ROC AUC across participants: 0.6-0.768
Liu et al. (2007)	China	China	not mentioned	not mentioned	113	Office[4]	June to October 2004	ANN	20 datapoints for training and 4 for testing	0	Ti, RH, ASp, MTr	Thermal sensation	Veracity[17] of approx. 80% after replacing the first 20 datapoints (paper only shows 1 participant's results)
Lu et al. (2019)	USA	China	775	362 to 413	2	Office[4]	6 days, March 2018	RF, SVM	80-20 split, 5-fold cross-validation	Clo SurfTemp, STemp (cheek), STemp difference between consecutive measurements	Ti, RH	Thermal sensation	Average[11] precision across participants: 37.9-98.75%[8] Average recall across participants: 42.75-97.5%[8] Average F1-score across participants: 38.5-98.05%[8]
Natarajan and Laftchiev (2019)	USA	USA	1017	97 to 400	5	Office[4]	Average 14 days per user	LinR with Active and Transfer Learning	50-50 split, 5-fold cross-validation	HR, STemp, CBTemp, PrefTemp [18]	Ti, RH, ASp [10]	Thermal sensation	Average RMSE across participants: 0.818
Pazhoohesh and Zhang (2018)	UK / China	not mentioned	not mentioned	not mentioned	9	Office	November 2016 - January 2017	FC	not mentioned	0	Ti	Thermal preference	Average margin of error across participants: 12.95% Percentage of occupants rating "Just Right" when model is used for HVAC control: 73%
Shan et al. (2020)	China	China	450	150	3	Office[4]	June - August	ANN	10-fold cross-validation, repeated 10 times	STemp (wrist, neck, of the point 2 mm above the wrist)	0	Thermal sensation	Average accuracy across participants: 89.2% Average MAE across participants: 0.16 Average MSE across participants: 0.06
Shan et al. (2018)	Singapore/Australia	Singapore	not mentioned	not mentioned	22	Office[4]	not mentioned	LDA	not mentioned	EEG [19]	0	(Thermal) Mental state	Average accuracy (classification rate) across participants: In Resting state: 98% In Task state: 99%
Sim et al. (2016)	South Korea	South Korea	840	not mentioned	8	Climate chamber	not mentioned	Stepwise LinR	not mentioned	STemp (fingertip, radial artery, ulnar artery, upper wrist temperature) [20]	0	Thermal sensation	Average RMSE across participants: 0.95-1.248
Xu et al. (2018)	China	China	not mentioned	not mentioned	4	Office	not mentioned	MLR	not mentioned	0	Ti	Thermal sensation	Consumed power of the VAV system with proposed approach: 23% less than the traditional fixed set point control strategy.

Zhao et al. (2014b)	China	China	2679	300 (average)	9	Office	November 2009 - January 2010	LLS	67-33 split	0	Ti, RH, MTr	Thermal sensation	Average11 across participants: Regression MSE: 0.4782 Prediction MSE: 0.53373 Regression Bias: -0.00188 Prediction Bias: 0.03382
Zhao et al. (2014a)	China	China	321	not mentioned	6 and 11	Climate chamber	June - August 2011 and same period in 2012	LLS	leave-one-out validation method	0	Ti, RH	Thermal complaint	Average11 FNR across participants: For Hot complaint: 0.0783 For Cold complaint: 0.055 Average FPR across participants: For Hot complaint: 0.5245 For Cold complaint: 0.365

1 "Dataset size" refers to the number of datapoints used in the studies, i.e., the total number of observations used for model training, validation and testing.
2 FC = Fuzzy Classification, RF = Random Forest, KNN = K-Nearest Neighbors, SVM = Support Vector Machine, DT = Decision Tree, LDA = Linear Discriminant Analysis, BI = Bayesian Inference/Classification, MLR = Multinomial Logistic Regression, GPM = Gaussian Process Model, LR = Logistic Regression, ANN = Artificial Neural Network, GB = Gradient Boosting, LVQ = Learning vector quantization, OP = Ordered Probit, LinR = Linear Regression, NB = Naive Bayes, RBC = Rule-Based Classifier, CART = Classification and Regression Trees, LLS = Least-squares linear estimation, J48 = J48 Decision Tree.
3 STemp = Skin Temperature, Clo = Clothing, NBTemp = Near Body Temperature, MET = Metabolic Rate, HR = Heart Rate, SCond = Skin conductance, Act = Activity level, SurfTemp = Surface Temperature, Acc = Accelerometry, CBTemp = Core Body Temperature, PrefTemp = Preferred Temperature, EEG = Electroencephalogram, PrefH = Preference History
4 Ti = Indoor Air Temperature, RH = Relative Humidity, aSp = Air Speed, mTr = Mean Radiant Temperature, Tr = Radiant Temperature, RHo = Outdoor Relative Humidity, To = Outdoor Air Temperature, OpT = Operative Temperature, ApT = Apparent Temperature, T = Temperature, GSR = Global Solar Radiation, SR = Solar Radiation, HVAC = Heating, Ventilation and Air Conditioning, PCS = Personal Comfort System, Precip = Precipitation
5 Definitions of Accuracy, Precision, Recall , Specificity, FNR, FPR, F1-score, ROC AUC can be found in (Powers, 2007); Right tendency = average percentage of votes whose signs are predicted accurately, defined in (Guenther and Sawodny, 2019); PSE = percentage signed error, defined in (Fay et al., 2017) ; RMSE = root mean squared error, MSE = mean squared error, MAE = mean absolute error, with further definitions found in (Botchkarev, 2019); Cohen's Kappa = inter-rater agreement, further defined in (Cohen, 1960; Ben-David, 2008) ; Logistic loss = loss function for logistic regression, defined in (Lee et al., 2017).
6 Treated as an experiment.
7 Instant measurement at the time of vote, min., max., average, std., overall change between first and last values in the time window, and average of the derivative of the measurements.
8 Ranges indicate max. and min. across different input set combinations, phases and/or modeling techniques compared in the studies.
9 Min., max., average, std. and median of measurements in the 5-min. window and of first derivative of the data stream; coef. obtained by fitting first degree and second degree polynomials to the measurements in the 5-min window; most recent measurement, average of last 10s, and average of first derivative for the last 10s.
10 Average and changes in the last 1, 5, 10 and 30min. prior to a vote for all features.
11 Average calculated by this review paper using available data from papers, to allow comparison between studies.
12 Scenario1 = training on first half of the experiment and testing on second half of the experiment; scenario 2 = training on the second half of the experiment and testing on the first half of the experiment; scenario 3 = cross validation on all the data points combined.
13 Approach 1 = thermal preference in scale heating demand, neutral, cooling demand; Approach 2 = thermal preference in scale heating demand, slightly heating demand and no change
14 Average cannot be calculated from graph supplied by the paper.
15 Measurement and its gradient, max., min. and average.
16 Average and gradient for 5min and 60min prior to a vote.
17 Term "veracity" not defined in the study.
18 Average, variance, median, min., max., simple moving average between 2 to 9 samples immediately prior to a vote.
19 42 frequency ranges (within 3–45 Hz range) for each of the 14 channels.
20 Average, time differential, average power of a specific frequency band, temperature gradient between positions.

3.3.1. Data collection approach and dataset size

From the papers that reported a total dataset size for all models developed (i.e., the sum of all individual models' dataset sizes), nearly half of them used up to 1000 data points. The smallest dataset reported was 321 data points presented in the study by Zhao et al. (2014a). The other half of the studies had total datasets ranging from 1017 (Natarajan and Laftchiev, 2019) to nearly 7000 points (Daum et al., 2011). These total set sizes, however, were divided, in each study, into different numbers of individual datasets, according to the number of participants involved in each analysis. The smallest individual datasets ranged from 5 points per model (Auffenberg et al., 2018; Fay et al., 2017) to slightly more than 400 points (Jayathissa et al., 2020; Lu et al., 2019; Natarajan and Laftchiev, 2019). Such a wide range of dataset sizes is, however, expected as these studies used different modeling methods (explained in **Section 3.3.5**).

The data collection approach can highly influence the number of data points available for the individual personal comfort models. Studies that used either climate chambers or office rooms treated as structured experiments, and of which sessions lasted longer hours over multiple weeks, seemed to have higher survey response frequencies, and, consequently, higher individual datasets for each participant involved. Lu et al. (2019), for instance, collected data through 14 2-hour sessions, where participants answered a thermal comfort survey every 5-minutes. This resulted in relatively large datasets for the individual models (i.e., 362 to 413 points) although the study only involved two participants. Studies that used freely operated office rooms (i.e., not treated as structured experiments) reached similar individual dataset sizes by prompting thermal comfort votes from participants with frequent reminders. This was the case of Zhao et al. (2014b), who required participants to answer the thermal comfort surveys every hour, by sending online reminders to users' computers while they were working in the office environment. Similarly, Jayathissa et al. (2020) reached on average 416 data points per participant through the use of a smartwatch, which not only served as the main data collection tool and user interface, but also prompted the occupants with a small vibration requesting feedback from them at different timed points in the day.

Similar to the influence of the data collection approaches on the final dataset size, the impact of data pre-processing in the final data size is highlighted in some of the papers analyzed. Missing, anomalous or unlikely data points, as well as highly unbalanced datasets, need to either be discarded, decreasing the final data point count, or dealt with by oversampling in order to avoid low dataset sizes. K-Nearest Neighbors, for instance, was used by Liu et al. (2019) to fill in missing data and avoid discarding relevant data points. Kim et al. (2018b) also used oversampling as a pre-processing tool to deal with unbalanced datasets (i.e., where one of the classification categories surpasses the other in number). Unlike undersampling, which discards data points until all classification categories match the minority category, oversampling avoids losing data points with the drawback of possible model overfitting.

Predicting thermal comfort without needing a large number of survey answers per user is, nevertheless, still possible. Natarajan and Laftchiev (2019), for example, developed an Active Transfer Learning Framework to reach larger dataset sizes, at the same time avoiding disturbing participants with long monitoring periods. The framework uses knowledge from prior users to add to new users' datasets, reducing considerably the necessary size of individual labelled datasets.

3.3.2. Number and type of participants involved

The selected reviewed studies involved 2 to 576 participants to develop personal comfort models. It is noticeable that more than half of the studies had up to 10 participants, as seen in the histogram presented in **Figure 3-3**. This can be partially explained by the common limitations of thermal comfort data collection processes, such as long monitoring periods or relatively intrusive data collection tools (e.g., repetitive survey and feedback required or continuous sensing), which might have affected subjects' willingness to participate.

The intrusiveness of thermal comfort prediction is, in fact, a recurrent topic throughout the studies analyzed, especially the ones involving human physiological parameters' sensing. Aryal and Becerik-Gerber (2019), for instance, emphasized that not only can wearing devices discourage participant engagement because of the intrusiveness and privacy concerns, but it can also cost considerably more than using environmental sensors alone. Hence, in their study, they evaluated the accuracy trade-offs between using a wrist-worn wearable device, a thermal camera, and an environmental sensor to predict the individual thermal comfort of 20 participants. Likewise, Lee et al. (2020) recognized the impracticability of long-term collection of occupant feedback through participatory interfaces. In their study, both voluntary and requested feedback data were explicitly incorporated as types of behavior into the thermal preference learning models, to analyze differences in the model accuracy for 5 participants. Similarly, Li et al. (2018), Shan et al. (2020) and Lu et al. (2019) tested different options for collecting skin temperature as inputs for personal comfort models using less intrusive and more accurate approaches. Their number of participants in each of those studies, however, was low (12, 3 and 2, respectively), and could have benefitted from further explorations, especially considering the diversity of subjects involved. Nevertheless, since the main objective of these studies was to analyze subjects at the individual level, having lower counts of participants is not necessarily negative.

From the 2 studies with more than 100 participants, Auffenberg et al. (2018) were able to reach the highest number of participants − 576 people – by using the ASHRAE RP-884 dataset (de Dear et al., 1997), plus their own experimental period. The dataset was then divided into subsets for each participant who answered at least 5 thermal comfort votes.

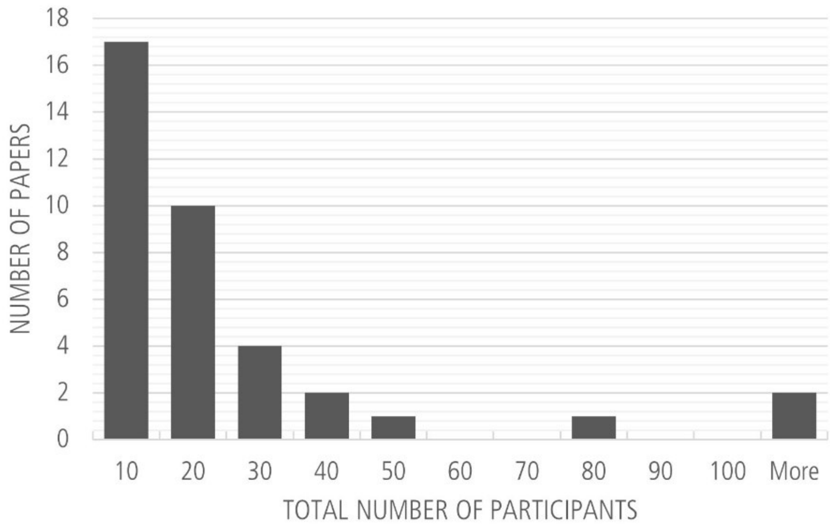

Figure 3-3 - Histogram of total number of participants in the studies selected

Although not all studies reported further details about the participants, it is still clear from the analysis that such studies involved younger adults in their twenties considered to be healthy and maintained an overall balance of female and male participants (**Table 3-3**). This is in line with the traditional approach of thermal comfort studies to select younger healthy adults (Fanger, 1970), possibly to avoid individual influences of age, health conditions, intellectual or physical impairment or medication use in thermal sensation and sensitivity (van Hoof, 2008; Mora and Meteyer, 2018). Participants who were office workers and students were also common in the studies analyzed, as seen in **Table 3-3**. Weight, height and BMI (Body Mass Index) were reported by few of the studies selected and deemed more relevant when considering personal and physiological parameters, such as skin temperature or heart rate, as inputs for the personal comfort models (Katić et al., 2020; Liu et al., 2019; Shan et al., 2020).

Table 3-3 - Participants details in each study analyzed

Ref.	No. of participants	M (male) / F (female)	Age group	Health	Body Composition	Other characteristics
Aguilera et al. (2019)	7	*	*	*	*	office workers
(Aryal and Becerik-Gerber, 2020)	15	11 M and 4 F	20s	healthy	H 168.9 ± 10.1cm, W 65.4 ± 7.3kg	*
(Aryal and Becerik-Gerber, 2019)	20	12 M and 8 F	20s – 30s	healthy	H 171.8 ± 10.9cm, W 73.8 ± 16.1kg	*
(Aryal et al., 2021)	14	4 M and 10 F	20' – 50s	*	*	office workers, researchers, students
(Auffenberg et al., 2018)	576	*	*	*	*	office workers, students (partially)
(Daum et al., 2011)	28	*	*	*	*	office workers, researchers
(Fay et al., 2017)	78	*	20s – 40s	*	*	office workers, researchers, students, diverse international background
(Ghahramani et al., 2015b)	33	*	*	*	*	office workers, researchers, students
(Guenther and Sawodny, 2019)	18	*	*	*	*	*
(Jayathissa et al., 2020)	30	15 M and 15 F	*	*	*	office workers
(Jazizadeh et al., 2014a)	4	*	*	*	*	office workers
(Jazizadeh et al., 2014b)	6	*	*	*	*	office workers
(Jiang and Yao, 2016)	20	*	20s	healthy	*	*
(Jung and Jazizadeh, 2019a)	6	*	*	*	*	office workers, researchers
(Jung et al., 2019)	18	12 M and 6 F	*	healthy	*	*
(Katić et al., 2020)	2	2 F	20s	healthy	W 57 and 62kg, BMI 26.7 and 22.9 kg/m^2, Fat 34.9 and 27.8%, BMR 38.2 and 38.6 W/m^2	*
(Kim et al., 2018b)	34	*	*	*	*	office workers
(Kim, 2018b)	24	*	*	*	*	office workers
(Konis and Annavaram, 2017)	45	*	*	*	*	office workers, researchers
(Lee and Ham, 2020)	10	6 M and 4 F	20s – 30s	*	H 163 to 195cm, W 51 to 100kg	office workers, white people and Asians
(Lee et al., 2017)	11	*	*	*	*	office workers
(Lee et al., 2019)	9	*	20s – 40s	*	*	*
(Lee et al., 2020)	5	4 M and 1 F	20s – 30s	*	*	students
(Li et al., 2017)	3 and 7 **	*	*	*	*	office workers
(Li et al., 2018)	12	7 M and 5 F	20s	healthy	*	students
(Li et al., 2020)	10	*	20s	healthy	*	students
(Liu et al., 2019)	14	8 M and 6 F	20s – 40s	healthy	H 163 to 185cm, W 52 to 86kg, BMI 17.4 to 28.7 kg/m^2	office workers, students
(Liu et al., 2007)	113	65 M and 48 F	20s (average)	healthy	H 165 cm (average), W 55 kg (average)	*

(Lu et al., 2019)	2	1 M and 1 F	20s	healthy	*	*
(Natarajan and Laftchiev, 2019)	5	3 M and 2 F	20s – 30s	*	*	*
(Pazhoohesh and Zhang, 2018)	9	*	*	*	*	researchers
(Shan et al., 2020)	3	3 M	20s	healthy	H 171 to 174cm, W 62 to 78kg, BMI 21 to 26.7 kg/m^2	*
(Shan et al., 2018)	22	14 M and 8 F	*	healthy	*	students
(Sim et al., 2016)	8	6 M and 2 F	20'	healthy	BMI 22.45 ± 2.63kg/m^2	*
(Xu et al., 2018)	4	*	*	*	*	*
(Zhao et al., 2014b)	9	*	*	*	*	researchers, students
(Zhao et al., 2014a)	6 and 11 **	2 M and 4 F, 7 M and 4 F	20' – 30s	*	*	office workers, students

* Not reported; ** Study had 2 phases.

3.3.3. Climate, seasons and type of building involved

As presented in **Table 3-2**, nearly all reviewed studies used office environments to collect data for the personal comfort models developed. When climate chambers were used or office spaces were treated as an experimental setting, the activities simulated were mainly sedentary (e.g., sitting down, working on computer, reading), which means activities undertaken in residential settings (e.g., eating, cooking, walking) were not explored. This can be limiting when considering the diversity of thermal conditions in residential environments in comparison with more controlled office environments. Likewise, while in offices the activity and clothing levels are normally similar throughout the year, in home environments they often change, providing more diverse thermal conditions (Daum et al., 2011).

Nevertheless, considering the application aimed for in these studies, focusing on office environments is an expected trend. This is because these studies mainly aimed to evaluate the application of personalized thermal comfort models as optimization and automation strategies for HVAC systems in highly controlled environments, which are more commonly found in office buildings. These studies will be discussed further in **Section 3.3.7**.

The USA and China are the main locations reported by the selected studies, followed by Singapore and a small number of European countries, as seen in **Figure 3-4**. The climate zones analyzed span from warm temperate (*Cfa*, *Cfb*, *Csb*) (Jung and Jazizadeh, 2019a; Aryal and Becerik-Gerber, 2019; Fay et al., 2017; Jung et al., 2019; Jazizadeh et al., 2014a; Aryal et al., 2021; Katić et al., 2020; Jiang and Yao, 2016; Xu et al., 2018; Katić et al., 2018; Liu et al., 2007; Konis and Annavaram, 2017; Ghahramani et al., 2015b; Kim, 2018b; Kim et al., 2018b; Liu et al., 2019; Daum et al., 2011; Lee and Ham, 2020; Aguilera et al., 2019; Aryal and Becerik-Gerber, 2020; Lu et al., 2019; Shan et al., 2020; Natarajan and Laftchiev, 2019; Jazizadeh et al., 2014b) , to equatorial (*Af*) (Jayathissa et al., 2020; Shan et al., 2018; Guenther and Sawodny, 2019), to colder climates (*Dfb* and *Dwa*) (Zhao et al., 2014b; Sim et al., 2016; Li et al., 2020; Li et al., 2018; Li et al., 2017; Zhao et al., 2014a), following the *Köppen-Geiger Climate Classification*.

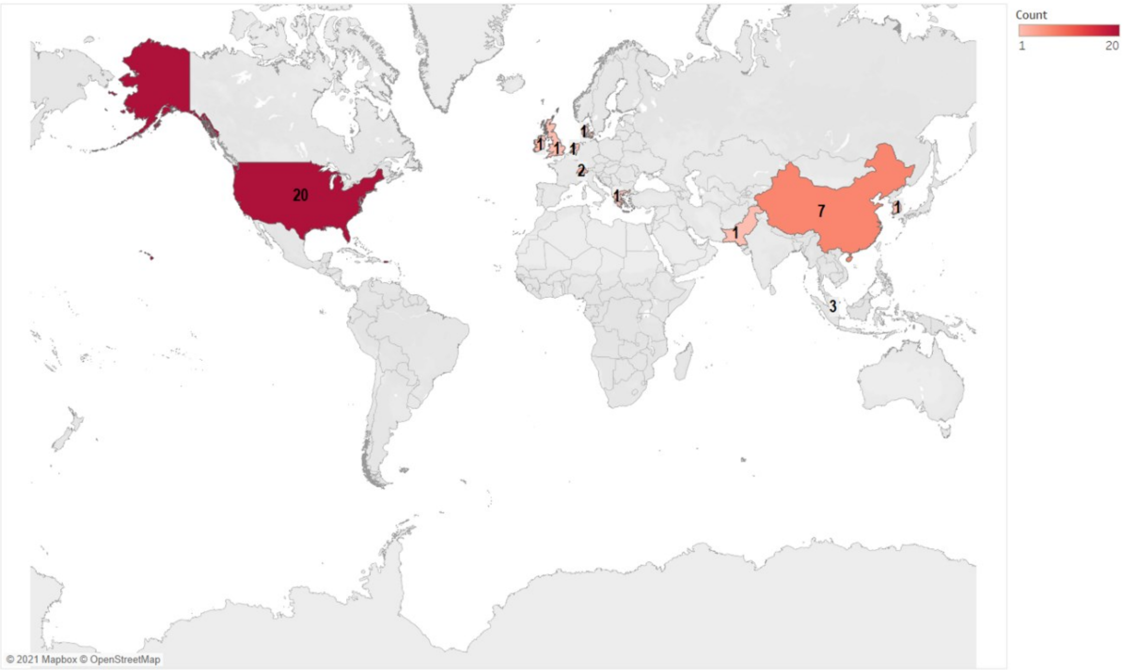

Figure 3-4 - Number of studies per data collection country.

In general terms, the studies screened have diverse monitoring periods, shown in **Table 3-2**. Summer and winter periods are understandably more common than autumn and spring throughout all studies, as capturing extremes in environmental conditions can help create a more diverse dataset upon which to develop thermal comfort models. There is a tendency, however, to analyze a single season in the individual studies (i.e., either summer or winter months), which can be limiting when attempting to capture the entire range of thermal sensations and preferences.

3.3.4. Model input and output variables

The range of the number of input variables to develop personal comfort models varied widely across the studies analyzed. While several studies used one to fifteen variables as features to predict thermal comfort, some studies used more than 100 features (Aryal and Becerik-Gerber, 2019; Shan et al., 2018; Natarajan and Laftchiev, 2019). In the latter, apart from the raw measurements collected for each input variable, the researchers extracted other properties from the measurements, such as mean, variance, minimum, maximum or standard deviation, to create additional input variables that could represent intrinsic properties of the data and increase the predictive performance of the models. This process is called feature engineering. Aryal and Becerik-Gerber (2019), for instance, used not only direct values of indoor air temperature and skin temperature measured on the wrist and 4 points on the face, but also the minimum, maximum, average, standard deviation and median of the measurements in the 5-min window; the minimum, maximum, average, standard deviation and median of the first derivative of the data stream; coefficients obtained by fitting first degree and second degree polynomials to the measurements in the 5-minute window; and the most recent measurement value, average value of the last 10 seconds, and average of the first derivative for the last 10 seconds. By extracting 108 features as input variables for the personal models, the researchers expected to capture overall values, trends, and patterns of changes in the data streams over time.

Likewise, Shan et al. (2018) used a high number of input features available. These, however, were extracted from electroencephalogram (EEG) measurements, where 42 frequency ranges for each of the 14 channels available from the measuring equipment resulted in the total number of 588 features available. It is important to highlight that, while the use of multiple input parameters can enhance the predictive power of models, it can also result in higher complexity and computational load when it comes to feature selection and model scalability (Storcheus et al., 2015). In the case of EEG-based studies, it is also noteworthy that although this type of data can provide a wide range of input variables to explore, it is knowingly more susceptible to high levels of noise resulting from muscular activity (Yilmaz et al., 2014; Muthukumaraswamy, 2013), which can greatly impact model's reliability especially in field studies.

The input variables used can be divided into environmental and personal variables, as shown in **Table 3-2**. Environmental variables include traditionally used parameters such as indoor air temperature and relative humidity, mean radiant temperature, outdoor air temperature and relative humidity and air speed. As presented in the Euler diagram in **Figure 3-5**, 32 out of the 37 studies selected used at least one of these variables as inputs. Less frequently used environmental variables were solar radiation, time of day, day of the week, and window, fan, and the HVAC system operational states. The control setting of personal comfort systems (PCM), such as heated or cooled chairs, was also used in two studies as input parameters for individual thermal comfort models (Katić et al., 2020; Kim et al., 2018b). Both studies highlighted the importance of occupant behavioral attitudes and interactions with thermal control devices as a non-intrusive and practical method to understand individuals' thermal needs and collect continuous streams of data.

Personal variables, on the other hand, include people's intrinsic characteristics, such as skin and body temperature, heart rate, clothing level, activity level and metabolic rate, or previous temperature preferences or preference histories. From the studies selected, more than half used at least one personal feature, although most of the time this was combined with environmental inputs, as presented in **Figure 3-5**. Among these features, skin temperature, captured by wearable sensors or thermal cameras, remained the main personal variable utilized (Aryal and Becerik-Gerber, 2019; Sim et al., 2016; Li et al., 2020; Jung et al., 2019; Katić et al., 2020; Li et al., 2018; Liu et al., 2019; Li et al., 2017; Lee and Ham, 2020; Aryal and Becerik-Gerber, 2020; Lu et al., 2019; Shan et al., 2020; Natarajan and Laftchiev, 2019).

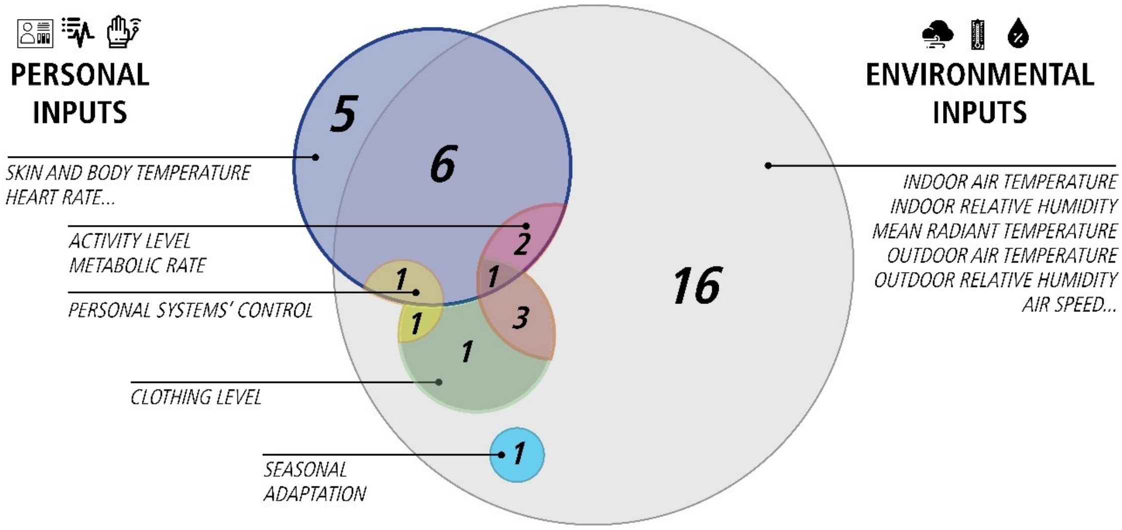

Figure 3-5 - Euler diagram of the number of studies that used personal and/or environmental inputs.

The models' predictive performance appeared to increase when a combination of both environmental and physiological variables was used as inputs. Aryal and Becerik-Gerber (2019), for instance, reported that using data from environmental sensors for predicting thermal comfort resulted in a higher accuracy compared to using just physiological data. However, combining data from both environmental and physiological sensors led to a slightly higher accuracy (3% - 4%) than using environmental sensors only. A further study from the same authors (Aryal and Becerik-Gerber, 2020) confirmed similar results. Jung et al. (2019) indicated a much greater increase in performance when including physiological features as input parameters to personal thermal preference models. The study's best performing modeling algorithm presented a median accuracy of 71% when using air temperature as a sole feature, 93% with the addition of skin temperature and 97% with the addition of heat flux. Likewise, Li et al. (2017) reported that the combination of both environment and human data (i.e., activity level, clothing, heart rate, skin temperature) achieved approximately 80% accuracy, improving the classification accuracy by 24% and 39% when compared to using only environmental features and only physiological factors, respectively. Similarly, Katić et al. (2020) evaluated different combinations of occupants' PCS heating behaviors, their mean and hand skin temperatures, and environmental data, producing the lowest accuracy when using just environmental data.

Although the impact of the input variables on the predictive performance of the models is a significant criterion when selecting the best options among possible variables, the choice of model parameters can also be dictated by the cost of data collection (Kim et al., 2018b). As mentioned in **Section 3.3.2**, the cost and intrusiveness of the data collection process can affect not only the participants' willingness to participate, but also the type of data available, their quantity and quality.

In terms of the output variables, thermal sensation and preference were the main targets chosen for prediction in the studies selected. The sensation or preference scales used, however, differed greatly across studies, as seen in **Table 3-4**. They differed from binary to 100-point scales, from discrete to continuous scales and across different terms and categories of sensitivity used. In addition, many scales were converted to lower numbers of points, shown in **Table 3-4**, depending on the study's approach, modeling technique and possible application. It should be noted that, in order to avoid incorrect interpretations of the studies and scales used, the outputs in **Table 3-4** are presented as they were in the studies (e.g., "thermal comfort", "thermal satisfaction", "thermal preference"), although some can be considered interchangeable.

Table 3-4 - Thermal scales used in the studies selected

Ref.	Output	Scale
(Shan et al., 2018)	Mental state	Cool, Neutral, Warm
(Auffenberg et al., 2018)	Thermal preference ("desired change")	I want it to be much colder, to be colder, be a bit colder, stay as it is, be a bit warmer, be warmer, be much warmer
	Thermal sensation	Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot
(Zhao et al., 2014a)	Thermal complaint	Complaint or comfortable
(Li et al., 2020)	Thermal comfort	Uncomfortably cold, Comfortable, Uncomfortably hot
(Aryal and Becerik-Gerber, 2019)	Thermal comfort	Cold, Comfortable, Hot
	Thermal satisfaction	Satisfied, Dissatisfied
	Combination of both	Cold and satisfied, Cold and dissatisfied, Comfortable and satisfied, Comfortable and dissatisfied, Hot and satisfied, Hot and dissatisfied
(Kim, 2018b)	Thermal discomfort	Cold to hot on a -6 to 6 scale (Normalized from a -100 to 100 scale)
(Lee et al., 2020)	Thermal preference	I prefer Warmer, I am Satisfied, I prefer Cooler
(Aguilera et al., 2019)		Much Warmer, Warmer, Slightly Warmer, No Change, Slightly Colder, Colder, Much Colder, as a Thermal Profile (from a 18-point scale converted in a 7-point scale)
(Jung et al., 2019)		Uncomfortably cool, No change, Uncomfortably warm (11-point scale converted to 3-point scale)
(Lee et al., 2017)		Want warmer, No change, Want cooler
(Li et al., 2017)		Warmer, Neutral, Cooler

(Pazhoohesh and Zhang, 2018)		Warmer, Neutral, Cooler (from a scale from -50 to 50, 10 in 10)
(Kim et al., 2018b)		Warmer, No Change, Cooler
(Li et al., 2018)		Warmer, No Change, Cooler
(Liu et al., 2019)		Warmer, No Change, Cooler
(Lee et al., 2019)		Warmer, No Change, Cooler, as Thermal Profile
(Jayathissa et al., 2020)		Prefer warmer, Comfy, Prefer Cooler
(Konis and Annavaram, 2017)	Thermal satisfaction	Satisfied/Dissatisfied or Bothersome/Non-bothersome (from a 5-point scale converted to binary)
(Shan et al., 2020)	Thermal sensation	Cold, Cool, Neutral, Warm, Hot (from a 7-point scale converted to a 5-point scale)
(Zhao et al., 2014b)		Cold, Cool, Neutral, Warm, Hot (on a continuous scale from -3 to 3)
(Jiang and Yao, 2016)		Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot
(Fay et al., 2017)		Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot (on a continuous scale)
(Liu et al., 2007)		Cool, Comfort, warm (from a 7-point scale converted to a 3-point-scale)
(Lee and Ham, 2020)		Cool, Neutral, Warm (from a 7-point scale converted to a 3-point scale)
(Katić et al., 2020)		Heating demand, neutral, cooling demand (from a 7-point thermal sensation scale)
(Guenther and Sawodny, 2019)		Much too cool, Too Cool, Comfortably Cool, Comfortable, Comfortably Warm, Too Warm, Much too warm
(Daum et al., 2011)		Too Cold, Comfortable, Too Hot, as a Thermal Profile (from a 7-point scale converted in 3-point scale)
(Xu et al., 2018)		Uncomfortably Cold, Comfortable, Uncomfortably Hot (from a 7-point scale converted to a 3-point-scale)
(Ghahramani et al., 2015b)		Uncomfortably Cool, Comfortable, Uncomfortably Warm (from a 11-point scale converted in a 3-point scale)
(Jung and Jazizadeh, 2019a)		Uncomfortably Cool, Comfortable, Uncomfortably Warm, as a Thermal Profile (from a 100-point scale converted in a 3-point scale)
(Natarajan and Laftchiev, 2019)		Very Cold, Cold, Chilly, Comfortable, Warm, Hot, Very Hot
(Lu et al., 2019)		Very Cold, Cold, Cool, Neutral, Warm, Hot, Very Hot
(Sim et al., 2016)		Very Cold, Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot, Very Hot
(Jazizadeh et al., 2014b)		Very Cold, Cold, Neutral, Warm, Very Warm, as a Thermal Profile
(Jazizadeh et al., 2014a)		Very Cold, Cold, Neutral, Warm, Very Warm, as a Thermal Profile (from a 7-point scale converted into a 5-point scale)
(Aryal and Becerik-Gerber, 2020)	Thermal sensation Thermal satisfaction	Cold, Comfortable, Hot Satisfied, Dissatisfied
(Aryal et al., 2021)		Cold, Comfortable, Hot Satisfied, Dissatisfied

Like the input variables, the choice of output variables and scales is subject to the cost of continuous survey feedback for both participants and researchers. According to studies by Katić et al. (2020) and Kim et al. (2018b), a practical solution to collect this sort of data would be the use of PCS control behavior to act as potential replacements for participants' feedback, standing as the "ground truth" of personal comfort models. According to the aforementioned authors, PCS could learn occupants' thermal preferences based on their control behavior and automatically activate heating or cooling according to the patterns recognized. Hence, user behavior could serve as a proxy for thermal comfort feedback so that long monitoring periods or experiments would not be necessary, data could be collected continuously in a practical way, and nuances in scale interpretations could potentially be avoided.

3.3.5. Modeling algorithm used

Overall, there seems to be a predominance of probabilistic modeling techniques among the studies selected. Unlike deterministic models, which give a single exact outcome for a prediction, probabilistic models provide a solution as a probability distribution to account for randomness and quantify uncertainty in the events analyzed (Ghahramani, 2015; Murphy, 2012). Probabilistic methods are especially relevant when analyzing systems that are inherently stochastic and/or highly uncertain due to insufficient data (Goodfellow et al., 2016). This, therefore, is in line with the nature of thermal comfort modeling in general, as thermal comfort perception and variables (e.g., people’s behavior) are naturally uncertain, and data, especially when developing comfort models at the individual level, can be relatively scarce.

As seen in **Table 3-5**, it is possible to identify a frequent use of (1) Bayesian classification and inference (Ghahramani et al., 2015b; Jung and Jazizadeh, 2019a; Auffenberg et al., 2018; Lee et al., 2017; Lee et al., 2019), (2) Fuzzy Classification (using the Wang-Wendel model to create Thermal Profiles) (Jazizadeh et al., 2014a; Pazhoohesh and Zhang, 2018; Aguilera et al., 2019; Jazizadeh et al., 2014b), and (3) common Machine Learning techniques, including Classification Trees (Katić et al., 2020; Kim et al., 2018b; Liu et al., 2019; Aryal and Becerik-Gerber, 2020), Gaussian Process Classification (Guenther and Sawodny, 2019; Fay et al., 2017; Katić et al., 2020; Kim et al., 2018b), Gradient Boosting Method (Kim et al., 2018b; Liu et al., 2019; Lee and Ham, 2020), Support Vector Machine (Aryal and Becerik-Gerber, 2019; Jung et al., 2019; Katić et al., 2020; Jiang and Yao, 2016; Kim et al., 2018b; Liu et al., 2019; Lee and Ham, 2020; Aryal and Becerik-Gerber, 2020; Lu et al., 2019), Random Forest (Aryal and Becerik-Gerber, 2019; Jung et al., 2019; Jayathissa et al., 2020; Aryal et al., 2021; Li et al., 2018; Kim et al., 2018b; Liu et al., 2019; Li et al., 2017; Lee and Ham, 2020; Aryal and Becerik-Gerber, 2020; Lu et al., 2019), K-Nearest Neighbors (Aryal and Becerik-Gerber, 2019; Aryal et al., 2021; Kim et al., 2018b; Lee and Ham, 2020; Aryal and Becerik-Gerber, 2020) and Artificial Neural Networks (Liu et al., 2007; Kim, 2018b; Liu et al., 2019; Shan et al., 2020). In fact, many of the studies tested and compared combinations of these techniques. Liu et al. (2019), for instance, applied 14 commonly used machine learning classification algorithms, divided into 4 groups: linear methods, non-linear methods, trees and rules, and ensembles of trees. According to the authors, the selections of these algorithms balanced the prediction biases and avoided the over or underestimations that could result from specific prediction systems. From the four algorithm categories used, the ensembles of Trees (e.g., Gradient Boosting, C5.0 and Random Forest) presented the best performance for the personal comfort models developed.

Table 3-5 - Modeling technique of papers selected

Ref.	FC	RF	KNN	SVM	DT	LDA	BI	MLR	GPM	LR	ANN	GB	LVQ	OP	LinR	NB	RBC	CART	LLS	J48	C5.0
(Aguilera et al., 2019)	X																				
(Aryal and Becerik-Gerber, 2020)		X	X	X	X																
(Aryal and Becerik-Gerber, 2019)		X	X	X		X															
(Aryal et al., 2021)		X	X																		
(Auffenberg et al., 2018)							X														
(Daum et al., 2011)								X													
(Fay et al., 2017)									X												
(Ghahramani et al., 2015b)							X														
(Guenther and Sawodny, 2019)									X												
(Jayathissa et al., 2020)		X																			
(Jazizadeh et al., 2014a)	X																				
(Jazizadeh et al., 2014b)	X																				
(Jiang and Yao, 2016)				X																	
(Jung and Jazizadeh, 2019a)							X														
(Jung et al., 2019)		X		X						X											
(Katić et al., 2020)				X	X				X												
(Kim et al., 2018b)		X		X					X	X		X						X			
(Kim, 2018b)											X										
(Konis and Annavaram, 2017)										X											
(Lee and Ham, 2020)		X	X	X								X	X								
(Lee et al., 2017)							X														
(Lee et al., 2019)							X														
(Lee et al., 2020)							X							X							
(Li et al., 2017)		X																			
(Li et al., 2018)		X																			
(Li et al., 2020)										X											
(Liu et al., 2019)		X	X	X	X	X				X	X	X				X	X	X		X	X

(Liu et al., 2007)											X										
(Lu et al., 2019)		X		X																	
(Natarajan and Laftchiev, 2019)															X						
(Pazhoohesh and Zhang, 2018)	X																				
(Shan et al., 2020)											X										
(Shan et al., 2018)						X															
(Sim et al., 2016)															X						
(Xu et al., 2018)								X													
(Zhao et al., 2014b)																			X		
(Zhao et al., 2014a)																			X		

* FC = Fuzzy Classification, RF = Random Forest, KNN = K-Nearest Neighbors, SVM = Support Vector Machine, DT = Decision Tree, LDA = Linear Discriminant Analysis, BI = Bayesian Inference/Classification, MLR = Multinomial Logistic Regression, GPM = Gaussian Process Model, LR = Logistic Regression, ANN = Artificial Neural Network, GB = Gradient Boosting, LVQ = Learning vector quantization, OP = Ordered Probit, LinR = Linear Regression, NB = Naive Bayes, RBC = Rule-Based Classifier, CART = Classification and Regression Trees, LLS = Least-squares linear estimation, J48 = J48 Decision Tree.

3.3.6. Performance indicators used

The performance of the personal comfort models analyzed is measured by a variety of indicators. When reported, the choice of metrics in these studies depended, for instance, on the model technique applied, the nature of the datasets used (e.g., unbalanced or balanced) or the need for easy comparison between or across studies or models. **Table 3-2** presents the studies' performance indicators and respective predictive performances.

Accuracy was one of the main performance meters used (Aryal and Becerik-Gerber, 2019; Li et al., 2020; Jung et al., 2019; Shan et al., 2018; Aryal et al., 2021; Katić et al., 2020; Jiang and Yao, 2016; Li et al., 2018; Ghahramani et al., 2015b; Liu et al., 2019; Li et al., 2017; Lee and Ham, 2020; Aryal and Becerik-Gerber, 2020; Shan et al., 2020). It represents the number of correct predictions (i.e., when the computed result is equal to the ground-truth from participants' feedback) divided by the total number of predictions and is normally presented in percentage form. It was used in nearly half of the studies and sometimes accompanied by other less common metrics such as Cohen's Kappa Coefficient and/ or RMSE (Root Mean Square Error). Accuracy, as described by Ben-David (2008), is a simple and straightforward indicator; however, it does not take into account the proportion of the correct predictions that result from random chance. When considering datasets in which thermal comfort categories are not evenly distributed, accuracy can be extremely misleading. Cohen's Kappa Coefficient complements the measurement of accuracy as its scalar meter compensated for the agreements that can be attributed to chance. It is normally represented on a 0 to 1 scale, with 1 being perfect agreement. The selected studies by Lee and Ham (2020) and Liu et al. (2019) acknowledge this metric.

Measuring error − the difference between the computed and the correct value − was also common among the studies, using diverse approaches (Auffenberg et al., 2018; Zhao et al., 2014b; Sim et al., 2016; Guenther and Sawodny, 2019; Fay et al., 2017; Jazizadeh et al., 2014a; Konis and Annavaram, 2017; Kim, 2018b; Lee et al., 2020; Shan et al., 2020; Natarajan and Laftchiev, 2019). The Root Mean Square Error, or the standard deviation of the prediction errors, was reported in many of the studies selected. Although it contains certain limitations, it is a common error measurement in many fields and recommended when the model errors follow a normal distribution (Chai and Draxler, 2014). Nevertheless, as stated by Chai and Draxler (2014), as with accuracy, caution is always required when interpreting error measurements, as "any single metric provides only one projection of the model errors, and therefore only emphasizes a certain aspect of the error characteristics".

Although less used among the studies analyzed, the Area Under the Receiver Operating Characteristic Curve, or the Area Under the Curve (AUC), is frequently used in machine learning studies (Ben-David, 2008) and can be an interesting performance indicator for the personal comfort models. It was used by Katić et al. (2020), Kim et al. (2018b), Lee et al. (2019) and Liu et al. (2019). The Receiver Operating Characteristic Curve provides a way of describing the predictive behavior of a binary classifier, by plotting the probability of true positive rate (i.e., "successes", also called sensitivity or recall) over false positive rate (i.e., "false alarms", also called fall-out) across all possible discrimination thresholds. By computing the area under this curve, it is possible to compare different models using a single performance indicator. The AUC can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement. The measure is, however, conceptually not intuitive, especially when analyzing non-binary classification problems (Ben-David, 2008).

Regardless of the indicator used, k-fold cross-validation was reported in most studies as the resampling technique used to estimate models' performance on unseen data, either during hyperparameter tuning (also known as model selection stage) or at the final model evaluation stage (Raschka, 2018). The most used values of k were 5 and 10, as seen in **Table 3-2**. Training, validation and testing dataset splits were normally chosen according to overall dataset size and modeling technique used.

3.3.7. Model final application

Automation and optimization of HVAC systems can be considered the main application for the personal comfort models in the papers selected. As already indicated by Jung and Jazizadeh (2019b), the research effort to explore the potential of personalization techniques in the control of HVAC systems has significantly increased, shifting the field towards Human-In-The-Loop (HITL) control strategies. By incorporating individual thermal comfort models in the system optimization, these studies investigate comfort-aware operation schedules and settings to enable higher energy efficiency in buildings.

Nevertheless, from the studies analyzed, most did not test the personal comfort models' application in HVAC systems, focusing more on the modeling aspect of the process. From the studies that evaluated the models' application, only a few evaluated tests in real environments − treated as experiments or during normal daily activities.

Zhao et al. (2014a) performed a validation experiment with 11 participants in two test-beds, where the model learning procedure was incorporated into the control of an air conditioning system. In their test, the system sequentially updated the user's complaint region after every feedback, using the method proposed, and updated the set point of the control target. They applied a post-experiment questionnaire for each participant to capture their subjective evaluation of the thermal environment of the test-bed. After 8 days of continuous experiments, the participants' evaluation scores tended to achieve a higher and steadier level and their number of complaints per day decreased from 3 to less than 1, on average.

Aguilera et al. (2019) incorporated the personalized models of seven participants into a user-driven HVAC control system and tested it in a real open-plan office scenario. Thermal preferences were used to create individual thermal discomfort profiles, which were later aggregated to calculate a single set point for the entire office. The results showed that only 29% of the occupants' thermal comfort improved. The performance of the control strategy was found to be influenced by insufficient and imbalanced data and the effect of thermal expectations on occupants' thermal responses across different times of day and after repeated thermal stimuli.

Li et al. (2017) used two real-life scenarios to demonstrate their framework to improve thermal comfort in single and multi-occupancy spaces. Their HVAC control loop included two algorithms: the Mode Selection Algorithm that chose the optimum conditioning mode and the Collective Decision Algorithm that evaluated the highest group comfort score that can be achieved in the mechanical conditioning mode. Participants' thermal preferences were continuously predicted to determine the optimum HVAC set point temperatures, adjusted by a programmable Wi-Fi enabled thermostat. They then compared a scheduled scenario where the thermostat followed a predefined fixed schedule, and a dynamic scenario where their personalized algorithm was implemented to adjust the temperature set points dynamically. On average, the total number of uncomfortable reports were reduced by as much as 53.7% on average after implementing their framework.

Jazizadeh et al. (2014b) conducted a study in a real building setting using the comfort profiles of six participants. After the personalized comfort profiles were obtained, each new request from occupants triggered the calculation of the desired temperature using the customized scale of each user's comfort profile, which was then passed to the HVAC controller. Using interviews at different stages of the experiments, the researchers assessed the comfort consequences of the framework and found that the average of participants' comfort rating was 4.7 out of 10 before enabling the framework; 6 during training; and 8.4 after model training. Additionally, the study showed an overall 39% reduction in daily average airflow when the desired temperatures were applied by the HVAC system, compared to the legacy HVAC system operations with predefined temperature set points. As airflow can be considered proportional to HVAC systems' energy consumption, the study also indicated an improvement in the energy efficiency of the building analyzed.

3.4. Discussion and future research directions

This systematic literature review has shown a plurality of approaches and frameworks to develop and evaluate personal thermal comfort models. Although some aspects can be considered similar in all studies, there seems to be an overall lack of a unified modeling approach that takes into account not only the methodology used, but also the performance evaluation tool that enables easy comparison across studies.

3.4.1. Considerations on data collection

Disparities begin from the data collection stages of the studies. While controlled climate chamber experiments allowed many of the studies to reach a larger size of datasets and a greater variability of thermal sensations recorded from participants, studies that used data from real scenarios appear more transferable to real applications, as discussed in **Section 3.3.7**. The recommendation for data collection on real scenarios, thus, lies on increasing the dataset size by encouraging more occupants to engage and interact with the surveys and the systems' controls. Studies that used wearable sensors with accessible feedback platforms, or that used occupants' behavior through personal comfort systems' operation as a proxy for thermal preference, are possible options to obtain a continuous data stream to enlarge datasets in real-world contexts.

In that regard, although larger dataset sizes are normally expected when dealing with more complex classification tasks and higher number of features (Raudys and Jain, 1991), the review also proves that individual dataset sizes can vary greatly. When machine learning models are used with insufficient training data, techniques such as transfer learning, where a pre-trained model is reused on a new problem, can be applied (Tan et al., 2018). In addition, although not treated in depth by all studies reviewed, the way the data is pre-processed is another key aspect to avoid data loss before model training. Properly dealing with noisy or missing data points, highly heterogeneous datasets in terms of granularity of raw features, or highly imbalanced datasets that might misrepresent the observed data is essential to maintain sufficient data size and avoid losing relevant information for prediction. Future research on personal thermal comfort models should, therefore, address the specificities of thermal comfort datasets and the challenges of data preparation associated with them.

3.4.2. Considerations on participants involved

Despite the low number of participants in most of the studies reviewed being coherent with the aim of personalizing comfort models for each individual, the generalization of the results, that is, the potential that personal comfort models will be applicable to anyone, is still debatable. This is because not only do the studies deal with small numbers of building occupants, but they also select participants with relatively similar characteristics. Although males and females are present in almost all studies in a relatively balanced way, the presence of younger adults is more prevalent, leaving out other age groups (e.g., children or older people) who may also profit from individualized comfort predictions in their associated environments. In the same way, although the use of healthy adults is commonly preferred in traditional generalized thermal comfort studies to avoid the influence of illness or health conditions on the averaged thermal predictions, the observed trend to use only healthy participants in personal comfort model studies does not correspond to the goal of individualizing comfort models, which is to deal with people whose personal characteristics and thermal preferences fall outside the averages. In fact, continuous health status measurements or self-rated feedback could be added as personal inputs in the models, allowing an interesting investigation on the impacts of health on thermal comfort perception, sensitivity, or preference.

Likewise, collected data on diverse body compositions, sociodemographic characteristics and activity contexts are missing in the studies reviewed. Including more heterogeneous occupants would enable a broader analysis and consequently increase the generalization power of the studies.

3.4.3. Considerations on climates, seasons and type of buildings involved

Further explorations in more diverse climates are necessary to identify associated challenges of personal comfort models in different locations. Longitudinal studies that span through several consecutive seasons or years could, in the same way, allow a more comprehensive analysis than the ones conducted so far. In addition, residential settings are yet to be better represented in the studies. Not only do living environments provide more diverse thermal conditions, activity and clothing opportunities in comparison with office environments, they also allow more possibilities for user intervention than the HVAC-controlled work environments. This includes considering easier or unrestrained window or blinds operations as well as refurbishment or layout modifications. Although this issue may add another level of complexity to the personalized models, adding diversity to the studies' environments can help, once again, create more balanced thermal preference datasets when collecting data, and expand the application of the personalized models to other settings.

3.4.4. Considerations on model input and output variables

When it comes to model input features used in the reviewed studies, the explorations are again coherent with the aim of investigating possible individual differences affecting thermal comfort. Both environmental and personal characteristics are used, although personal features using physiological sensing could still be explored further, especially in light of the rapid advances seen today in wearable sensors technologies. Personal comfort systems, including heated chairs or personal fans, are promising tools not only to collect larger datasets but also to reduce the need for occupants' long-term feedback. Personal comfort systems could also help avoid the potential misinterpretations caused by the nuances in the thermal comfort, sensation or preference scales used, which vary greatly across studies and approaches.

3.4.5. Considerations on modeling algorithm and performance indicators

When analyzing the modeling methodology applied so far, it is evident that the field lacks a more unified and systematic framework. As already highlighted by Kim et al. (2018a) and confirmed by this literature review, instead of developing a structured and ultimately transferable approach to apply the models in real scenarios, the main studies on personal thermal comfort models are focused on the final predictive accuracy of specific modeling techniques. This is clear in the plurality of modeling techniques and performance evaluators used in the publications reviewed. Model evaluation, especially, needs uniformity to allow a clear comparison between studies and approaches, and consequently to enable a more straightforward decision-making process. Kim et al. (2018a) highlighted three main criteria that could help the model evaluation process: prediction accuracy, prediction consistency, and model convergence. Although the metrics used in each of these criteria may differ depending on the technique used (e.g., deterministic or probabilistic), they represent a more systematic way of assessing model performance.

3.4.6. Considerations on model interpretation, input parsimony and redundancy

With the majority of the studies using different forms of machine learning techniques, it becomes important to highlight the presence of "black box" models among them and acknowledge their challenges. The term black box refers to models that, although open to inspection of isolated components, are less interpretable, in the sense that their complexity and sometimes recursive mathematical nature are not easily comprehensible by humans (Rudin, 2019). Generally, the main objective of predictive modeling is to generate accurate predictions, leaving interpretation of the models and understanding of why they work as secondary objectives (Kuhn and Johnson, 2013). When prediction accuracy is the primary goal, increasing performance is normally derived from increasing models' complexity, and likely decreasing their parsimony (i.e., increasing number of parameters involved), which, in turn, renders models' interpretation more difficult. This trade-off between accuracy/performance and interpretability/parsimony is a common issue discussed in many fields using predictive modeling.

Less interpretable models can have negative implications, especially in situations where feature interactions matter more than the final outcomes. In the field of thermal comfort in general, being able to understand the underpinning laws between variables as well as distinguish between relevant, irrelevant, and redundant input parameters is undeniably beneficial to enhance the current knowledge on human thermal comfort. Nevertheless, the tradeoff between the cost of comfort and energy use associated with thermal comfort model's lower predictive accuracy and the reward of interpretability has not been addressed in the field, let alone in the studies reviewed here.

Nonetheless, although still frequently debated (Castelvecchi, 2016; Rudin, 2019; Lipton, 2018; Barredo Arrieta et al., 2020), explainable artificial intelligence is an emerging topic in many sectors (Barredo Arrieta et al., 2020) and aims to produce more interpretable models while maintaining high performance levels. Techniques such as the use of Input Feature Selection Algorithms are also alternatives to measure predictor importance in thermal comfort research, decreasing input redundancy, increasing performance and lowering computational efforts (Kwak and Choi, 2002). Lastly, some machine learning models are intrinsically resistant to redundant predictors, such as Tree- and rule-based models (Kuhn and Johnson, 2013), comprising a middle ground between easily interpretable models (like linear regression) and opaque methods (such as neural networks).

3.5. Conclusion

This chapter has presented a systematic review of personal thermal comfort models based on the literature published in the last two decades. Thirty-seven publications have been selected for screening and subsequently analyzed regarding: (1) their data collection approach and dataset size; (2) the number and type of participants involved; (3) the climate, seasons and building types in which the studies were undertaken; (4) the model inputs and outputs features utilized; (5) the modeling techniques used; (6) the performance indicators used; and, finally, (7) the application of the proposed model.

The review highlights a number of issues of personal comfort models:

- The field still lacks a more unified and systematic modeling framework. Model evaluation, especially, needs to allow for clear comparison between studies and approaches, thus enabling a more straightforward decision-making process.
- The generalization of the results is still debatable as many studies deal with small numbers of participants sharing relatively similar characteristics. Diversity needs to be introduced, considering different age groups, health status, body compositions, sociodemographic characteristics, and activity contexts.
- Diversity in climates, seasons and building types is not represented in many of the studies. Addressing these can help create more balanced datasets and expand the application of the personalized models into other types of environments.
- With the majority of the studies analyzed using different forms of machine learning techniques, it is important to understand “black box” models’ challenges in the field of thermal comfort, investigating the tradeoffs between inherently interpretable models and less transparent techniques.

- Although both environmental and personal characteristics have been used in most studies, personal features gathered through physiological sensing technologies could be further explored, especially in light of the rapid advances in wearable sensor technologies. Personal comfort systems are promising tools to complement data collection, enlarge data sizes and reduce the need for occupants' long-term feedback periods.

Future research can, therefore, profit from the topics highlighted above and advance the knowledge on personal thermal comfort models from a uniform and holistic perspective.

Chapter 4. Research Methodology

The research design adopts a quantitative framework and methodology that draws on a multidisciplinary approach, comprising the fields of architectural sciences, gerontology and public health, as well as computer sciences. This chapter presents an overview of the materials and methods chosen according to the thesis' three research objectives. Specific and detailed methods are presented within the results in **Chapters 5, 6, 7 and 8**.

4.1. Methods to achieve Objective (1)

Objective (1) *To investigate older South Australians' thermal environment, thermal preferences, behaviours, and physiological responses during hot and cold weather.*

In order to investigate the thermal environments of older people in South Australia, two datasets were used. The first dataset was collected from 71 older people (23 males and 48 females) from 57 households located in South Australia[7] who participated in the research project *ARC DP180102019 - Improving the thermal environment of housing for older Australians* (Soebarto et al., 2019a; van Hoof et al., 2019), recruited through press releases in various media formats (e.g., newspaper and radio calls for volunteers and tear-off posters). All participants were aged 65 years or above, lived independently, and were required to be able to communicate in English. The project had approval from The University of Adelaide's Human Research Ethics Committee (approval H-2018-042) (**Appendix B**). Participants consented to the use of the data collected through a Consent Form (**Appendix C**) and were informed about the research details through a Participant Information Sheet (**Appendix D**).

Their dwellings were located in hot dry (*BSk*), warm temperate (*Csa*) and cool temperate (*Csb*) climate zones, according to the Köppen–Geiger climate classification system, or Climate Zones 4, 5 and 6, respectively, according to the Australian National Construction Code (Australian Building Codes Board, 2019) (**Figure 4-1**). The data collection started in mid-January 2019 and lasted 9 months until mid-

[7] While this data collection was part of the broader research project *ARC DP180102019 - Improving the thermal environment of housing for older Australians*, the author of this thesis acted as a research assistant at the project, participated actively in and co-managed the data collection.

October 2019, comprising both hot/warm and cold/cool seasons, which provided the range of variations in environmental conditions necessary for a comprehensive analysis.

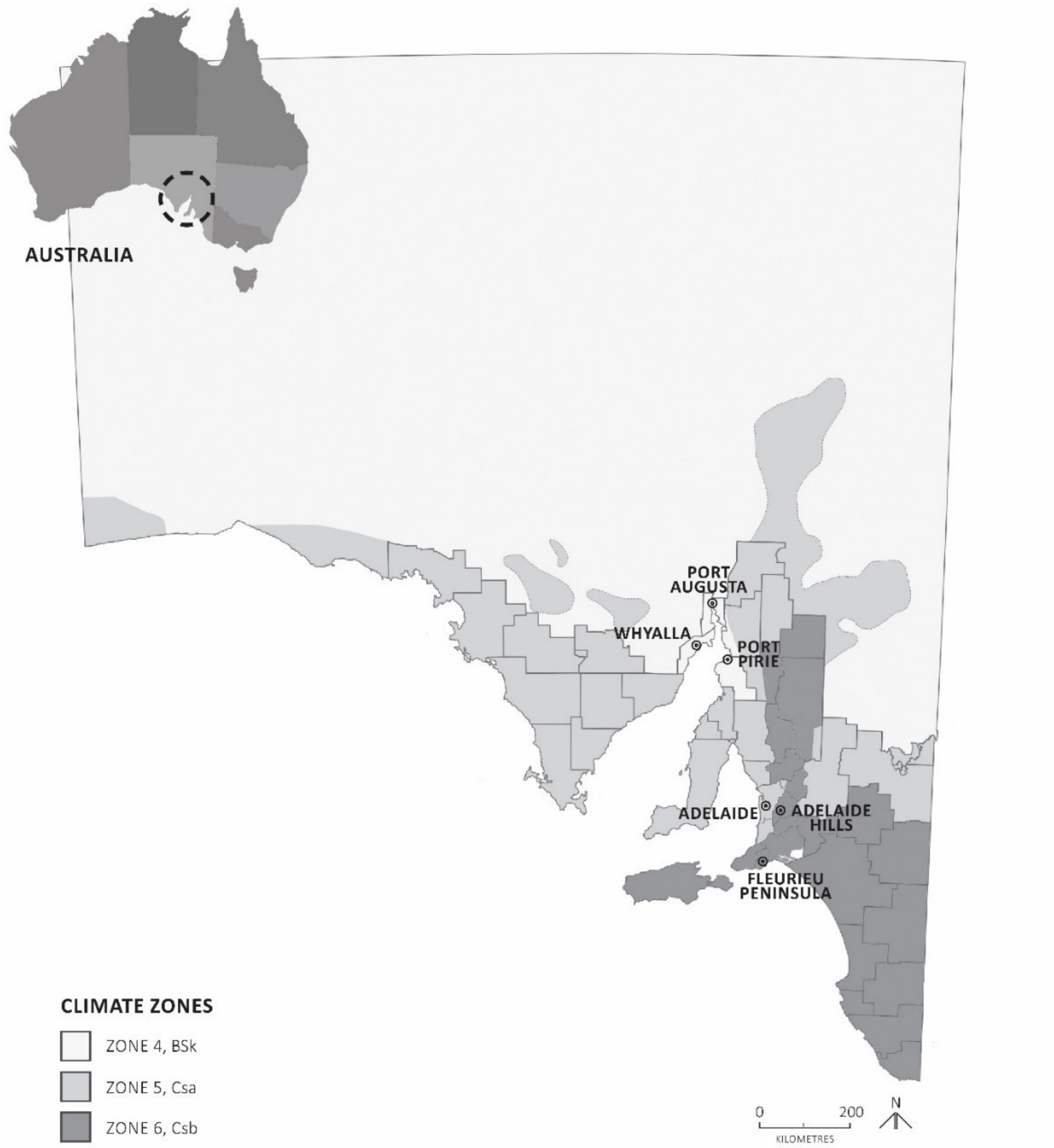

Figure 4-1 - Climate Zones of South Australia, where the monitored houses were located.

The dwellings included in the research represented common construction typologies in housing of older people in South Australia. These included double brick, brick veneer (also known as masonry veneer) and timber or steel framed constructions (insulated and uninsulated); detached and semidetached layouts; from 1 to more than 100 years old; and 1 or 2 storeys high. Samples of the buildings involved are shown in **Figure 4-2**.

Figure 4-2 - Sample of the 57 houses involved in the study. Source: Photographed by the author.

The data collection process involved visiting each house at least twice. In the first visit, the following tools were used to collect data about the participants and their houses:

(a) A questionnaire about individual socio-economic information, as well as chronic disease and symptoms, behaviours, preferences and responses during hot and cold weather, applied by the project team. A copy of the questionnaire is presented in **Appendix E**.

(b) An open-ended interview about the house details (directed by a checklist), including the collection of energy bills, building plans, elevations, and photos, applied by the candidate. A copy of the check-list is presented in **Appendix G**.

(c) The installation of *indoor environment data loggers* (**Figure 4-3**), which allowed the subsequent environmental monitoring of each house's main living room and bedroom, every 30 minutes and whenever a participant answered a thermal comfort survey, for 9 months.

(d) The installation of a *thermal comfort survey tablet* (**Figure 4-3**), which allowed the participants to answer thermal comfort surveys electronically at any time, across 9 months.

The *indoor environment data logger* included sensors that measured the dry-bulb temperature, globe temperature, air speed, relative humidity, CO_2 and VOCs in the houses' main living area. The logger coordinated measurements from the sensors, undertaken at 30-minute intervals and when a participant completed a comfort survey. The data were automatically sent to a web-based server via radio and were accessed remotely.

The *thermal comfort survey tablet* included questions about participants' clothing level, activity level (later converted to metabolic rates), thermal sensations and preferences, window and door operations, as well as heating/cooling/fan operations. The survey also included questions about perceptions of indoor environment quality, as well as health/wellbeing perception. The survey's tablet screens, corresponding to each question, are presented in **Appendix H**. Participants also received a printed booklet to aid with the navigation of the tablet and the understanding of the survey answer choices (see **Appendix I**).

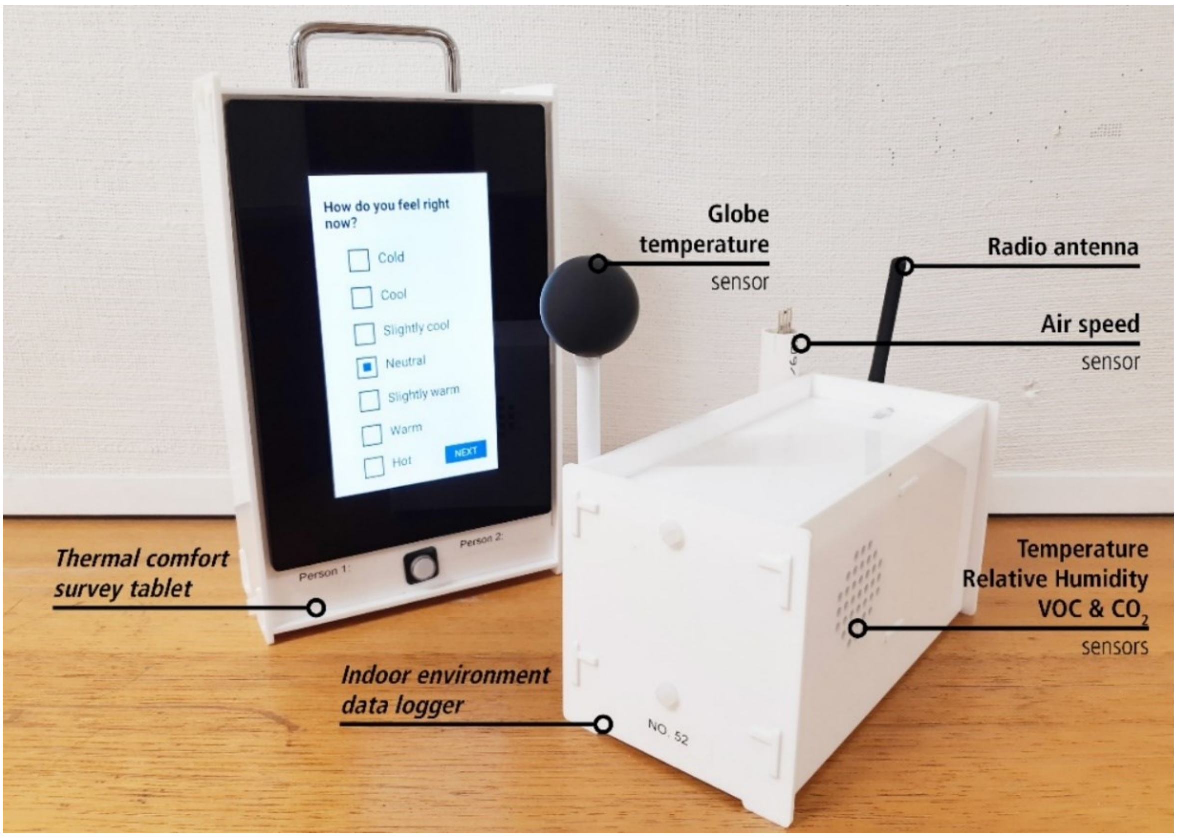

Figure 4-3 - Indoor environment data logger and thermal comfort survey tablet

Further details on the data logger and tablet, as well as on the sensors' accuracy, testing and calibration were previously published by Soebarto et al. (2020).

The dry-bulb temperature and relative humidity were also measured in 30-minute intervals in the houses' main bedroom, using a HOBO® U12-013, with data downloaded at the end of the monitoring period and merged with the overall data for the surveys answered in the bedroom.

The second visits to participants' houses were carried out to finalise the data acquisition, retrieve the logger and tablet and collect any missing information needed.

Upon a preliminary analysis of the data collected and a further literature review, other factors that affect thermal comfort of older adults were identified as relevant for the study. Therefore, the second visit also included:

(e) A body composition assessment, conducted by the candidate, using a Tanita Inner Scan RD-953 scale (Tanita Corporation, 2016; Volgyi et al., 2008) and a tape measure tool for measuring body height.

(f) An additional questionnaire, conducted by the candidate, to assess frailty status using the Modified Reported Edmonton Frailty Scale (Rose et al., 2018), as well as the participants' use of outdoor spaces. A copy of the additional questionnaire is presented in **Appendix F.**

All data collection tools were designed to gather a wide range of variables and factors that were relevant in the context of the architectural science, gerontology and public health fields of study to influence and affect thermal comfort. More details of this specific data collection process are described in **Chapters 5 and 6**.

After the conclusion of the first data collection period, a preliminary analysis of the data and further literature investigations highlighted a lack of physiological factors being investigated in the first stage of the study. Therefore, a second collection was conducted, involving 11 of the original 71 participants. Only a portion of the monitoring participants were willing to participate in this follow-up monitoring study due to the time commitment required for the activities. In addition, in this second data collection process, the survey tablet was modified to include a non-contact infra-red temperature sensor to measure the skin temperature of the back of participants' non-dominant hand after they completed each point-in-time survey (**Figure 4-4**). Since this equipment modification was only possible in a single pair of logger-tablet, the number of participants involved, as well as the length of the monitoring period, had to be reduced.

Each house was monitored during 2 consecutive weeks, one house after the other, between the months of September 2020 and February 2021. The other environmental measurements and the comfort survey questions remained the same from the first collection period. Frailty and body composition assessments were retaken to check variations between the two data collection periods.

Figure 4-4 - Thermal comfort survey tablet with infra-red skin temperature sensor and indoor environment data logger (left), and back of hand skin temperature measurement being taken (right).

Human hands are known to contain a high number of arteriovenous anastomoses (AVAs), which are valves that influence heat loss by changing the body's peripheral blood flow (Hales, 1985). This makes the skin temperature of hands a possible indicator of a person's thermal state (Wang et al., 2007). The skin temperature of the back of the hand (i.e., the dorsal side of the hand) was chosen for this study in line with previous research that correlated thermal sensation to this specific body part (Soebarto et al., 2019b; Wang et al., 2007; Katić et al., 2020; Childs et al., 2020) and according to ISO9886:2004 (ISO, 2004). Details of this specific methodology, including the skin temperature sensor's details, are described in **Chapters 5 and 7**.

Statistical analyses, including descriptive and regression analyses, were subsequently conducted to investigate the factors influencing the cohort's thermal sensations and preferences. These analyses were conducting using IBM SPSS Versions 26 and 27 (IBM Corp., 2020).

4.2. Methods to achieve Objective (2)

Objective (2) *To develop personal thermal comfort models for older people from the data collected, considering their personal and behavioural characteristics as well as the conditions of their thermal environments, and compare the results with the predictions by established models such as the PMV model.*

In order to develop personal thermal comfort models for the older adults involved in the study, *deep learning* (also known as *artificial neural networks*) (Goodfellow et al., 2016) was applied. Deep learning is a class of machine learning technology, based on the representation-learning method (LeCun et al., 2015). It solves tasks such as classification, regression or anomaly detection by introducing multiple layers of representations, or features, expressed in terms of other, simpler representations. By learning from previously seen data, this method avoids the need for a human engineer to formally specify these multiple layers of representations (Goodfellow et al., 2016). Justifications for the use of this class of machine learning are presented in **Chapters 6 and 7**.

The overall modelling process was based on the framework for personal thermal comfort model development described by Kim et al. (2018a) and the framework for machine learning model development described by Raschka (2018). The overall steps involved are shown in **Figure 4-5**.

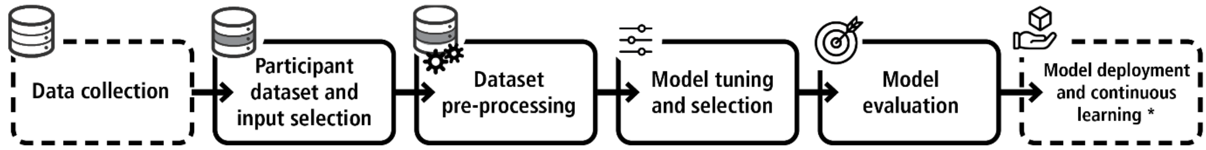

Figure 4-5 - Overall modelling process steps. *Model deployment and continuous learning, although present in the referenced frameworks, were beyond the scope of this study.

After initial data collection, the general dataset was separated into the 71 individual datasets to be analysed. The chosen modelling process, however, required that each participant voted at least 6 times in at least one of the three thermal preference classes (wanting to be cooler, no change, warmer), to allow a minimum of 5-fold stratified cross-validation during model training, plus a minimum of 1 vote per category for testing (Raschka, 2018). Further details of the cross-validation procedure are explained in **Chapter 6**. Excluding the participants who did not meet this requirement resulted in 28 individual datasets out of the 71 participants to be selected for modelling.

The input features were then selected to cover a combination of the environmental factors traditionally used in aggregate models such as the PMV (i.e., dry bulb temperature, radiant temperature, relative humidity, air speed), in addition to a selection of the personal factors captured in the study (i.e., clothing, metabolic rate and health perception), according to the outcomes of *Objective (1)*. Other personal characteristics such as age and sex were incorporated into a corrected version of the metabolic rates, which were also used as input variables.

Data were subsequently pre-processed, involving undersampling (i.e., a balancing technique) and normalization. The datasets were then randomly split into training, validation and testing sets to allow data cross-validation and avoid drawbacks such as overfitting (i.e., when the model fits well against its training data, including its noise, thus performing poorly when tested against new data).

The models were then scripted and their hyperparameters were tuned and selected according to their predictive performance, measured using Accuracy (Ferri et al., 2009), Cohen's Kappa Coefficient (Cohen, 1960) and the Area Under the Receiver Operating Characteristics Curve (Ben-David, 2008).

The models were programmed to perform a multiclass classification task. This meant that their task was to specify to which of the k categories an example (or data point) belongs. In general terms, deep learning models are shown an example and follow a set of non-linear mathematical expressions between hidden layers of representation units (or "neurons") to produce an output in the form of a probability for each classification category. A function then measures the error between the outputs and the desired probability patterns and the model modifies its internal parameters to reduce the error. The model is then shown a never-before-seen set of data points (i.e., the testing set) and produces a new and final set of probability outputs (Goodfellow et al., 2016; LeCun et al., 2015).

Therefore, in this study, the models are programmed to classify occupants' thermal preference (TPV) on a 3-point-scale ("preferring to be cooler", "preferring no change" or "preferring to be warmer") using up to 7 input variables[8]. The survey's TPV was used as the ground truth to train and validate the models and later evaluate the predicted values using the testing set. The models have an input layer, a hidden layer, and an output layer, and use Rectified Linear Unit (ReLU) (Agarap, 2018) as the activation function between the input layer and the hidden layer, and Softmax as the activation function between the hidden layer and the output layer. The Cross Entropy function was used to measure the error of the classification rounds and the Stochastic Gradient Descent was used as the optimiser algorithm to minimise the loss. Anaconda version 2019.3 (Anaconda, 2019) was utilised as the package management platform and Jupyter Notebook (Thomas Kluyver, 2016) was used as the scripting and computing platform for the development of all models, using Python version 3.7 and PyTorch tensor library (Paszke et al., 2017).

The models' final performance indicators were then compared with the PMV model, converted from the 7-point thermal sensation scale to the 3-point thermal preference scale. Further details on the

[8] Further details on the choice of output and input variables are presented in **Chapters 6 and 7**.

terminology used and the specifics of this methodology are described in **Chapter 6**. A further exploration was conducted by adding skin temperature as one of the input features of the personal models, and the specific methodology for the inclusion of this new variable is described in detail in **Chapter 7**.

4.3. Methods to achieve Objective (3)

Objective (3) *To investigate the application of personal thermal comfort models in managing the thermal environment of older people's dwellings and the health and wellbeing of older people in general.*

In order to investigate possible application opportunities of the personal thermal comfort models for older adults developed to address Objective (2), two explorations were conducted. The first exploration demonstrated how the models can be used to calculate preferred HVAC (Heating, Ventilation and Air Conditioning) thermostat settings, which can subsequently be used as inputs in building performance simulations to predict heating and cooling energy use more accurately. From the 28 participants whose personal thermal comfort models were developed in the previous phase of the study, 2 were selected for this assessment based on the quality of information about their houses and other details. Their houses were first modelled in Design Builder/Energy Plus Version 7.0.0.088 (Design Builder Software Ltd, 2021) according to the construction details, house operation trends and other relevant information collected during the monitoring period. The building models were then calibrated using the measured data from the monitoring period, based on the calibration framework by Soebarto (1997), and the International Performance Measurement and Verification Protocol (Efficiency Valuation Organization, 2012) and the ASHRAE Guideline 14 (ASHRAE, 2002).

In order to assess whether the new heating and cooling set points calculated from the personal thermal comfort models accurately represented participants' real preferences, the study conducted a comparison between the simulated energy loads for heating and cooling using the new personal set points and the actual energy loads for heating and cooling of the participants' households. Actual household energy use for at least a 3-year period was obtained for each house from the bills provided from their appropriate electricity retailers. Following the work by Williamson et al. (2006), heating and cooling related energy consumption was disaggregated from the total consumption data using a least squares methodology, and later converted into energy loads according to each house's HVAC system coefficient of performance.

Once the personal heating and cooling temperature set points were determined using the personal models, they were inserted as inputs in the building simulation models to predict the HVAC energy loads to achieve and maintain such temperatures throughout the year. The simulated energy loads were then compared with the actual disaggregated HVAC energy loads to assess the error and accuracy of the personal set points. **Figure 4-6** presents the steps of this first exploration. Weather data from the Australian Bureau of Meteorology were used not only in the building model calibration procedure, but also in the energy data disaggregation process and in the final simulation assessments. Details of these specific methodologies are described in **Chapter 8, Section 8.1**.

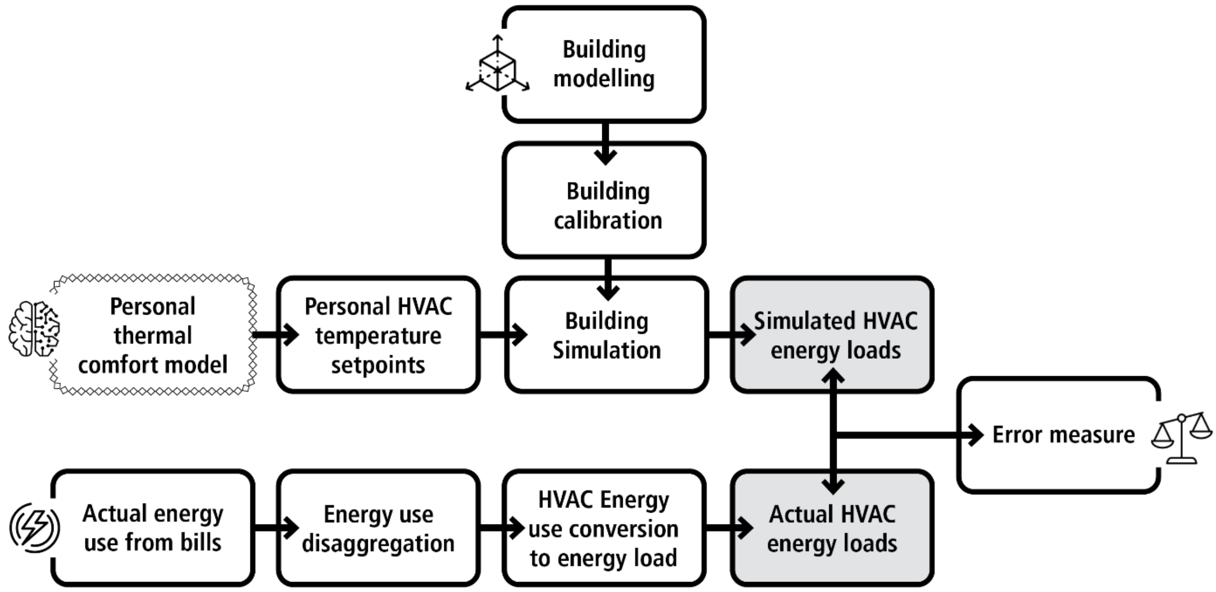

Figure 4-6 - Building simualtion application steps

The second application investigation explored the use of the personal models in a web-based smart device application, which allows the automatic calculation of thermal preferences for older individuals, aimed at aiding the control and adaptation of older people's environments to increase their comfort. The app interface and general concept are based on other, similar thermal comfort projects such as the *CBE Thermal Comfort Tool* (Tartarini et al., 2020) and the *Arup Advanced Comfort Tool* (Jones et al., 2021), as well as on evidence-based apps for caregivers and health care professionals.

To develop the app, first the final state of each deep learning model was transferred from the *Jupyter Notebook* (Thomas Kluyver, 2016) to a spreadsheet in *Microsoft Excel* (Microsoft Corporation, 2021), where the neural network was reconstructed using the functions described in Chapter 6. The spreadsheet was then imported to the online developing tool *Open As App* (Open As App GmbH, 2021), where a smart device interface was developed based on the personal model for one of the participants, as an example (**Figure 4-7**). Details of these specific methodologies are described in **Chapter 8, Section 8.2**.

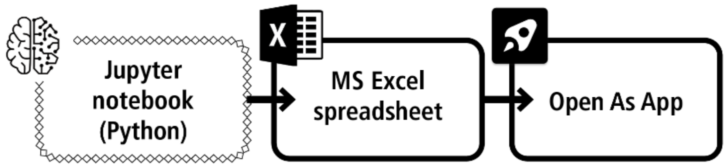

Figure 4-7 - Personal thermal comfort smart device tool development steps

4.4. Summary

This chapter has introduced a summary of the methodologies used to address the research questions outlined in this thesis. In-depth discussions of each of the methods are presented within the pertinent upcoming **Chapters 5 to 8.**

Chapter 5. Field study and initial analysis of factors associated with older people's thermal comfort

5.1. Introduction

As discussed in the literature review presented in **Chapter 2**, ageing is generally associated with physiological changes that affect people's thermal perception, sensitivity and regulation. The ability to respond effectively to temperature fluctuations is compromised with physiological ageing, upsetting the homeostatic balance of health in some. As a result, older people can become vulnerable at extremes of thermal conditions in their environment. With populations ageing globally, it is imperative that there is a comprehensive understanding of older people's thermal needs and preferences so that their comfort and wellbeing in their living environment can be optimised and healthy ageing achieved.

This chapter aims to answer research questions A and B:

A. What thermal conditions exist in the houses occupied by the older people participating in the study, and what are their thermal preferences and sensations?

B. What variables are significant in explaining the thermal preferences and sensations of the older people participating in the study?

These questions are related to **Objective (1)**: Investigate older South Australians' thermal environment, thermal preferences, behaviours, and physiological responses during hot and cold weather.

Therefore, the first step taken in this research was to investigate the thermal comfort and related requirements of a sample of older people in South Australia, through an in-depth field study. From the extensive data collected from this initial study, the quantitative analysis presented in this chapter provides new insights into older people's thermal environments, thermal sensations, preferences, and behaviours, as well as physiological responses, through the lens of a range of underlying factors or variables.

The investigation of these factors was divided into 4 parts. The first part presents the overall characteristics of the cohort analysed, their dwellings' details and other related factors that could affect their thermal environments. The second part covers an investigation of traditionally assumed thermal comfort predictors (i.e., indoor temperature, mean radiant temperature, relative humidity, air speed, clothing, and activity levels), in order to validate the continuing use of these predictors and to better understand them in the context of the cohort of older people involved. The third exploration introduces a new health/wellbeing indicator as a potential factor explaining the thermal sensations, preferences and behaviours of the cohort. Finally, the fourth investigation analysed the physiological factors of the sample as represented by their skin temperatures.

Note that the analyses presented in this chapter are generalised (i.e., using the aggregate datasets from all participants) and serve as an initial analysis of the thermal environments and variables that will be later used for the development of personal thermal comfort models presented in **Chapters 6, 7 and 8**.

5.2. Methods

5.2.1. Data collection

To achieve the before-mentioned goals, two separate data collections were conducted.

First data collection

The first data collection involved a field study with 71 participants (23 males and 48 females) living in 57 households located in South Australia[9]. The participants were drawn from the first two stages of the research project '*ARCDP180102019 - Improving the thermal environment of housing for older Australians*' (Soebarto et al., 2019a; van Hoof et al., 2019) and through press releases in media formats such as radio programs and local newspaper articles. All participants were aged 65 years or above and were living independently. Their dwellings were located in hot dry (BSk), warm temperate (Csa) and cool temperate (Csb) climate zones, according to the Köppen–Geiger climate classification system or Climate Zones 4, 5 and 6, respectively, according to the Australian National Construction Code (Australian Building Codes Board, 2019).

The data collection process involved visiting the houses to apply questionnaires, conduct an open-ended interview about the house details and install indoor environment data loggers in the house's main

[9] While this data collection was part of the broader research project '*ARCDP180102019 - Improving the thermal environment of housing for older Australians*', the author of this thesis was a research assistant on the project and participated actively in the collection of data.

living room and main bedroom, which would continuously monitor the environmental conditions of the houses for 9 months (from mid-January to mid-October 2019). A thermal comfort survey tablet was also provided to be used by the participants to answer point-in-time surveys about their thermal environment and their preferences and sensations throughout these 9 months.

All data collection tools (e.g., questionnaire, interview, and environmental loggers) were designed to cover a wide range of variables and factors known in the architecture, science, gerontology and public health fields of study to influence and affect thermal comfort, sensation and preference. In addition, the results from a previous investigation with seven focus group sessions involving 49 older South Australians (van Hoof et al., 2019) also contributed to highlight less quantifiable aspects of older people's thermal perceptions and responses, which are often overlooked in comfort studies (e.g., personal beliefs and experiences). Unique factors such as use of outdoor spaces, self-rated health, and habituation to climatic zones, which are also often ignored in thermal comfort studies or extremely hard to obtain, were included in the study as well.

The one-time questionnaire covered participants' personal data (e.g., sex, age, level of education, living arrangements, income level, and chronic diseases or conditions) and their general behaviour towards thermal comfort. It was conducted using a paper-based form (**Appendix E**), taking from 10 to 40 minutes to complete. An additional questionnaire (**Appendix F**), applied at the end of the monitoring period, also included a frailty assessment, using the Modified Reported Edmonton Frail Scale (Rose et al., 2018) questions about the use of the outdoor spaces of the homes. Data from body composition assessments, using a Tanita Inner Scan RD-953 scale (Tanita Corporation, 2016; Volgyi et al., 2008) and a tape measure tool for height measurements were also recorded in this questionnaire. The body composition equipment uses principles of bioelectrical impedance (Peterson et al., 2011; Shaikh et al., 2007) to measure several body variables (e.g., body water, fat, bone, muscle mass or percentages), which were automatically calculated and reported through the scale's interface.

An open-ended interview guided by a paper-based check-list (**Appendix G**) gathered information about participants' houses (e.g., main envelope construction materials, air conditioning systems' details and use, and blind and curtain materials and use) and took from 10 to 40 minutes, depending on the size of the house, complexity of systems used and level of detail shared by the participants. Building drawings, photos, and overall space measurements (including ceiling heights), as well as air conditioning and photovoltaic panels' details (when present) were also collected. The audio of the interviews was also recorded so it could be revisited in case details were not captured in the check-lists. Both questionnaire answers and house details check-lists were then compiled as MS Excel spreadsheets for analysis.

The house monitoring and thermal comfort survey involved the use of indoor environment data loggers and a thermal comfort survey tablet in each house. The indoor environment data logger contained sensors that measured air temperature, globe temperature, air speed, relative humidity, CO_2 and Volatile Organic Compounds (VOC). The logger was positioned in the main living area and coordinated measurements from the sensors, undertaken at 30-minute intervals and when a participant completed a comfort survey. Note that the loggers were positioned to allow a single measurement point, at approximately 1 m high from the floor, preferably close to where the participants were normally seated, and away from sources of heat or direct solar radiation.

The logger and tablet were self-contained and did not require connection to the dwelling's electricity or Internet systems. A radio component was incorporated in the logger, allowing communication with the tablet. Once survey answers were received by the logger, both the time-stamped environmental measurements and survey answers were stored locally on a Secure Digital (SD) card as a daily text file. Once per day, the text file was transmitted to an external web-based server through a 3G cellular modem present in the logger, allowing the data to be accessed remotely. The daily files were subsequently downloaded and aggregated as a single text file using batch scripts. Further details on the logger and tablet tools, including sensor accuracy and logger system architecture, have been previously published by Soebarto et al. (2020).

The dry bulb temperature and relative humidity were also measured at 30-minute intervals in the houses' main bedrooms using HOBO® U12-013 data loggers. Data were downloaded from them at the end of the monitoring period and merged to the final dataset for the comfort surveys answered in the bedroom.

The thermal comfort survey tablet allowed participants to complete comfort surveys electronically, at any time, about their point-in-time thermal sensations, thermal preferences, thermal satisfaction, as well as their clothing, activity, curtains/blinds state, windows and doors state, and heating, cooling and fan states. The survey also included questions about the participant's perceptions of the indoor environment quality as well as their self-reported health/wellbeing perceptions at that particular point in time. Further details on the survey questions have been previously published by Soebarto et al. (2020).

The thermal sensation vote (TSV) and the thermal preference vote (TPV) were answered by participants and later analysed using the 7-point ASHRAE scale and the 3-point McIntyre scale, respectively (**Table 5-1**). Although collected through the surveys, the participants' thermal satisfaction votes, on a 5-point scale from "very satisfied" to "very dissatisfied", are less commonly used in thermal comfort studies and were therefore not analysed in this thesis.

Table 5-1 - Thermal sensation vote (TSV) and thermal preference vote (TPV) scales used in the study

Thermal sensation vote scale	**Thermal preference vote scale**
Answer to survey question: "How do you feel right now?"	Answer to survey question: "Would you prefer to be…?"
7-point ASHRAE scale	**3-point McIntyre scale**
-3 Cold	
-2 Cool	
-1 Slightly cool	3 Warmer
0 Neutral	2 No change
1 Slightly warm	1 Cooler
2 Warm	
3 Hot	

Each survey took no more than a few minutes to complete, and, since the tablet could be carried easily, participants could choose whether to answer the survey in the main living area or in the main bedroom. The tablet could be used by up to 2 participants living in the same house. Participants were assigned as Person 1 or Person 2 at the beginning of the study and had to indicate their identification every time a survey was answered. The tablet survey screens, as well as the accompanying printed booklet with further instructions and explanations on the surveys' answer choices, can be found in **Appendix H and I**.

Second data collection

After the conclusion of the first data collection period[10], a preliminary analysis of the data and further literature investigations highlighted a lack of physiological factors being investigated in the first stage of the study. Therefore, a second collection was conducted, involving 11 (6 males and 5 females) of 71 participants from the first data collection period. In this second data collection, the survey tablet was modified to include a non-contact infra-red temperature sensor to measure the skin temperature of the back of the participants' non-dominant hand after they completed each point-in-time survey. As highlighted in **Chapter 4**, since this equipment modification was only possible in a single logger-tablet

[10] The first data collection period was part of the broader research project 'ARCDP180102019 - Improving the thermal environment of housing for older Australians', in which the author of this thesis was a research assistant. The second data collection period was conducted separately by the author of this thesis.

pair, the number of participants involved, as well as the length of the monitoring period, had to be reduced. In addition, only a portion of the monitoring participants were willing to participate in this follow-up monitoring study due to the time commitment for participation, which required answering the thermal comfort surveys more frequently (i.e., at least 2 times a day). Therefore, for this second data collection, each house was monitored across 2 consecutive weeks, one house after the other, between the months of September 2020 and February 2021. The environmental measurements and the comfort survey questions remained the same from the first collection period. Frailty and body composition assessments were redone to check variations between the two data collection periods. **Table 5-2** presents the data acquisition tools used in each of the collection periods.

Table 5-2 - Data acquisition tools used in the 1st and 2nd data collection periods

Data acquisition tool (data collected)	1st data collection (9 months, Jan-2019 to Oct 2019)	2nd data collection (2 weeks, Sept-2020 to Feb-2021)
Questionnaire (socio-demographics, chronic diseases, overall behaviours)	✓	not collected*
House construction check-list	✓	not collected*
Additional questionnaire (use of outdoor spaces, frailty and body composition assessment)	✓	✓ (except for use of outdoor spaces)
Data logger (Indoor environment conditions)	✓	✓
Tablet (thermal comfort surveys)	✓	✓ (in addition to hand skin temperature measurements)

✓ = collected; * considered not varying between October 2019 and February 2021.

The skin temperature of the hands was chosen in this study as a possible indicator of people's thermal sensation and preference because human hands are known to contain a high number of arteriovenous anastomoses (AVAs), valves that regulate vasoconstriction and vasodilatation, and therefore influence heat loss by changing the peripheral blood flow (Hales, 1985). The skin temperature of the dorsal side of the hand was chosen according to ISO9886:2004 (ISO, 2004) recommendations and in line with previous publications on the associations between this indicator and thermal sensation (Leijon-Sundqvist et al., 2017; Soebarto et al., 2019b; Schellen et al., 2010). Since the back of one's hand is more frequently exposed to the environment than other body parts, the choice of this skin area also reduced the intrusiveness of the method. In addition, the use of the dorsal side of the hand allowed the most comfortable position for older participants to take the measurements whilst seated. The non-dominant hand was chosen to minimize the effect of frequent hand movements during the skin temperature measurements.

The skin temperatures were measured in degrees Celsius, using a non-contact infra-red temperature sensor (MLX90614-DCC). The sensor had a ±0.5°C precision of temperature measurement and a field of view (FOV) of 35 degrees. To measure a spot with a radius of approximately 1 cm in the back of participants' non-dominant hand, participants positioned their hands at a maximum distance of 1.5 cm from the sensor. In addition, a line trace sensor (LB-LR0005) was included in the modified tablet as a proximity sensor to allow measurements only when the participant's hand was close enough to the infra-red sensor. To notify participants that a skin temperature measurement was successfully recorded, a buzzer was included in the equipment. The modified equipment and skin temperature measurement procedure were tested with 3 people (in their late fifties to mid-seventies) before deployment to ensure suitability for the cohort involved in the study. The accuracy of the setup was compared with a medical grade infra-red temperature device, presenting a ±0.5°C error range.

5.2.2. Investigation parts, factors analysed and statistical methods

The analysis presented in this Chapter is divided into four parts, investigating:

(1) the characteristics of the dwellings and participants involved in the research, as well as their overall TSV and TPV distributions throughout the monitoring period;

(2) whether the environmental conditions, clothing levels and metabolic rates (i.e., the well-known PMV/PPD model variables) remain as significant predictors of older adults' thermal sensation and thermal preference (in an aggregate/generalised way);

(3) whether health/wellbeing perception could be a predictor of the cohort's thermal sensation and thermal preference (in an aggregate/generalised way); and

(4) whether skin temperature could be a predictor of the cohort's thermal sensation and preference (in an aggregate/generalised way).

To conduct investigation 1, the data collected from the interviews and questionnaires were gathered, formatted, and analysed using graphical representation and descriptive statistics.

To conduct investigations 2 to 4, first, the datasets comprising the environmental conditions measured and point-in-time survey answers were formatted, and experimental measurement errors were removed. Operative temperatures and mean radiant temperatures were then calculated from the measured dry bulb temperatures, globe temperatures and air speeds measurements applying the methods from ISO 7726:1998 (ISO, 1998). In addition, participants' activity level answers in the surveys were converted to metabolic rates, in MET units, according to the Compendium of Physical Activities (Ainsworth et al., 2011), and later corrected based on participants' sex, height, weight and age, according to Byrne et al. (2005) and Kozey et al. (2010). This variable is termed the "Corrected Metabolic Rate" in this thesis. One MET is defined as 1 kcal/kg/hour and is roughly equivalent to the energy cost of sitting quietly. A MET can also be defined as oxygen uptake in ml/kg/min, with 1 MET equal to the oxygen cost of sitting quietly, equivalent to 3.5 ml/kg/min (Ainsworth et al., 2011).

Furthermore, clothing levels (in the scale 1 = very light, 2 = light, 3 = moderate, 4 = heavy, 5 = very heavy) were used in this analysis, instead of clothing insulations in *clo* (as commonly used in thermal comfort studies), because these were not measured as continuous variables by the researchers and were rather reported by the participants as categorical approximations. Clothing levels were converted into averaged clothing insulations in *clo* only in **Chapters 6 and 7** to calculate the PMV index used for comparison with the personal comfort models.

Descriptive statistical indicators (e.g., mean, median, maximums, and minimums) were then calculated for the following factors: the operative temperature, dry-bulb temperature, mean radiant temperature, relative humidity, air speed, clothing level, metabolic rates and health/wellbeing perception. The variables were also checked for normality using the normal Q-Q Plots.

Following this initial analysis, linear regression analysis was conducted to draw insights into these variables' individual relationships with participants' TSV and TPV recorded during the surveys. TSV and TPV were modelled as dependent variables and the other factors as individual independent variables. First, the independent variables were binned individually. Operative, dry bulb and mean radiant temperatures were binned in 0.5°C increments, air speed in 0.1m/s increments, relative humidity in 5% increments, corrected metabolic rates in 0.1 MET increments, and clothing level and health/wellbeing in their original 1 increment categories. The mean of the independent variables and corresponding TSVs and TPVs (dependent variables) were subsequently calculated for each bin. Once the independent data is binned, the mean of the dependent categorical variable is determined at each bin and can be treated as a continuous variable. Linear regression models were then fitted to the binned data points, weighted by the number of votes in each bin, using the weighted least squares regression method, which is widely used in thermal comfort field studies (Wang, 2006; Nakano et al., 2002; de Dear and Fountain, 1994; Wang et al., 2018).

Finally, Mann-Whitney U tests were used to analyse the relationship between air speed (i.e., the dependent variable) and the use of fans, heating and cooling, and opening of windows (i.e., the independent variables). This test was chosen specifically to this variable since air speed measurements are continuous variables and are not considered normally distributed from the normal Q-Q tests, in addition to the independent variables being categorical, with two independent groups and all measurements being independent. For all analysis in this thesis, statistical significance was assumed at $p < 0.05$.

Note that the skin temperatures' effects on thermal preference and sensation were analysed as a separate dataset, since only a limited number of participants were involved in the second data collection period when skin temperatures were measured. For this exploration, as in the previous exploration, point-in-time skin temperature measurements were first binned in 0.5°C increments. Then, the means of the skin temperatures and corresponding TSVs and TPVs were calculated for each bin, until linear regression models could be fitted to the binned data points, weighted by the number of votes in each bin, using the weighted least squares regression method.

All analyses in this chapter were conducted using the SPSS statistical package Versions 26.0.0 and 27.0.0 (IBM Corp., 2020).

5.3. Results

The following subsections present the results of the four-part exploration conducted in this Chapter.

5.3.1. First investigation: dwellings and participants' characteristics and overall TSV and TPV

The 71 participants involved in this study lived independently in 57 dwellings located in the State of South Australia, as presented in **Figure 5-1**. Their approximate location in the 3 main geographical areas studied (i.e., the Iron Triangle, the Adelaide Metropolitan Area + Adelaide Hills, and the Fleurieu Peninsula) are shown in **Figure 5-2**, **Figure 5-3** and **Figure 5-4**.

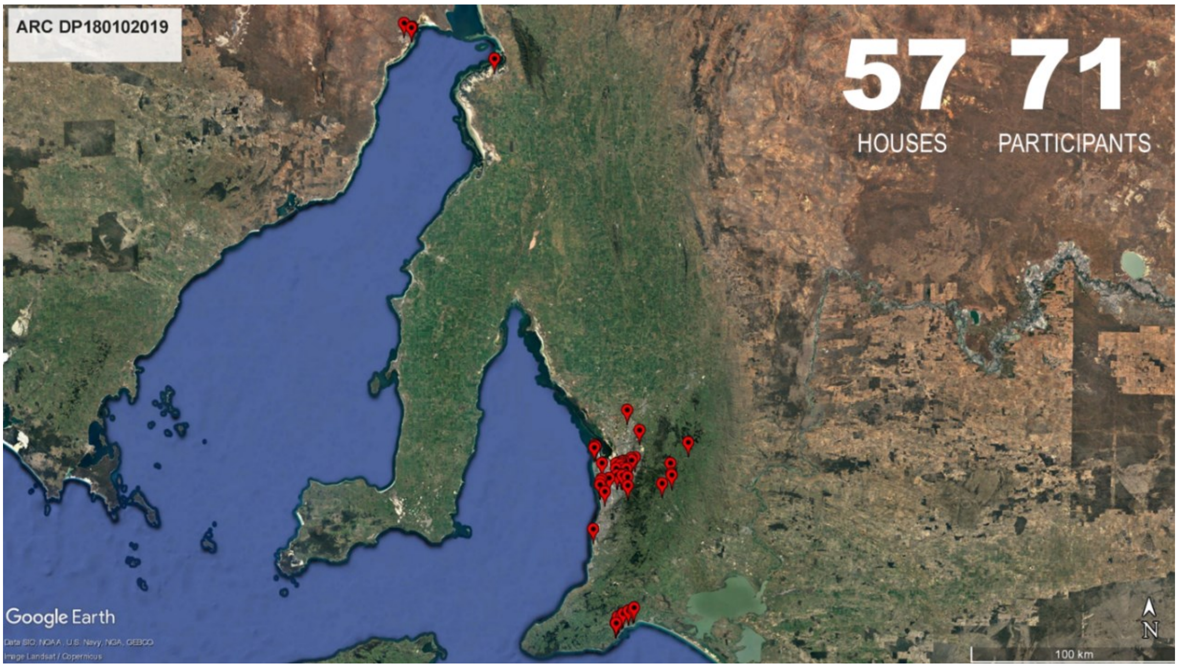

Figure 5-1 - All dwellings' locations in South Australia

Figure 5-2 - Dwellings' locations in the Iron Triangle (BSk climate zone)

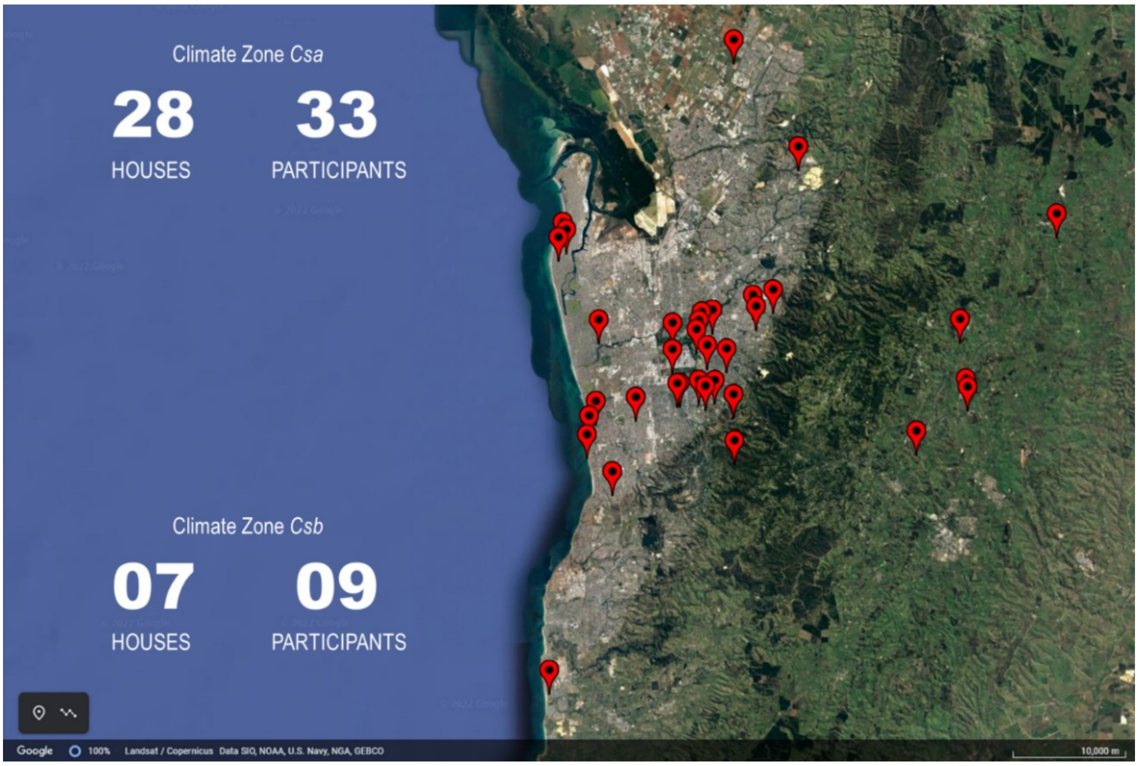

Figure 5-3 - Dwellings' locations in the Adelaide Metropolitan area (Csa climate zone) and the Adelaide Hills (Csb climate zone)

Figure 5-4 - Dwellings' locations in the Fleurieu Peninsula (Csb climate zone)

Table 5-3 presents a summary of the participants' house characteristics. Among the dwellings monitored, most of them were either semidetached or detached houses. Only 3 were apartments in multi-storey buildings and 1 was a "granny flat" (i.e., free-standing constructions built in the backyard of a family's main house). Most houses were 1 storey high. They were mostly constructed with external walls of double brick or brick veneer, and roofs of corrugated steel sheeting. External walls were insulated in 45% of the buildings, and 69% of dwellings had insulated ceilings and/or roofs. The dwellings' age ranged from 1 to 169 years old, with areas ranging from $50m^2$ to $480m^2$. Older houses generally had suspended timber floors and the newer houses had concrete slab-on-ground construction.

Most dwellings' main living areas had heating (ranging from reverse cycle split or ducted systems, electric heaters, gas heaters, radiant panel heaters, wood fires and underfloor heating) and cooling (including reverse cycle split or ducted systems, ducted evaporative cooling systems, window-mounted or portable cooling devices), as shown in **Table 5-3**. The presence of ceiling or pedestal fans was also common among dwellings. In addition, internal blinds were present in all dwellings, while external blinds were present in 56% of the dwellings.

It is worth noting that 12 of these 57 houses were located in retirement villages, which are housing developments targeted for people aged 65 or over, where they live independently in their own houses. Although some retirement villages provide services, they are considered examples of independent living.

Table 5-3 - Summary of participants' house characteristics

Climate Zone	Partici-pant ID	House Type	No. of floors	Total area (m^2)	Age of dwelling (years)	External Wall Construction	Main Living area Cooling system[3]	Main Living area Heating system[3]
Csa	1	Detached	1	113.9	169	Double brick	RC-Split	RC-Split
	2	Detached	1	134	60	Double brick	Evap-Ducted	Gas Heater
	3	Detached	1	129.5	115	Double brick[2]	Evap-Ducted	Wood fire
	4	Detached	1	51.3	31	Brick-veneer[2]	None	Wood fire
	5	Apartment	On 1st floor	56.4	3	Prefabricated Concrete Panels	RC-Split	RC-Split
	8	Detached	2	158.9	24	Brick-veneer[2]	Evap-Ducted	Gas heater
	11	Semi-detached	2	234.2	10	Reverse brick-veneer[2]	RC-Split	RC-Split and underfloor heating
	12	Detached	1	68.9	25	Brick-veneer[2]	RC-Split	RC-Split
	14	Granny-flat	1	53.45	5	Steel framed[2]	RC-Split	RC-Split
	17	Detached	1	87.45	44	Brick-veneer[2]	RC-Ducted	RC-Ducted
	18	Detached	1	172.4	104	Double brick	Window-mounted	Gas heater
	20	Apartment	On 2nd floor	50	30	Double brick	RC-Split	RC-Split
	27 28	Semi-detached	1	230.6	17	Brick-veneer[2]	RC-Ducted	RC-Ducted
	33	Semi-detached	2	138.7	40	Double brick	Portable Air-conditioner	Gas heater and Wood Fire
	34	Detached	1	142.3	43	Double brick	Evap-Ducted	Gas heater

	35	Semi-detached	1	144.5	30	Double brick	RC-Split	RC-Split
	36	Detached	1	133	21	Brick-veneer[2]	Evap-Ducted	Electric blanket
	38 39	Semi-detached	1	241.5	22	Brick-veneer[2]	Evap-Ducted	Underfloor heating
	41	Semi-detached	1	49.1	30	Double brick[2]	RC-Ducted	RC-Ducted
	42	Apartment	On 1st floor	167.7	40	Double brick	RC-Split	Electric heater
	43	Semi-detached	2	251.8	28	Double brick[2]	RC-Ducted	RC-Ducted
	45	Detached	1	145.4	9	Brick-veneer[2]	Evap-Ducted	None
	53	Detached	1	68	Not available	Double brick	RC-Split	RC-Split and electric heater
	59	Detached	1	208.2	110	Sold brick with sandstone	RC-Ducted	RC-Ducted
	62 63	Detached	1	253.3	17	Brick-veneer[2]	RC-Ducted	RC-Ducted and Gas heater
	66 67	Detached	1	154.4	60	Double brick	RC-Split	RC-Split
	68 69	Detached	1	216.6	23	Brick-veneer[2]	Evap-Ducted	Gas heater
	71	Detached	1	143.9	12	Brick-veneer[2]	RC-Split	RC-Split and electric heater
Csb	6 7	Detached	1	103.4	15	Brick-veneer	RC-Split	RC-Split
	9	Semi-detached	1	60.1	45	Double brick	RC-Split	RC-Split and Fan heater
	13	Detached	2	191.6	26	Brick-veneer[2]	RC-Ducted	RC-Ducted
	16	Detached (elevated)	1	121	19	Timber framed[2]	RC-Split	RC-Split
	19	Detached	1	127.8	60	Brick-veneer	RC-Split	RC-Split
	21	Detached	1	66.4	63	Timber framed[2]	None	Wood stove
	22	Semi-detached	1	71.8	22	Brick-veneer	RC-Split	RC-Split
	23	Detached	1	128.7	40	Timber framed	RC-Split	RC-Split
	24	Semi-detached	1	139.1	12	Brick-veneer[2]	RC-Split	RC-Split
	25 26	Detached	1	154.4	9	Brick-veneer	RC-Ducted	RC-Ducted
	29 30	Detached	1	137	8	Brick-veneer[2]	RC-Ducted	RC-Ducted
	31	Detached		257.6	15	Brick-veneer	None	Gas heater
	37	Detached	1	175.6	14	Brick-veneer[2]	RC-Split	RC-Split and radiant panel heater
	40	Detached	1	94.8	16	Timber framed[2]	RC-Split	RC-Split and Gas heater
	44	Detached	2	315.4	35	Block work filled with concrete[2]	Evap-Ducted and RC-Split	Wood Slow Combustion Heater
	46 47	Detached	2	483.6	30	Double brick	None	Wood Fire, Electric heater
	48 49	Semi-detached	1	169.5	2	SIP[1]	RC-Split	RC-Split
	50	Semi-detached	1	198.8	1	SIP[1]	RC-Split	RC-Split
	51 52	Detached	1	159.9	20	Brick-veneer[2]	RC-Ducted	RC-Ducted
	56 57	Detached	1	197.4	24	Brick-veneer[2]	RC-Ducted	RC-Ducted
	58	Semi-detached	1	171.5	3	SIP[1]	RC-Split	RC-Split

	60	Detached (elevated)	1	125.7	20	Timber framed[2]	RC-Split	RC-Split and electric heater
	61	Semi-detached	1	163.6	5	SIP[1]	RC-Split	RC-Split
	64 65	Detached	1	171.3	8	Brick-veneer[2]	RC-Ducted	RC-Ducted
	70	Detached	1	149.2	27	Brick-veneer	RC-Split	RC-Split
BSk	10	Semi-detached	1	51.4	33	Double brick	RC-Split	RC-Split and Fan heater
	15	Detached	1	117.2	103	Double brick	RC-Split	RC-Split and Gas Fire
	32	Semi-detached	1	82	58	Double brick	RC-Split	Gas heater
	54 55	Detached	1	210.8	80	Double brick	RC-Split	RC-Split and gas heater

Obs.: Participants' ID numbers were randomly assigned for each person. They are used for the personal thermal comfort models presented in Chapters 6, 7 and 8.

[1] SIP = Structural Insulated Panel

[2] Insulated

[3] RC-Ducted = Reverse Cycle Ducted System; RC-Split = Reverse Cycle Split System; Evap-Ducted = Ducted Evaporative Cooling

As shown in **Table 5-4**, among the 71 participants involved in the study, 48 were females and 23 were males. They were aged from 65 to more than 85 years old. Their body composition and frailty assessments showed wide individual differences in health-related factors. Although most were not considered frail, participants with mild to moderate frailty were present. Note that a few participants were not able or chose not to answer the additional questionnaire that involved body composition and frailty assessments. The averages, maximums and minimums showed in **Table 5-4**, therefore, do not take into account these cases. From the questionnaire on health and chronic diseases, 73% of participants reported at least one diagnosed chronic disease, with high blood pressure being the most reported (i.e., 40 out of the 71 participants).

Table 5-4 - Participants' characteristics

ID	Sex	Age	Body Composition									Frailty[5] (1 to 5)
			Height (cm)	Weight (kg)	BMI[1] (kg/m^2)	Body Fat (%)	Muscle Mass[2] (kg)	Physique Rating[3] (1 to 9)	Bone Mass	Visceral Fat Rate[4] (1 to 59)	Body Water (%)	
1	F	71	157.2	78.9	32.0	40.3	44.7	3	2.4	12.0	41.1	1
2	M	86	179.5	86.4	26.8	---	---	---	---	---	---	1
3	F	79	156.5	64.6	26.2	42.5	35.3	2	1.9	11.5	40.2	1
4	F	81	163.0	58.2	21.9	32.4	37.4	5	2.0	9.0	44.5	2
5	F	79	161.0	97.6	37.6	46.4	49.6	3	2.6	16.5	36.5	1
6	M	76	175.5	88.5	28.6	29.4	59.4	2	3.1	17.5	48.4	1
7	F	76	149.5	75.1	33.4	43.8	40.1	3	2.2	14.0	39.4	1
8	M	82	174.0	89.9	29.7	36.4	54.4	2	2.9	22.0	52.4	2
9	F	67	150.0	82.4	36.6	49.0	39.9	3	2.1	15.0	37.7	4
10	F	86	151.0	110.4	48.4	58.6	43.4	3	2.3	25.0	31.4	4
11	F	78	156.5	72.1	29.6	40.8	40.6	2	2.2	12.5	43.2	1
12	F	75	149.0	62.2	28.0	---	---	---	---	---	---	1
13	M	90	173.0	94.5	31.6	35.9	57.5	2	3.0	24.0	49.2	1
14	F	76	161.0	56.8	21.9	35.1	35.0	4	1.9	---	46.0	1
15	M	68	178.0	80.6	25.4	23.3	58.7	5	3.1	13.0	53.2	1
16	F	72	151.5	63.1	27.3	37.5	37.4	2	2.0	10.5	45.4	1
17	F	76	157.0	89.1	36.1	47.1	44.7	3	2.4	15.5	35.6	1
18	F	73	179.5	101.8	31.6	---	---	---	---	---	---	1

19	F	92	153.0	66.1	28.2	42.5	36.1	2	1.9	14.0	40.1	1
20	F	75	160.0	61.6	24.1	33.5	38.9	5	2.1	9.0	45.1	1
21	F	78	158.5	78.1	30.9	44.2	41.3	2	2.2	13.5	39.4	1
22	F	69	160.0	70.9	27.7	39.3	40.8	2	2.2	10.5	41.8	1
23	F	76	164.5	86.4	31.9	---	---	---	---	---	---	2
24	F	77	160.5	84.6	32.6	44.7	44.4	2	2.4	14.0	36.1	1
25	M	88	168.0	83.6	29.6	---	---	---	---	---	---	1
26	F	81	154.5	76.1	32.1	46.8	38.4	2	2.1	14.5	43.0	1
27	F	75-79	---	---	---	---	---	---	---	---	---	2
28	M	85	170.0	81.0	28.0	33.8	50.9	2	2.7	20.5	52.2	1
29	F	65-69	---	---	---	---	---	---	---	---	---	---
30	M	72	173.0	118.2	39.5	41.3	66.0	3	3.4	27.5	41.9	2
31	F	74	162.5	86.9	32.7	46.2	44.4	2	2.4	14.0	37.2	1
32	F	82	145.0	64.0	30.4	47.0	32.2	2	1.7	14.5	42.1	2
33	M	80	171.5	109.1	36.9	37.3	65.0	3	3.4	25.5	42.2	1
34	F	66	162.5	79.5	29.9	38.8	46.1	2	2.5	10.5	37.5	1
35	M	73	160.0	119.0	46.5	44.8	62.4	3	3.3	33.5	45.2	3
36	F	74	160.5	95.4	37.0	---	---	---	---	---	---	2
37	F	75	168.5	85.7	30.0	42.8	46.6	2	2.5	12.5	36.4	1
38	F	82	166.0	71.9	26.1	37.1	42.9	2	2.3	11.0	42.1	1
39	M	84	173.0	99.1	33.1	32.5	63.6	2	3.3	22.0	46.7	1
40	M	86	175.0	85.9	28.0	33.0	54.7	2	2.9	20.5	52.1	1
41	F	71	159.0	78.3	31.0	---	---	---	---	---	---	1
42	F	75	156.5	75.9	31.0	---	---	---	---	---	---	2
43	M	73	172.0	66.3	22.4	24.4	47.6	4	2.6	13.5	52.1	1
44	M	76	172.5	83.1	27.8	29.4	55.7	2	2.9	17.5	48.7	1
45	F	74	152.0	79.7	34.5	46.3	40.7	3	2.2	14.5	37.7	1
46	F	66	166.5	117.0	41.9	53.2	52.0	3	2.8	18.0	36.8	1
47	M	65	183.0	56.5	16.9	11.1	47.7	7	2.6	7.0	78.9	1
48	F	77	156.0	81.2	33.3	43.5	43.5	3	2.3	14.0	37.1	2
49	M	83	163.5	68.6	25.8	28.0	46.9	2	2.5	17.5	50.9	1
50	F	81	162.0	60.0	22.8	29.4	40.2	5	2.2	9.0	46.9	1
51	F	72	150.5	64.6	28.3	39.6	37.0	2	2.0	11.0	41.6	2
52	M	76	180.0	69.1	21.3	22.8	50.7	4	2.7	13.0	50.4	1
53	F	82	153.5	45.8	19.3	37.4	27.2	1	1.5	9.5	49.0	4
54	F	75-79	---	---	---	---	---	---	---	---	---	---
55	M	83	170.0	74.2	25.7	---	---	---	---	---	---	3
56	F	78	159.0	64.8	25.6	36.3	39.2	2	2.1	10.5	40.9	1
57	M	79	177.5	77.9	24.6	24.1	56.2	5	3.0	15.0	50.2	1
58	F	74	162.0	75.3	28.7	40.6	42.4	2	2.3	11.5	41.4	1
59	F	75	161.0	57.6	22.2	34.6	35.8	4	1.9	9.0	43.6	1
60	F	71	151.0	55.2	24.2	32.8	35.2	5	1.9	8.5	42.9	1
61	F	81	164.0	75.3	28.0	43.0	40.8	2	2.2	12.5	41.8	1
62	F	76	158.0	85.5	34.2	49.0	41.4	2	2.2	15.5	38.1	2
63	M	80	167.5	79.8	28.3	29.4	53.5	2	2.8	18.5	49.8	1
64	M	77	170.0	91.7	31.7	---	---	---	---	---	---	1
65	F	78	166.0	91.3	33.1	46.4	46.5	2	2.5	14.5	37.0	3
66	F	72	151.5	70.2	30.4	39.4	40.4	3	2.2	11.5	40.7	1
67	M	73	166.0	70.5	25.6	23.8	51.0	5	2.7	14.0	50.5	1
68	F	77	156.0	77.4	31.8	41.6	42.9	3	2.3	13.0	41.7	1
69	M	77	172.0	111.7	37.8	---	---	---	---	---	---	1
70	F	87	159.0	90.7	35.8	50.6	42.5	2	2.3	17.5	39.4	2
71	F	>85	---	---	---	---	---	---	---	---	---	---
Average		77	163.1	79.8	30.0	38.2	45.5	3	2.4	14.9	43.8	1
Standard Deviation		5.7	9.0	15.9	5.8	8.7	8.6	1.2	0.4	5.2	7.1	0.8
Min		65	145.0	45.8	16.9	11.1	27.2	1	1.5	7.0	31.4	1
Max		92	183.0	119.0	48.4	58.6	66.0	7	3.4	33.5	78.9	4

[1] BMI = Body Mass Index, calculated from height and weight measurements.

[2] Sum of skeletal muscle, smooth muscle and water in muscle, calculated by the Tanita scale (Tanita Corporation, 2016).

[3] Calculated according to the ratio between fat and muscle, by the Tanita scale (Tanita Corporation, 2016).

[4] Calculated according to the amount of fat that is in the internal abdominal cavity, surrounding the vital organs in the abdominal area, by the Tanita scale (Tanita Corporation, 2016).

[5] Assessed according to the Modified Reported Edmonton Scale (MRES) (Rose et al., 2018), where 1 = not frail, 2 = apparent vulnerability, 2 = mild frailty, 3 = moderate frailty, 4 = severe frailty.

In terms of income, 3 of the 71 older adults worked part time to complement either a part pension or a self-funded retirement; 39 received full pension, 9 received part pension in addition to self-funding themselves, and 20 were entirely self-funded. Their living arrangements comprised of 52% of the cohort living with a spouse, 42% living alone and 6% with their children or their spouse and children. A considerable proportion of the participants (50 out of 71) were born in Australia, with the rest born in the United Kingdom (19 out of 71), Ireland (1 out of 71) or Indonesia (1 out of 71).

Furthermore, when asked about their general weather preference, 30% reported preferring hot weather, another 30% preferred cold weather, 18% reported disliking both types of weather, and 22% reported no preference, which indicates an interesting diversity within the group.

When asked how concerned they were about the cost of running their air conditioning systems, 69% of participants reported some level of concern (from somewhat to extremely concerned) about running their heating, and 66% reported some level of concern about running cooling.

It is worth noting that, when asked about the first thing they do to stay thermally comfortable on hot and cold days, the participants reported using an adaptive behaviour by first adjusting their clothing layers, as seen in **Figure 5-5**. To keep cool on a very hot day, reducing clothing layers was participants' most frequent first action (23% of participants) followed by turning on the cooling system (20%). Likewise, to keep warm in very cold days, adding clothing layers was the main answer (68%), followed by turning on heating systems (15%). Noticeably, changing clothing insulation is a more frequent priority on cold days than on hot days.

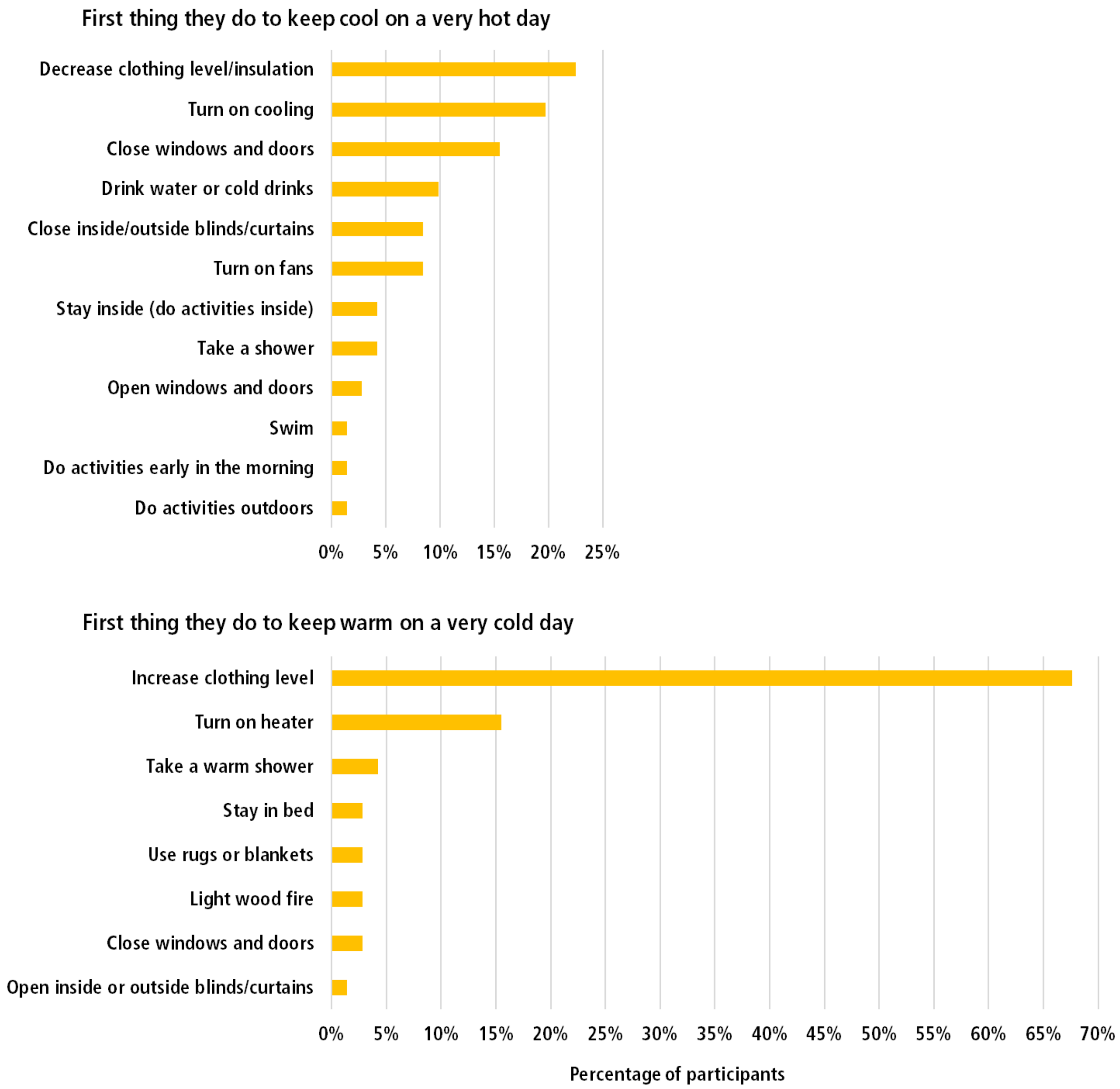

Figure 5-5 - First thing participants do to keep cool on a hot day and warm in a cold day

This initial investigation on participants' characteristics also analysed their overall thermal sensations and preferences throughout the 9-month monitoring period. Up to the end of the monitoring period, 10,787 votes (i.e., complete survey answers) were recorded from the occupants' survey and more than 600,000 indoor environmental conditions sets were recorded in the loggers. Some participants answered surveys more frequently than others, with an average of 152 votes per participant in the 9 months of monitoring, a maximum vote count of 672 votes and a minimum of 18 votes in the period. Survey answers occurred throughout the 24 hours of the day, with the highest frequency of votes occurring between 4 and 5pm (**Figure 5-6**). Only one house (House 4) opted to withdraw from the study for personal reasons. This house's data were removed from the datasets, although the houses were not renumbered after this withdrawal.

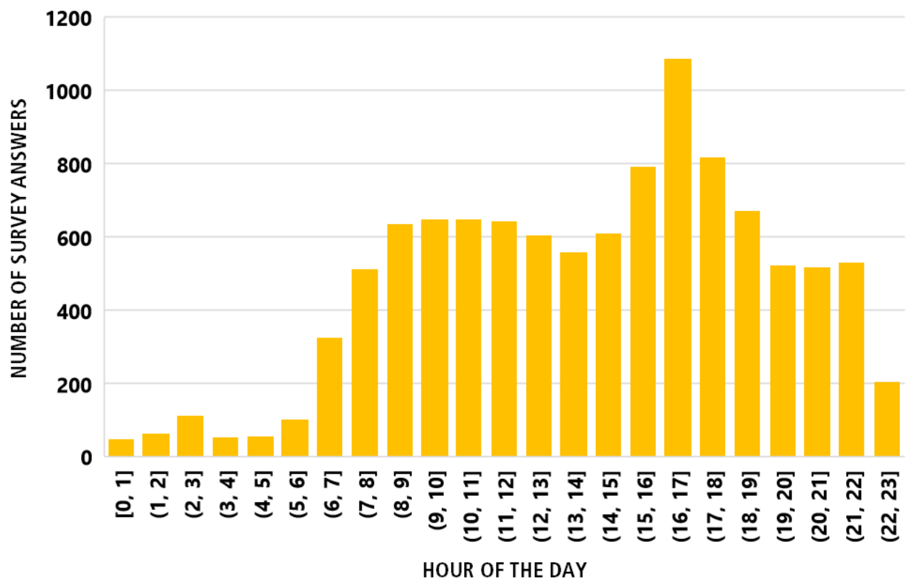

Figure 5-6 - Number of survey answers per hour of the day

From the 10,787 survey answers, the thermal sensation and thermal preference votes were normally distributed, although a slight skewness was observed on the cooler side of the TSV scale and in the preference to be on the warmer side of the TPV scale, as seen in **Figure 5-7**.

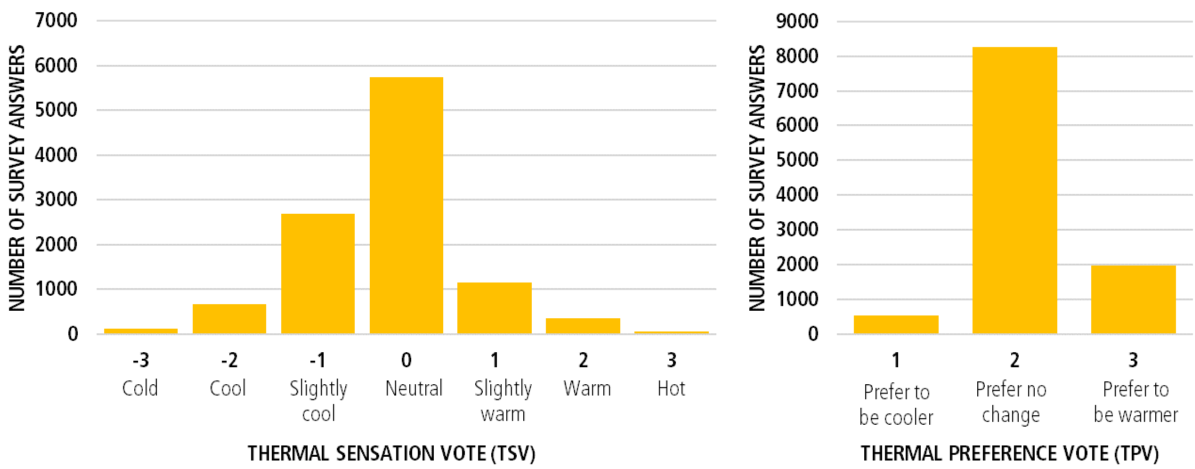

Figure 5-7 - Total number of votes cast for each TSV category and TPV category

The cross-tabulation of the thermal preferences versus the thermal sensation vote count is shown in **Table 5-5**. Although a preference for no change was more frequently matched to a neutral thermal sensation, the data show a considerable proportion of occupants reporting other than neutral thermal sensations without the preference for change, as highlighted in grey in the table. **Figure 5-8** visually illustrates the same conclusion. This contradicted the notion of "neutrality seeking", as explained in **Chapter 2**, and has also been evidenced in previous studies with the general Australian population (Williamson et al., 1995). Saman et al. (2013), in a study with a cohort of the general South Australia population, and Bills (2019), on a study involving another cohort of older South-Australians, reported similar distributions between thermal sensations and preferences.

Table 5-5 - Cross-tabulation of thermal preference and thermal sensation vote count

Thermal sensation	Thermal preference			Total Count
	Prefer to be cooler (1)	**Prefer no change (2)**	**Prefer to be warmer (3)**	
Cold (-3)	0	1	116	117
Cool (-2)	6	270	403	679
Slightly cool (-1)	16	1446	1230	2692
Neutral (0)	53	5519	168	5740
Slightly warm (+1)	297	804	50	1151
Warm (+2)	126	215	15	356
Hot (+3)	51	1	0	52
Total Count	549	8256	1982	10787

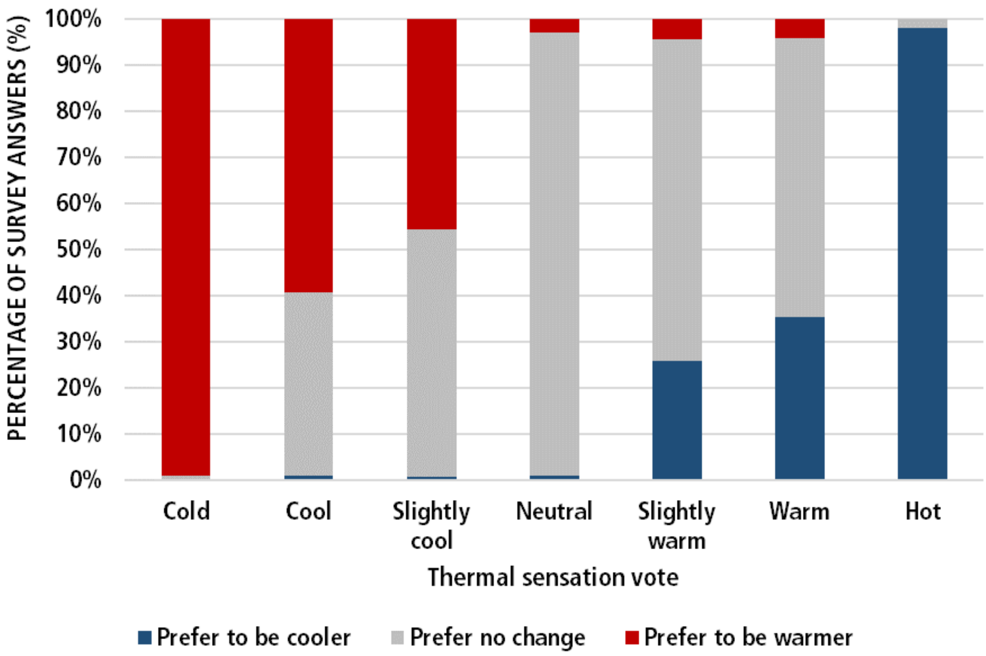

Figure 5-8 - Percentage of survey answers in each thermal sensation category for each thermal preference category

5.3.2. Second investigation: environmental factors, clothing level and corrected metabolic rate

With an overall understanding of the dwellings and participants involved in the monitoring study, as well as their general thermal sensations and preferences throughout the 9 months, the related environmental conditions, clothing levels and corrected metabolic rates were analysed and the results are presented in the subsections below.

Indoor temperatures

The hourly indoor operative temperatures recorded in the main living area and main bedroom of the houses, throughout the 9-month monitoring period, showed considerable variation among the houses. The recorded maximum and minimum hourly operative temperatures, per day, in each house, as well as the average among the houses, are shown in **Figure 5-9** and **Figure 5-10** for the three climate zones. The figures also highlight that the variation in maximum and minimum hourly operative temperatures among the monitored buildings was especially evident during colder periods of the year (from mid-May until mid-September). This reflects not only the external weather variations within climate zones, but also factors such as the occupants' behaviour, their use of heating appliances, as well as diverse aspects of the house design and construction details that influence the thermal environment.

Hourly operative temperatures reached as high as 40.71°C and hourly indoor temperatures reached as low as 5.01°C, when considering all houses. Extreme indoor operative temperatures, however, might indicate times when the houses were not occupied and, therefore, when heating or cooling was off or windows or blinds were shut or not operated.

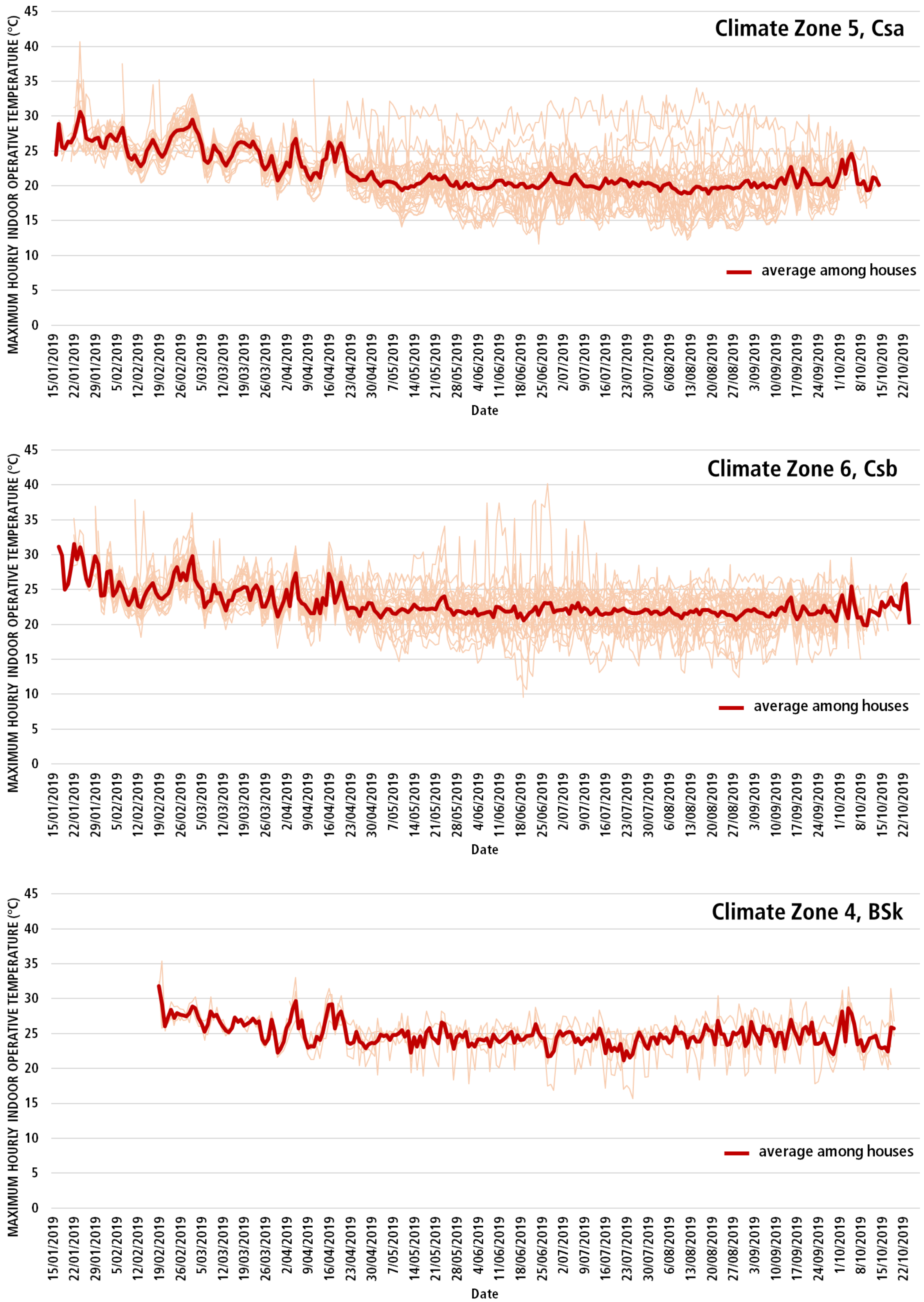

Figure 5-9 - Maximum hourly indoor operative temperatures, per day, for houses located in Climate 5 (Csa), Climate 6 (Csb) and Climate Zone 4 (BSk), thoughought the 9-month monitoring period

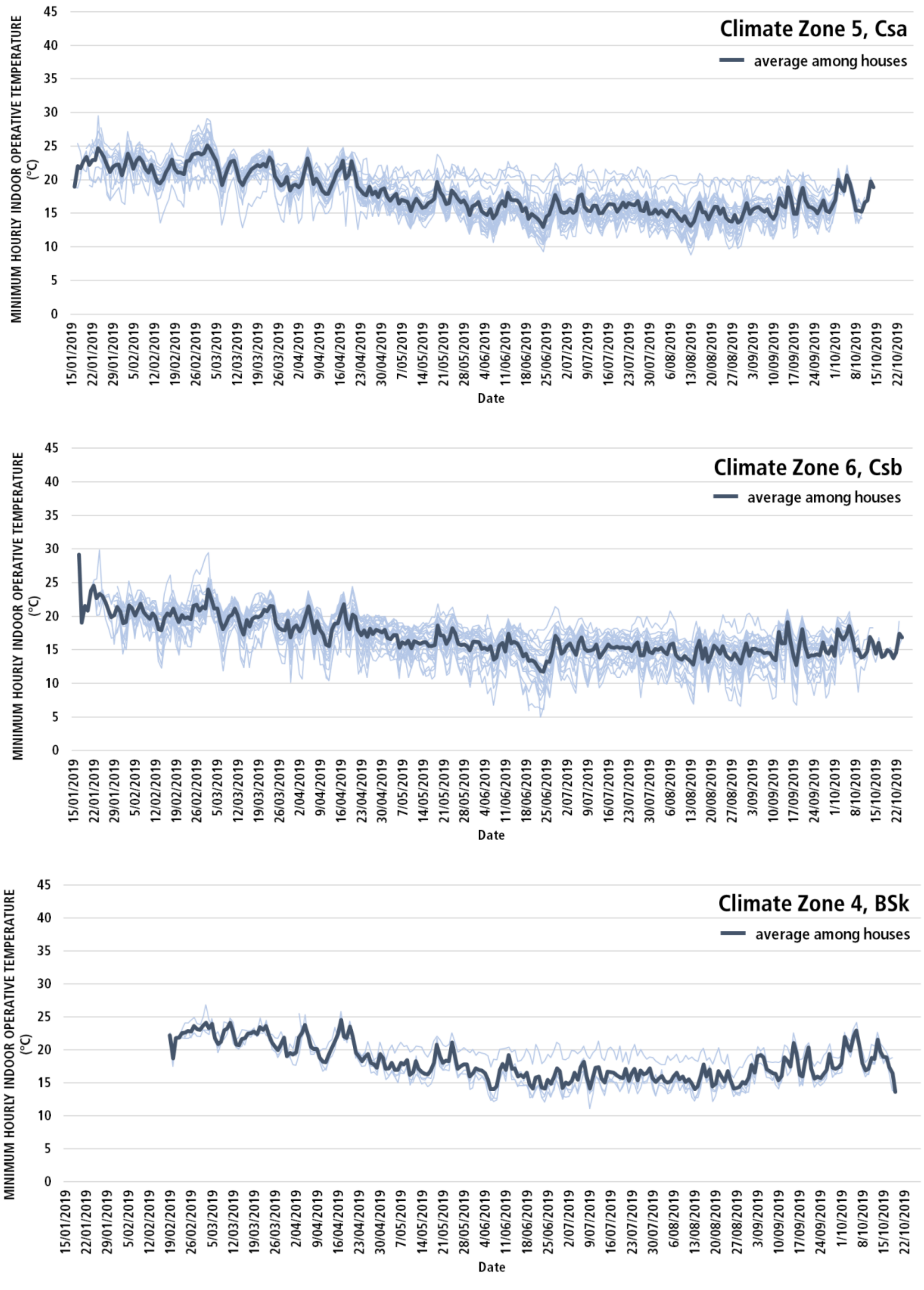

Figure 5-10 - Minimum hourly indoor operative temperatures, per day, for houses located in in Climate 5 (Csa), Climate 6 (Csb) and Climate Zone 4 (BSk), thoughought the 9-month monitoring period

The box plots presented in **Figure 5-11** emphasise the different thermal environments to which the participants might have been exposed during the monitoring study. The operative temperature spreads among the houses' plots show that while some houses (e.g., House 12) had narrow temperature variability and possibly more controlled environments, some others (e.g., Houses 9 or 18) had considerably more variable temperatures throughout the period. This reiterates differences in house design and house operations by participants. The box plots also show a slight skewness in some of the temperature distributions, such as the case of houses 41 and 42, where the medians and means are not aligned. In general, the plots also show that most of the outliers in the houses' indoor temperature distributions are located after the upper whisker limit (and not the lower whisker limit), which could indicate a tendency to find lower temperatures inside the majority of these houses. Outliers in this study are considered as datapoints located further than 1.5 times the interquartile range from each box end. Note that experimental measurement errors in the dataset had already been removed.

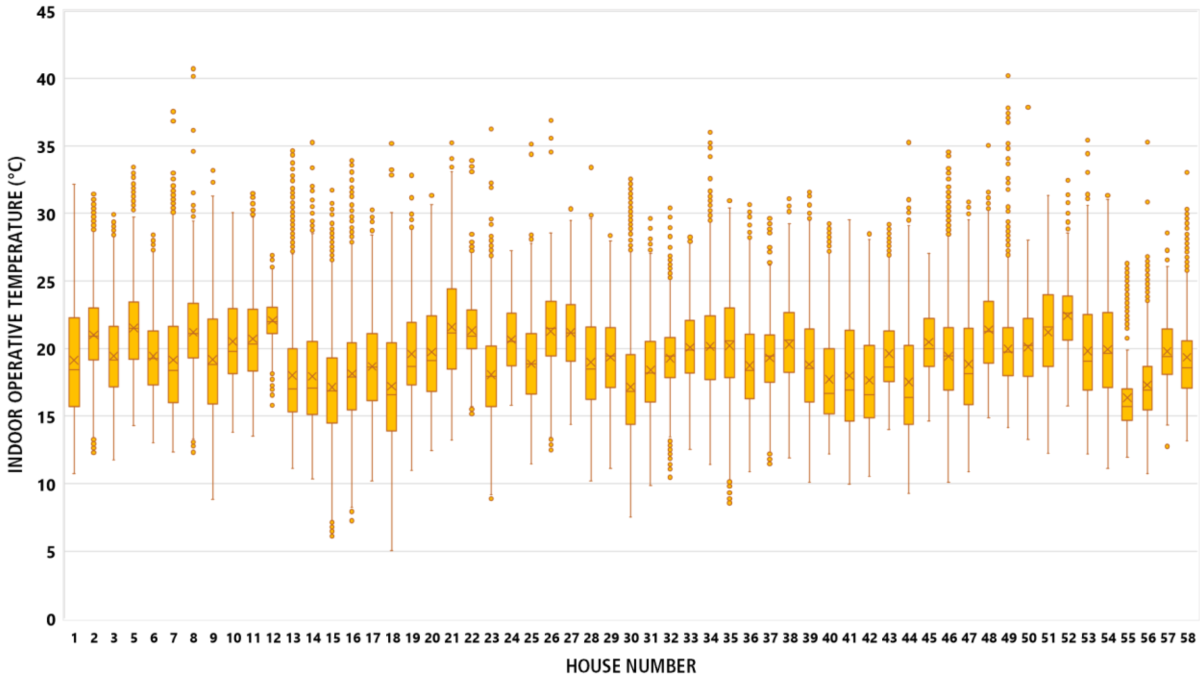

Figure 5-11 - Box plot of the hourly recorded indoor operative temperatures in each house throughout the monitoring period

When looking into participants' thermal sensation (TSV) and thermal preference (TPV) votes recorded from the point-in-time thermal comfort surveys, and the corresponding measured indoor temperatures, it is possible to observe strong correlations. **Figure 5-12** highlights the significant relationship between participants' TSV and TPV with operative temperatures. This was indicated by higher R-squared values (i.e., the coefficient of determination, indicating the percentage of the TSV and

TPV variance that the independent variable explains) of the weighted linear regression model, a statistically significant independent variable coefficient (i.e., regression coefficient B has $p < 0.05$) and a general visual indication in the raw data scatter plots. Although the variances (R-squared value) were inflated as a result of binning, they still serve as an indicator of comparison between models for exploratory analysis.

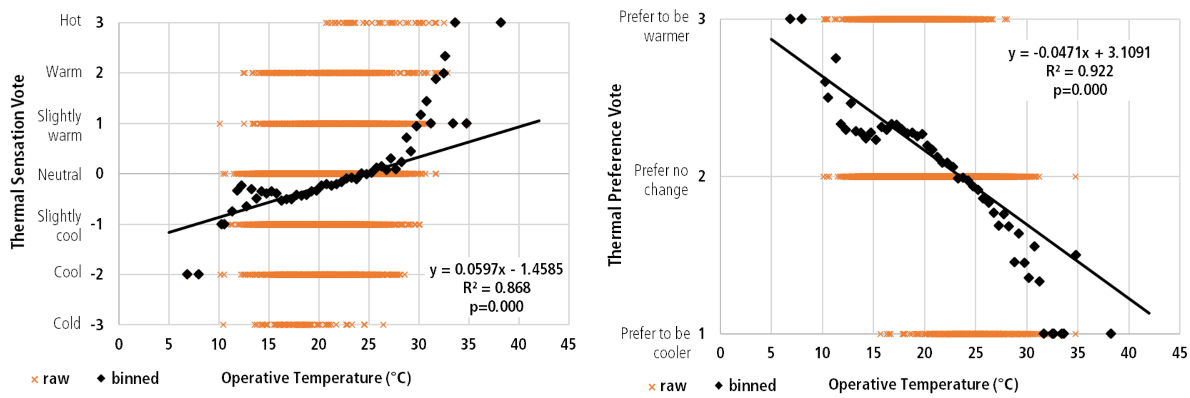

Figure 5-12 - Raw and binned correlations of operative temperatures for thermal sensantion votes (left) and thermal preference votes (right)

Solving the thermal sensation regression equation for a neutral sensation (y = 0) resulted in a "neutral indoor operative temperature" of 24.4°C for the older adults analysed. Separating the dataset for the hot/warm season (considered to be from January until March) and following the same regression procedure yielded a higher neutral sensation of 25.1°C. In contrast, the regression analysis on the dataset of the cool/cold season (considered from June to August) resulted in a lower neutral temperature of 23.5°C. This could indicate important seasonal adaptations from the cohort analysed.

Similar relationships are observed when exploring the TSV and TPV relationship with the dry-bulb temperature and mean radiant temperature. These variables, can, therefore, be considered good predictors for the thermal sensations and preferences of the older cohort analysed, and will be used for further analysis in **Chapters 6 and 7**.

Relative humidity

The hourly relative humidity recorded in the houses varied between 15.6% and 78.9%, with an average of 53.11% throughout the 9-month period, for houses located in climate zone 4 (BSk). For the ones located in climate zone 5 (Csa), the hourly relative humidity measurements were naturally slightly higher, varying between 19.6% and 90%, with an average of 57.17%. Likewise, houses located in climate zone 6 (Csb) recorded hourly relative humidity between 16.7% and 95.8%, with an average of 58.7%. Similar to the measured temperatures, the relative humidity measurements presented significant variations across the houses, indicating diverse combinations of house design, construction details, and operation.

Considering the relative humidity measurements taken when participants recorded the thermal sensation and preference votes, the data show significant correlations, although not as visually evident as the ones observed in the temperature analysis, as seen in **Figure 5-13**. While cooler sensations and preferences for warmer conditions tended to be perceived when the relative humidity increased, and vice-versa, a stronger influence of indoor temperatures is clear.

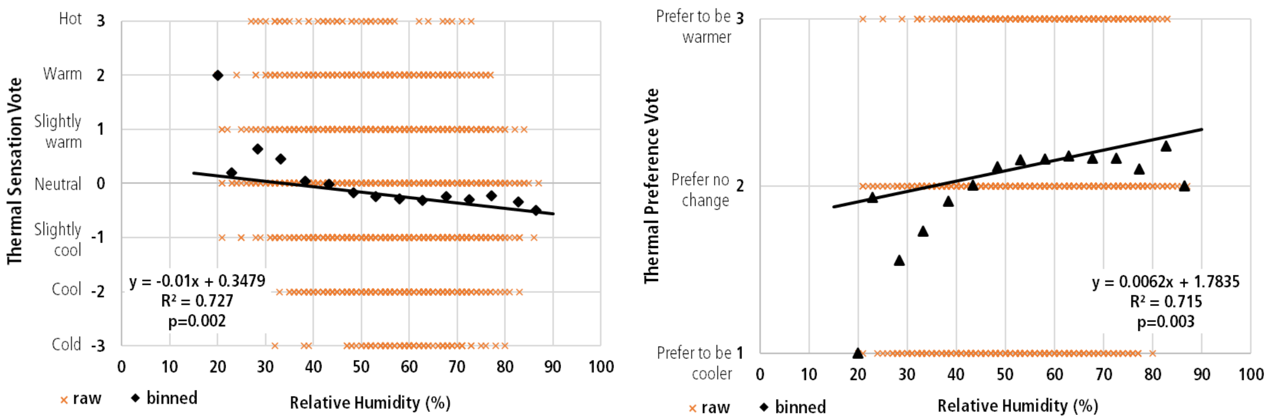

Figure 5-13 - Raw and binned correlations of relative humidity with thermal sensation votes (left) and thermal preference votes (right)

Air speed

Hourly air speed measurements throughout the monitoring period varied between 0.09 and 4.90 m/s in the houses, although air speeds higher than 2.5 m/s were considerably less frequently recorded (1.29% of the hourly measurements). High air speeds could be associated with the use of fans, the use of cooling and heating appliances or the opening of windows. When analysing participants' survey answers and corresponding air speed measurements, the Mann-Whitney U test showed that air speeds were significantly higher when fans were reported on, compared with when fans were reported off ($U = 2041091$, $p = 0.000$). The same test showed the same conclusion when heating ($U = 6745047$, $p = 0.0000$) or cooling ($U = 3389531$, $p = 0.000$) were on in comparison with off, or when windows were reported all opened in comparison with all closed ($U = 4132001$, $p = 0.000$).

Fitting a weighted linear regression model to participants' TSV and TPV against the air speed measurements presented statistically significant independent variable coefficients (i.e., $p < 0.05$). The correlation between the variables, however, is less strong than for the cases of indoor temperatures and relative humidity, indicated by lower R-squares (**Figure 5-14**). When considering the relationship between TPV and air speeds, **Figure 5-14** shows a tendency for preferring to be cooler with the increase of air speeds. This could mean that, instead of air speeds influencing the thermal preferences, air speeds were the result of said preferences and, therefore, an indication of participants' adaptive behaviours, such as the increase in air movement by using fans or opening windows. In other words, participants' air speeds were higher because participants preferred to be cooler and not the other way around (participants preferred to be cooler because air speeds were higher).

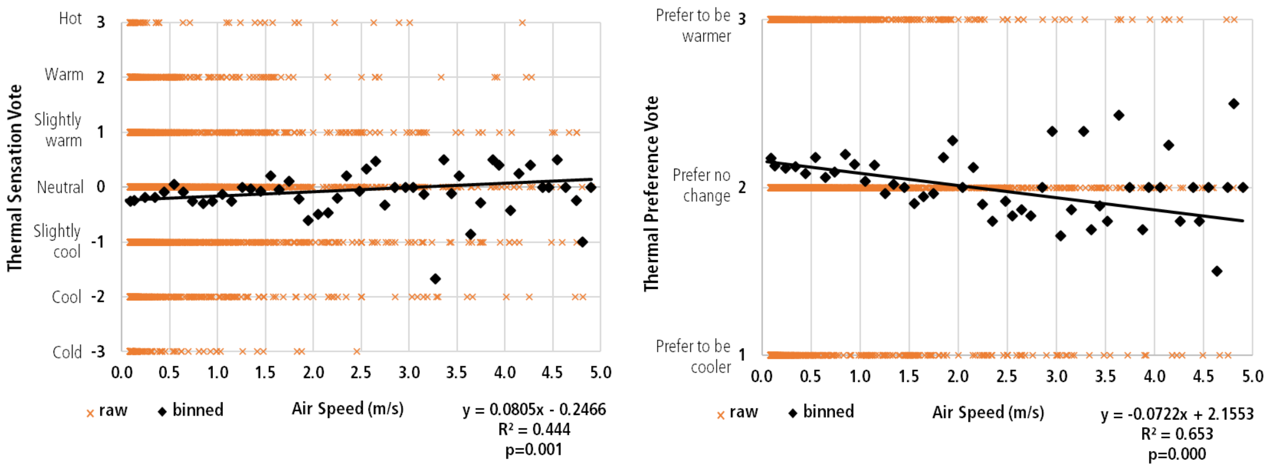

Figure 5-14 - Raw and binned correlation of air speeds with thermal sensation votes (left) and thermal preference votes (right)

Clothing

The clothing level reported by participants when answering the thermal comfort surveys varied throughout the entire scale (from 1 to 5) with an average of 2.86. Interestingly, the linear regression analysis (**Figure 5-15**) showed that cooler thermal sensations and a preference for wanting to be warmer were more sensitive to clothing than the opposite thermal sensations and preferences. This could indicate that changing clothing levels is a more common adaptive behaviour when a preference for being warmer is higher, than when a preference for being cooler is higher. Similarly, lighter clothing levels were not as common in lower thermal sensations (e.g., cold, cool, slightly cool) than higher clothing levels were in higher thermal sensations (e.g., hot, warm, slightly warm).

Figure 5-16 reiterates this conclusion. While heavier clothing was more frequently linked to cooler sensations, lighter clothing was more frequently matched with neutral sensations (and not warmer sensations). This is clear as the graphs in **Figure 5-16** are not visually symmetrical around the middle clothing level category. Likewise, most of the times that participants reported heavier clothing were linked to preferences to being warmer, but most of the times lighter clothing was associated with preferences for no change (and not a preference to be cooler).

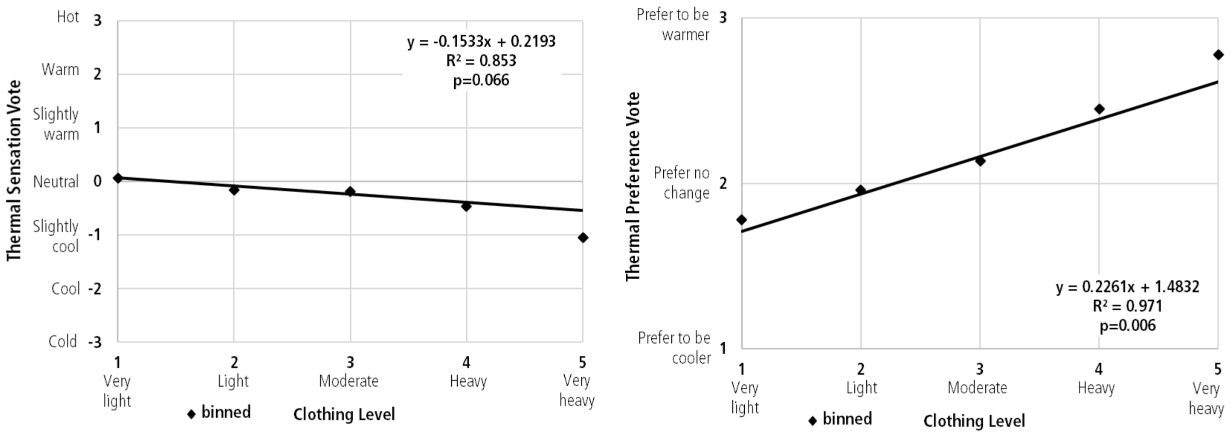

Figure 5-15 - Correlation of clothing levels with thermal sensation votes (left) and thermal preference votes (right)

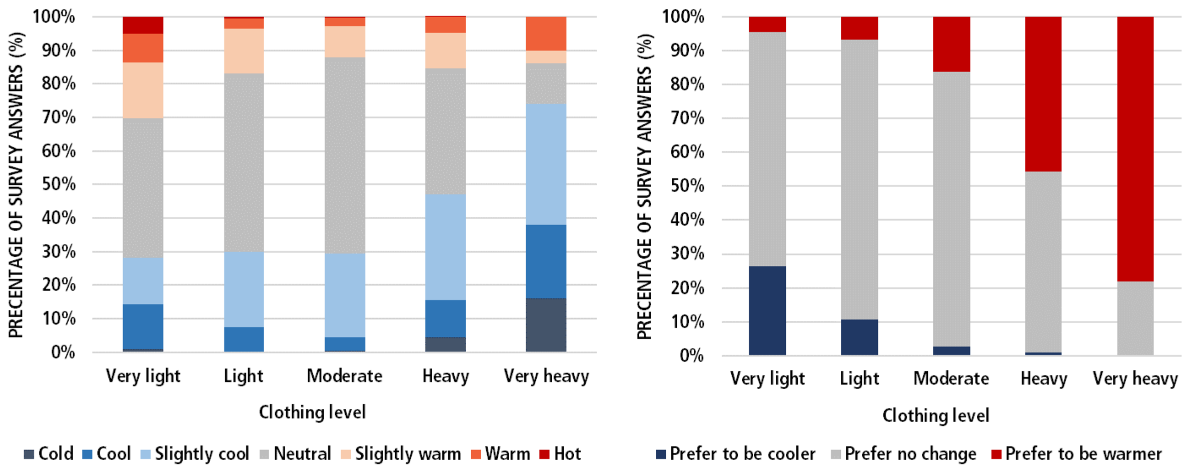

Figure 5-16 - Percentages of survey answers for each clothing level for each thermal sensation category (left) and for each thermal preference category (right)

This assumption was already partially indicated in **Figure 5-5** (in **Section 5.3.1** of this chapter), where changing clothing insulation was reported as the first action to keep warm by 68% of participants, but as the first action to keep cool by only 23% of them, in the initial questionnaire. Further insights into clothing levels were made evident once individual datasets (in the context of personal comfort models) were analysed and a discussion about these can be found in **Chapter 8**.

Corrected metabolic rates

Corrected metabolic rates related to the activity levels reported by participants throughout the surveys were not normally distributed, with lower corrected metabolic rates more frequent than higher corrected metabolic rates. They presented an average of 1.72 MET, a minimum of 0.66 MET and a maximum of 4.84 MET. This could indicate a tendency for a lower level of activity among the participants, as well as a combination of age, sex, body composition and activity levels that resulted in lower metabolic rates.

Although less than the environmental variables, the corrected metabolic rates showed correlations with TSV and TPV, as shown in **Figure 5-17**, with lower metabolic rates linked to cooler thermal sensations (and a preference to be warmer) and with higher metabolic rates corresponding to warmer thermal sensations (and a preference to be cooler).

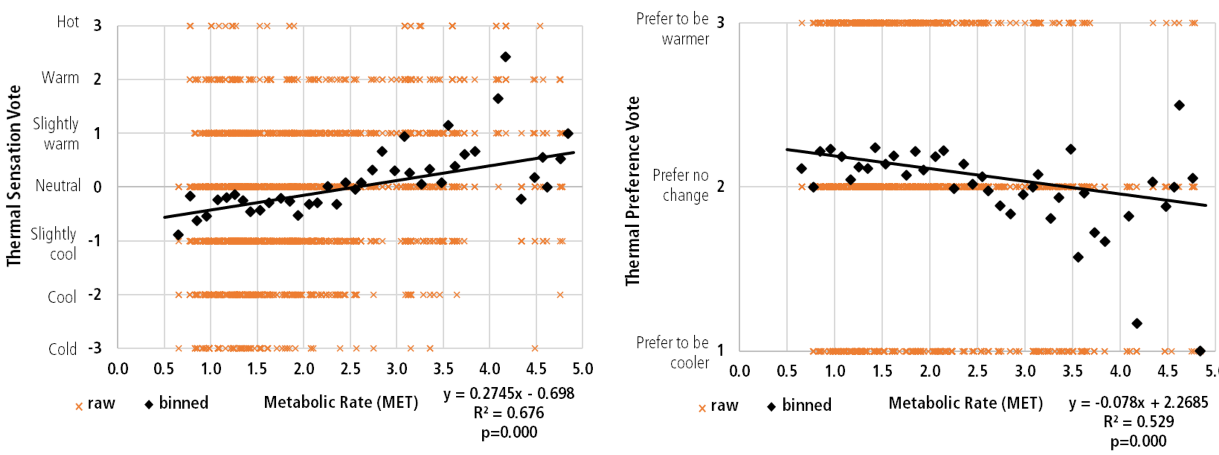

Figure 5-17 - Raw and binned correlation of corrected metabolic rates with thermal sensation votes (left) and thermal preference votes (right)

5.3.3. Third investigation: health/wellbeing perception

The third part of the investigation presented in this Chapter introduces health/wellbeing perception – a variable often overlooked in architectural sciences and building engineering research studies − as a potentially significant variable to be taken into consideration when understanding thermal sensation and preference of older adults.

Overall, the participants' point-in-time health/wellbeing perception answers throughout the 9-month monitoring period ranged from 1 to 5 (on the scale 1 = very good, 2 = good, 3 = reasonable, 4 = poor and 5 = very poor), with a mean of 2.25 (between good and reasonable). When analysing the binned health/wellbeing perception answered in relation to TSV, the data showed a tendency for poor health to be perceived in cooler sensations, although a statistical significance of the weighted linear regression coefficient was not observed. Likewise, participants' health was perceived as poorer with a thermal preference for being warmer, as shown in **Figure 5-18**.

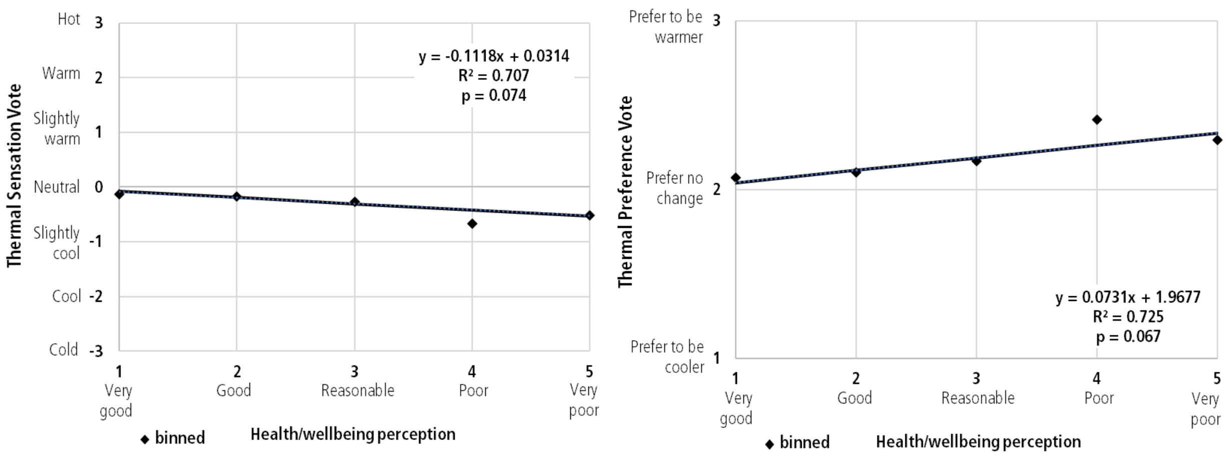

Figure 5-18 - Correlation of health/wellbeing perception with thermal sensation votes (left) and thermal preference votes (right)

This relationship can be seen **Figure 5-19**, which indicates the percentages of survey answers in each health/wellbeing perception for each thermal sensation category and for each thermal preference category. Thermal sensations for cold, cool and slightly cool were more frequent within the poor and very poor health/wellbeing perceptions. Similarly, preferences for warmer were more frequent with the poorer health/wellbeing perception answers.

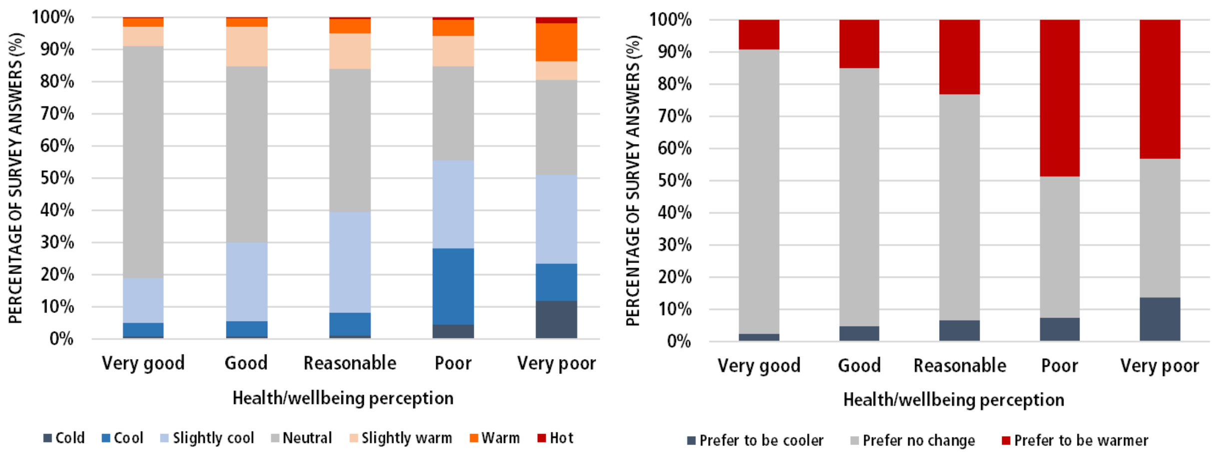

Figure 5-19 - Percentages of survey answers in each health/wellbeing perception for each thermal sensation category (left) and for each thermal preference category (right)

A strong correlation between indoor temperatures and health/wellbeing perception was also found through the analysis of this dataset, and the implications and details of this analysis have been published separately by Hansen et al. (2022).

5.3.4. Fourth investigation: skin temperatures

The last exploration conducted in this study, based on a separate dataset from the second data collection period, investigated the aggregate/generalised relationship between participants' back of the hand skin temperatures and their corresponding thermal sensation and preference votes.

From the 565 survey answers and environmental and skin temperature measurements derived from the 11 participants of the second monitoring period, the measurements errors, missing values, and evident outliers were removed, resulting in 470 valid datapoints. From these, the skin temperatures measured ranged from 22.10°C - 35.23°C, with a mean of 30.58°C among the participants. Note however, that this data collection was conducted only during warm/hot weather in South Australia, which might have resulted in a higher average than if a longer data collection had been conducted to include a cooler season. The limitations of this analysis are acknowledged in this chapter's limitations section.

As shown in **Figure 5-20**, the weighted linear regression analysis showed that cooler thermal sensations were associated with lower hand skin temperatures, and that warmer sensations corresponded with an increase in hand skin temperatures. Similarly, a preference to be warmer was associated with lower hand skin temperatures, while a preference to be cooler was related to higher skin temperatures. Further explorations on the general skin temperature dataset are presented in **Chapter 7**.

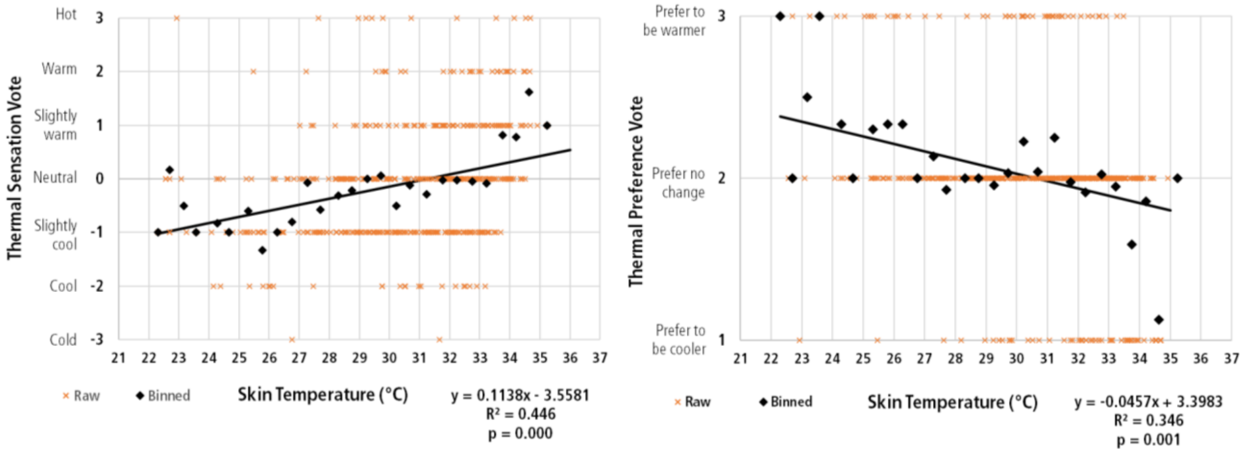

Figure 5-20 - Raw and binned correlation of skin temperatures with thermal sensation votes (left) and thermal preference votes (right). Note that the skin temperature is measured at the back of participants' non-dominant hand.

5.4. Discussion

Overall, the investigation of the participants and dwellings involved in the study yielded a number of new insights on the thermal conditions of the living environments of older adults and their corresponding thermal sensations, preferences and behaviours towards thermal adaptation.

5.4.1. First investigation

From the first part of the investigation, it became evident that the houses investigated had a certain homogeneity as a group, in terms of external wall, roof and floor construction. The age and size of the buildings, however, varied greatly, which could result in a considerable difference in the way the environments performed in terms of thermal comfort. In addition, the lack of wall insulation and external blinds/shading in half of the homes could lead to greater variations in indoor thermal conditions. Similar results have been found in a previous study involving telephone surveys about older adults' thermal environments involving 250 participants in South Australia (Soebarto et al., 2019a).

The study also confirmed the increasingly widespread use of heating and cooling devices in Australia, with all houses in the study having at least one mechanical device for either cooling or heating. In terms of types of air conditioning, the households in the study also presented reverse cycle air conditioning as the main system of cooling, which again is in line with the general Australian figures, as reported by the Australian Bureau of Statistics (2014).

When looking into participants' personal characteristics, although most of them were assessed as not frail, the body composition indicators showed great variability that could result in diverse health characteristics that could potentially influence thermal sensations and responses. Body fat percentages in the study, for instance, varied from 11 to 58%, while weight varied from 45 to 119kg. Although this study was not able to measure a direct association between these body indicators and thermal comfort responses, several studies have considered, among numerous aging-related physiological parameters, weight, height and body fat percentage as closely related to thermoregulation in older adults (Ma et al., 2017; Shibasaki et al., 2013; Tsuzuki and Ohfuku, 2002).

Participants' first action to keep cool in hot days or warm in cold days showed a variety of practices, although more varied actions were taken to keep cool in hot weather than to keep warm in cold weather. This range of actions was in line with a similar survey with older adults in South Australia by Hansen et al. (2015) (for hot weather) and Soebarto et al. (2019a) (for both kinds of weather). Nevertheless, while, in this study, increasing clothing level was the most frequent action taken by participants to keep warm in cold weather (68% of participants), in the study by Soebarto et al. (2019a) of a larger cohort, the first action taken by the respondents to keep warm was divided between turning on the heater (41%) and adjusting clothing level (40%). When analysing participants' first action to keep cool on hot days, the results of this study showed that adjusting clothing level (23% of respondents) and turning on cooling systems (20% of respondents) were the two most frequent actions taken by the cohort. Interestingly, Soebarto et al. (2019a) reported turning on the air-conditioner (32%), and closing indoor blinds and curtains during the day (23%) as the most frequent answers in this case, with adjusting clothing as only the 4th most answered option. Noticeably, changing clothing insulation was especially important as an adaptive behaviour for the cohort analysed in this study, and will be analysed in further detail in the subsequent chapters.

Considering the participants' overall thermal preference and sensation answers throughout the monitoring study, this investigation also highlighted that a preference for non-neutral thermal sensations is possible, and that low and high thermal sensation values do not always represent a state of discomfort for a relevant number of older adults. This indicates the need for careful consideration of the scales used for thermal comfort modelling, not only for younger adults, as highlighted in **Chapter 2**, but for older adults as well. Depending on the objectives of the models developed, thermal sensation might not be the ideal scale to guide actuation systems.

Furthermore, as already highlighted by Schweiker et al. (2018), several recent research studies have pointed to the health benefits resulting from experiencing dynamic thermal conditions beyond those temperature ranges regarded as neutral or comfortable (Lichtenbelt et al., 2014; Hanssen et al., 2016; Johnson et al., 2011). These studies have shown that the exposure to non-neutral thermal sensation could enhance thermoregulatory capabilities, which opens the field of thermal comfort to interesting new research opportunities. Nevertheless, further studies are needed to understand the links between these health benefits and dynamic thermal conditions in the context of older adults.

5.4.2. Second investigation

The second investigation presented in this study indicated that the six main variables traditionally used to explain and/or predict thermal sensation and preference for the general population were also significant in explaining the results for the participating cohort. The investigation also showed that the variables related to the thermal conditions of the dwellings analysed presented a wide range of variation among houses, probably related to differences in design, orientation, presence of insulation, use of shading/blinds, climatic variations within climate zones, or occupants' heating and cooling use behaviours. These differences in thermal performance among houses could indicate the need for a more granular analysis, either through the individual occupant-centric level or through clustering cases according to building types or occupant behaviour profiles.

The investigation into the neutral temperatures of the older adults analysed showed interesting differences when compared with similar studies. While the cohort in this study presented a neutral temperature of 24.4°C when considering data for the entire monitoring period (comprising both summer and winter months), a similar study with older South Australians by Bills (2019) reported an almost 2 K lower neutral temperature of 22.5°C. Similarly, when considering only the winter months, while this study yielded a 23.8°C neutral temperature, Bills (2019) reported a 19.4°C neutral temperature. The neutral temperatures for summer were also considerably different between studies: 25.1°C in this study and 22.0°C in the study by Bills (2019). Furthermore, when comparing the neutral temperature of this study for the summer period (i.e., 25.1°C) with the neutral temperature of younger adults in a study in Adelaide in summer months (i.e., 22.7°C) (Saman et al., 2013), a 2.4 K difference can be observed. This indicates that the older cohort, at the population level, tend to feel neutral at higher temperatures than younger populations. Similar observations were drawn from a study by Schellen (2012). In this work, during climate chamber sessions with a stable temperature condition (21.5°C) with both younger and older adults, the older group preferred a higher temperature, while the younger adults requested no change in temperature. Nevertheless, since these are aggregate analyses, individual differences could be masked under the averaged values and further investigation into individual thermal sensations and, more importantly, individual thermal preferences, is required.

5.4.3. Third investigation

Among the factors that might affect thermal comfort, health and wellbeing related parameters such as body composition, diseases or illness symptoms, physical disabilities and fitness status have been identified in many studies (Bluyssen, 2019; Schweiker et al., 2018; Wang et al., 2018; Zhang et al., 2001). Although they seem to be considered important factors explaining human thermal comfort responses and perceptions, health and wellbeing indicators are still rarely included as input variables in predictive modelling for architectural sciences or building engineering use. This might be a result of the difficulties in acquiring such data as varying point-in-time series, especially in long-term field studies. Therefore, the introduction of health/wellbeing perception in the surveys was a way found by this study to comprise an often-overlooked health-related personal factor that might affect how older people perceive their environments.

The previously-mentioned study by Bills (2019) analysed older South Australians' 256 thermal sensation votes that included reported health symptoms in the 24 hours before each vote was cast (e.g., headache, dizziness, tiredness, sleeplessness, joint pain). The study indicated an increase in symptoms at slightly warm to hot sensations, as well as at times of cool to cold sensations. The analysis, however, while interesting, focussed on the impact of thermal conditions and sensations on health conditions, instead of the effects of health conditions on thermal sensation, perception and/or preference. The study presented in this thesis, therefore, investigated the latter hypothesis, exploring the point-in-time health/wellbeing indicator as a possible predictor of thermal preference and sensation.

Although the general findings presented in this chapter showed that thermal sensations for cold, cool and slightly cool were more frequent when poor and very poor health/wellbeing were perceived, the relationships were not as statistically strong as hypothesised, and further analysis at the individual level might prove more beneficial, especially for individuals experiencing extremes in health conditions.

5.4.4. Fourth investigation

The fourth investigation present in this Chapter aimed at introducing a physiological indicator in the list of factors analysed as potential predictors of thermal sensation and preference. As expected, the results showed that cooler thermal sensations were associated with lower hand skin temperatures, and that warmer sensations corresponded with an increase in hand skin temperatures. Similarly, a preference to be warmer was associated with lower hand skin temperatures, while a preference to be cooler was related to higher hand skin temperatures. These results are in line with recent work on 22 older people's thermal sensations by Soebarto et al. (2019b), which showed significant correlations between thermal sensations and hand, neck, scapula and shin skin temperatures, with the highest correlation with thermal sensation being with the hand's skin temperatures. The mean hand skin temperatures among participants in the study varied depending on the environmental conditions and clothing levels whilst undergoing the experiment in a climate chamber, but remained similar to the average hand skin temperature measured in the present study (i.e., 30.58°C).

A study by Childs et al. (2020) with sixty-nine older adults, with and without dementia, living in residential care in the UK, in mean ambient temperatures of 21.4 to 26.6°C, revealed slightly higher hand skin temperatures: a mean finger-tip temperature of 30.9°C, wrist temperature of 31.9°C (the closest position to the one used in the current study) and a forearm temperature of 31.9°C. The study also observed that while older adults had lower mean skin temperatures and were in lower indoor temperatures than studies with younger adults in work environments, a comparable percentage of residents rated their thermal sensation as neutral, which might indicate a decline in thermosensitivity. Similarly, a tendency for lower thermal sensations and higher neutral temperatures than younger adults has been observed in the current study. The work of Childs et al. (2020) also highlighted how varied the thermal comfort responses of older people were, even under the same environmental temperature, which once again reinforces the need for more individualised analysis. In addition, a significant difference in thermal sensation votes was noted between residents with and without dementia, which confirms the need to analyse health-related indicators when understanding thermal comfort prediction.

The variations in skin temperatures reported in the current study could be related to several factors, including the environments' thermal conditions, participants' activity levels and metabolic rates when answering the surveys, or their clothing insulation level. These relationships, as well as the skin temperature relationships with thermal preferences at the individual level, were further explored and presented in **Chapter 7**.

5.5. Limitations

The current study presents the following limitations. Firstly, the older adults involved in this research chose to participate voluntarily, introducing a self-selection bias to the analysis. Secondly, despite the study including 3 different climate zones, it is still limited to a specific climatic context of older people in South Australia. Future research is required to advance knowledge of other scenarios and their related challenges. Likewise, although the older participants in this study represent a diverse cohort in terms of body composition, age, sex, health, frailty and living environment, other socio-cultural and economic factors that affect their thermal environments, as well as their thermal sensitivity and behaviour, still need to be addressed to build a more holistic image of their diversity.

Furthermore, the environmental conditions were measured at a single point in each participant's living area, which could mask relevant spatial temperature variations. A weighted average of multiple points could best represent the spaces; however, having multiple points of measurements in each of 57 houses was not possible in this research due to practical and resource constraints.

Moreover, given the nature of the study, only self-reported health/wellbeing perception was used, which might lack the accuracy of records from healthcare providers.

Finally, the data collection involving skin temperature was conducted between the months of September and February, covering only a warm and hot season in South Australia. Further data collection periods in cool and cold seasons are required to allow a broader understanding of the effects of thermal exposure in skin temperatures of older adults.

5.6. Summary

This chapter presented the results of field studies conducted to gather information about the thermal environments of older people's dwellings, as well as on this cohort's general thermal sensations, preferences, and behaviours throughout different seasons. Although the buildings analysed presented similarities as a group in terms of overall construction details, they also showed considerable differences in terms of age, size, design and operation. In addition, participants' personal characteristics also differed within the group, which could indicate the need for a more granular and individualised analysis.

Furthermore, the study confirmed the continuing use of environmental measures, such as indoor air temperature, relative humidity and air speeds, as important variables when explaining thermal sensations and preferences. Varying clothing levels and metabolic rates were also found to be relevant in the analysis of older people's thermal responses, and were identified as potential adaptive behaviours taken by participants in general to adjust thermal sensations and preferences.

Personal factors such as health and wellbeing perception were considered equally relevant for further analysis, although their relationships with the cohort's general thermal sensation and thermal preference were not as statistically strong as hypothesised. Finally, skin temperatures, as a representation of participants' physiological responses to thermal stimuli, are also found to be significant in explaining thermal sensations and preferences of older people.

In conclusion, the analyses presented in this chapter have provided a greater understanding of the overall thermal environments and preferences of the older adults included in this research. Drawing from the significant variables explored in this chapter, the next step will comprise investigating each older adults' dataset individually, through the lens of personal thermal comfort models.

Chapter 6. Personal thermal comfort models for older people using environmental, behavioural and health variables

Building on the insights drawn from the initial analysis of the datasets and potential thermal preference predictors presented in **Chapter 5**, this chapter explores the development of 28 personal thermal comfort models for a subset of older adults included in this research and assesses the models' performances compared with aggregate approaches. This chapter, along with **Chapter 7**, aims to answer research questions C and D:

C. How will the accuracy of personal thermal comfort models be affected by individuals' particular variables?

D. How can the use of personal thermal comfort models lead to a more accurate prediction of older people's thermal preferences, in comparison with the prediction by a generalised model such as PMV?

These questions are related to ***Objective (2)****: Develop personal thermal comfort models for older people from the data collected, considering their personal and behavioural characteristics as well as the conditions of their thermal environments, and compare the results with the predictions made by established models such as the PMV model*.

This chapter has been produced as a journal article, published as:

Arakawa Martins, L., Soebarto, V., Williamson, T., Pisaniello, D. (2021) "Personal thermal comfort models: a deep learning approach for predicting older people's thermal preference", Smart and Sustainable Built Environment, Vol. ahead-of-print, No. ahead-of-print, https://doi.org/10.1108/SASBE-08-2021-0144

The paper is presented here in a reformatted version for consistency of the thesis presentation. The accepted manuscript can be found in **Appendix A**.

Statement of Authorship

Title of Paper	Personal thermal comfort models: a deep learning approach for predicting older people's thermal preference
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Principal Author

Name of Principal Author (Candidate)	Larissa Arakawa Martins		
Contribution to the Paper	Study design and concept, data acquisition, data analysis and interpretation, manuscript preparation, manuscript editing, and corresponding author		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	24/02/2022

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

iv. the candidate's stated contribution to the publication is accurate (as detailed above);

v. permission is granted for the candidate in include the publication in the thesis; and

vi. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Veronica Soebarto		
Contribution to the Paper	Study design and concept, data acquisition, manuscript editing		
Signature		Date	24/2/2022

Name of Co-Author	Terence Williamson		
Contribution to the Paper	Study design and concept, data acquisition, manuscript editing		
Signature		Date	24/02/2022

Name of Co-Author	Dino Pisaniello		
Contribution to the Paper	Study design and concept, manuscript editing		
Signature		Date	24/02/2022

Personal thermal comfort models: a deep learning approach for predicting older people's thermal preference

Authors names and affiliations:

Larissa Arakawa Martins[a], Veronica Soebarto[a], Terence Williamson[a], Dino Pisaniello[b]

[a] School of Architecture and Built Environment, The University of Adelaide, South Australia, 5005, Australia
[b] School of Public Health, The University of Adelaide, South Australia, 5005, Australia

Structured Abstract

Purpose: This paper presents the development of personal thermal comfort models for older adults and assesses the models' performance compared to aggregate approaches. This is necessary as individual thermal preferences can vary widely between older adults, and the use of aggregate thermal comfort models can result in thermal dissatisfaction for a significant number of older occupants. Personalised thermal comfort models hold the promise of a more targeted and accurate approach.

Design/methodology/approach: Twenty-eight personal comfort models have been developed, using deep learning and environmental and personal parameters. The data were collected through a 9-month monitoring study of people aged 65 and over in South Australia, who lived independently. Modelling comprised dataset balancing and normalisation, followed by model tuning to test and select the best hyperparameters' sets. Finally, models were evaluated with an unseen dataset. Accuracy, Cohen's Kappa Coefficient and Area Under the Receiver Operating Characteristic Curve (AUC) were used to measure models' performance.

Findings: On average, the individualised models present an accuracy of 74%, a Cohen's Kappa Coefficient of 0.61 and an AUC of 0.83, representing a significant improvement in predictive performance when compared to similar studies and the 'Converted' Predicted Mean Vote (PMV_c) model.

Originality: While current literature on personal comfort models have focussed solely on younger adults and offices, this study explored a methodology for older people and their dwellings. Additionally, it introduced health perception as a predictor of thermal preference – a variable often overseen by architectural sciences and building engineering. The study also provided insights on the use of deep learning for future studies.

Keywords: personal comfort models; machine learning; thermal comfort; older people; health; personalised comfort

6.1. Introduction

International standards, such as ANSI/ASHRAE Standard 55 (ANSI/ASHRAE, 2020), adopt the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) model (Fanger, 1970) and the adaptive model (de Dear and Brager, 1998; Humphreys et al., 2016) as the bases to stablish the thermal requirements for human occupancy in the built environment. Both PMV/PPD and the adaptive models are aggregate models, which means they are designed to predict the average thermal comfort of groups of people. These models however have limitations when used to predict occupant's comfort in real case scenarios, as individual thermal sensations and preferences can vary significantly (Wang et al., 2018; Schweiker et al., 2018; Shipworth et al., 2016). Furthermore, these models' inability to be calibrated with new feedback or to incorporate new input variables (e.g., age, health status, body mass index) other than their pre-defined factors (Kim et al., 2018a) prevent them to be updated for different individuals. In addition, the models used in standards have been developed based on data from either climate chambers (Fanger, 1970) or field studies in office buildings (de Dear and Brager, 1998; Humphreys et al., 2016). This can also be limiting when considering the diversity of thermal conditions and adaptive opportunities residential settings generally provide in comparison to controlled office environments (Karjalainen, 2009).

To address these limitations, recent studies have shown an increasing number of strategies to develop personal thermal comfort models as an alternative to the conventional approaches (Kim et al., 2018a). Instead of an average response from a large population, personalised models are designed to predict individuals' thermal comfort responses, using a single person's direct feedback and/or personal characteristics as calibration inputs. This represents a relevant paradigm shift in the field today, replacing the centralised and fixed-set points approach with occupant-centric thermal conditioning management in the built environment (Wang et al., 2018). In addition, with the rapid development of Internet of Things (IoT) and smart sensors, predicting individual's needs directly from data collected in their everyday environment and acting upon these predictions has become substantially easier.

Significant advances have been made in the last decades in the personalised models' field, comprehending a plurality of approaches. A systematic literature review, conducted by the present authors, analysed 37 recent publications on personal thermal comfort models, emphasising current trends and future research directions in the field (Arakawa Martins et al., 2022a). The use of personal comfort systems (PCS), such as heated and cooled chairs or personal fans (Katić et al., 2020; Kim et al., 2018b; André et al., 2020), for instance, has been highlighted as a promising option for individual data collection, leveraging integrated data acquisition techniques that can potentially replace occupant survey feedback as proxy for thermal comfort. In addition, there is an increasing body of research focusing on personal comfort models driven by physiological variables, such as skin temperature or heart rate (Jung et al., 2019; Lee and Ham, 2020; Shan et al., 2020; Natarajan and Laftchiev, 2019).

The review (Arakawa Martins et al., 2022a) pointed to a vast variety of modelling approaches explored in the field, such as Bayesian classification and inference (Jung and Jazizadeh, 2019a; Auffenberg et al., 2018; Lee et al., 2019), Fuzzy Classification using the Wang-Wendel model (Pazhoohesh and Zhang, 2018; Aguilera et al., 2019; Jazizadeh et al., 2014b), and Machine Learning techniques. The latter includes more interpretable approaches such as Classification Trees (Aryal and Becerik-Gerber, 2020), or less transparent but relatively more accurate techniques such as Gaussian Process Classification (Guenther and Sawodny, 2019; Fay et al., 2017), Gradient Boosting Method (Lee and Ham, 2020), Support Vector Machine (Aryal and Becerik-Gerber, 2019; Jung et al., 2019; Jiang and Yao, 2016; Lu et al., 2019), Random Forest (Jayathissa et al., 2020; Aryal et al., 2021; Lu et al., 2019), K-Nearest Neighbours (Aryal and Becerik-Gerber, 2019; Aryal et al., 2021) and Artificial Neural Networks (Kim, 2018b; Shan et al., 2020). Artificial Neural Networks (ANN), specifically, have shown promising results. Kim (2018b) reported an average MSE (Mean Squared Error) of 0.00298 across 24 personal models' predictions, using ANN trained with environmental variables from an office setting. Similarly, Shan et al. (2020), on a study involving 3 people in offices, reported an average accuracy of 89.2%, an average MAE (Mean Absolute Error) of 0.16 and an average MSE of 0.06 across participants' ANNs trained using skin temperature measurements.

Nevertheless, although representing an important paradigm shift, studies on personal comfort models maintained the traditional trend to focus on office environments and younger adults. Studies on personal comfort models for older adults and dwellings are still absent in current literature (Arakawa Martins et al., 2022a). In addition, people with acute or chronic diseases or people with disabilities are not included in recent studies. These gaps in knowledge are especially relevant because, despite intragroup diversity being present in both younger and older cohorts, this heterogeneity tends to be greater in older than in younger ages. Older adults have been submitted to a greater range of cumulative social, economic and environmental factors across their individual life courses, which affect their health, needs and perceptions in significantly different ways (World Health Organization, 2015b). For this reason, understanding diversity in older age becomes crucial to target specific requirements more efficiently and support healthier and independent ageing.

In addition, previous studies have emphasised the importance of smart technologies to help older people live independently (Kimberly Miller, 2013; van Hoof et al., 2017b). In this context, personal thermal comfort models have the potential to be applied in automation systems for the control of windows, blinds, or air-conditioning, allowing older people to manage their environments with less reliance on others.

Hence, this chapter explores the development of personal comfort models, using real feedback as well as environmental and personal characteristics as input variables, to accurately respond to older adults' thermal needs in their own homes. In addition, this study aims to evaluate the modelling methodology proposed using deep learning as the engine behind the prediction of individual people's thermal preferences.

Focusing on South Australia, one of the Australian states with the largest proportion of people aged 65 years and over (Australian Bureau of Statistics, 2021b), data were first collected through environmental monitoring and thermal comfort surveys in dwellings of older people, excluding those who live in residential aged care facilities. Individual datasets were balanced and normalised and models were subsequently tuned by testing different hyperparameters combinations, which were subsequently selected according to their predictive performance. The models were then evaluated using an unseen testing dataset and compared with a 'converted' PMV model on the same testing datasets. Finally, recommendations for the application of the models in HVAC (Heating, Ventilation and Air Conditioning) systems' control, as well as in diagnostic tools for design and retrofitting and in a broader public health context were discussed.

6.2. Data collection

The sample for this study derived from a research project that monitored 71 participants (23 males and 48 females) aged 65 years and over from 57 households located in South Australia, in 3 climate zones: hot dry (*BSk*), warm temperate (*Csa*) and cool temperate (*Csb*), according to the *Köppen–Geiger Climate Classification System* (Beck et al., 2018). All older adults who participated in the first two stages of the research project (van Hoof et al., 2019; Soebarto et al., 2019a) were invited to participate voluntarily in the house monitoring stage and further volunteer recruitment was done through press releases in various media formats (e.g., radio and newspaper calls for volunteers). The inclusion criteria were participants who: (1) were 65 years old or over; (2) lived independently in the State of South Australia; and (3) were able to communicate in English. Data were collected during a period of 9 months, from mid-January to mid-October in 2019.

Each dwelling was visited at least twice. During the first visit, a questionnaire about sociodemographic information, health and overall thermal preferences was applied and an open-ended interview was conducted about buildings' details. In addition, indoor environment data loggers were installed in each dwelling's main living room and main bedroom. The indoor environment data logger contained sensors that measured air temperature, globe temperature, air speed, and relative humidity. The data logger coordinated measurements from the sensors, undertaken at 30-minute intervals and when a participant completed a comfort survey.

A thermal comfort survey tablet was also installed to be used by the participants to answer a survey about their thermal environment and their preferences and sensations at least once a week, throughout the 9-month period. The thermal comfort survey tablet allowed participants to complete surveys electronically about their clothing, activity levels, window and door state, heating, cooling, and fan state, as well as their thermal sensation (TSV) and thermal preference (TPV). Thermal sensation was assessed using the question 'How do you feel right now?' with possible responses being 'Cold', 'Cool', 'Slightly cool', 'Neutral', 'Slightly warm', 'Warm' or 'Hot'. Thermal preference was assessed using the question 'Would you prefer to be...' with possible responses being 'Cooler', 'No change' or 'Warmer'. The survey also included a question about their self-reported health and wellbeing perception at that point in time: 'How would you describe your health and wellbeing at the moment?', with possible answers being 'Very good', 'Good', 'Reasonable', 'Poor' and 'Very poor'. Participants were asked to answer the survey whenever possible, but no less than 2 times a week.

Figure 6-1 shows the data loggers and user interface used. More details on the data acquisition tool, including its applicability for studies with older users, have been reported by Soebarto et al. (2020).

Figure 6-1 - Indoor environmental data logger and thermal comfort survey tablet

During the second visit to each dwelling, conducted at the end of the monitoring period, an additional questionnaire was used to collect further information about the participants, including their frailty status according to the Modified Reported Edmonton Scale (Rose et al., 2018). Each participant's body composition was also assessed to measure height, weight and body mass index (BMI), using a Tanita Inner Scan RD-953 scale (Tanita Corporation, 2016).

6.3. Modelling methodology

6.3.1. Learning technique and task

This study applies artificial neural networks, also known as deep learning (Goodfellow et al., 2016), to develop personalised comfort models for a subset of the participants of the monitoring study. Deep learning is a class of machine learning technology, based on the representation-learning method (LeCun et al., 2015). It solves tasks such as classification, regression, and anomaly detection, by introducing multiple layers of representations, or features, expressed in terms of other simpler representations. By learning from previously seen data, this method avoids the need of a human engineer to formally specify these multiple layers of representations (Goodfellow et al., 2016).

The models' task is to specify to which of the k categories an example (or data point) belongs. In general terms, the model is shown an example and follows a set of mathematical expressions to produce an output in the form of a score (or probability) for each category. A function then measures the error between the outputs and the desired patterns of scores and the model modifies its internal parameters (or weights) to reduce the error. The model is then shown a never-before-seen set of data points and produces a new and final set of probability outputs.

In this study, the models were developed to perform a multiclass classification task of occupants' thermal preference (TPV) on a 3-point-scale (preferring to be cooler, preferring no change or preferring to be warmer), and according to seven environmental and personal input features. The survey's thermal TPV was used as the ground truth to train the models and later verify the predicted values. Instead of the thermal sensation vote (TSV) scale — which is commonly used in thermal comfort studies —, the TPV was used because it not only represents a measure of what ideal conditions would be for each person, but also suggests to which direction the change is desired, as already confirmed by Kim et al. (2018b). This is particularly relevant when considering the use of these models for the control of HVAC systems. In addition, using TPV rather than TSV avoids the assumption of associating comfort with neutral thermal sensation, which may not always be true (Humphreys and Hancock, 2007).

In this study, following common practices in computer sciences' studies (Kuhn and Johnson, 2013; Goodfellow et al., 2016; LeCun et al., 2015; Huang et al., 2019), the input variables are called 'features' and the thermal preferences classes corresponding to each of these combinations of input variables are called 'labels'. Anaconda version 2019.3 (Anaconda, 2019) was used as the platform to run all models using Python version 3.7 and PyTorch tensor library (Paszke et al., 2017).

6.3.2. Input features selected

Both environmental and personal variables were used as input features for the personalised models. In total, 7 input variables were used, 4 of which representing the environmental conditions of participant's rooms (i.e., dry bulb temperature, mean radiant temperature, relative humidity, and air speed) and 3 of which representing participant's personal characteristics (i.e., corrected metabolic rate, clothing level and health perception).

The corrected metabolic rate variable was calculated from participant's activity level answers in the survey. These were first converted to MET values according to the Compendium of Physical Activities (Ainsworth et al., 2011), and then later corrected based on participants' sex, height, weight and age, according to (Byrne et al., 2005) and (Kozey et al., 2010) studies. **Table 6-1** shows the activity level scale points and corresponding MET values.

These 7 variables were selected to cover a wide range of variables and factors known in the architectural science, medicine, and public health fields of study to influence thermal comfort, sensation, and preference. Each input feature's data collection tool and unit or scale is shown in **Table 6-1**.

A second round of models was also developed with the same datasets and variables, except for health perception, to check the relevance of health as a predictor of thermal comfort for each individual participant. Independent-measures t-test was used to evaluate if there is a significant difference between the results with and without health perception as an input variable.

It is important to note that personal characteristics such as height, weight, or health, although present in thermoregulation and physiology studies, are often overseen by architectural sciences and building systems engineering studies, hence the significance of their inclusion in the study.

Table 6-1 - Input features and units or scales

Type	Input features	Data collection tool	Unit or scale
Environmental	Dry Bulb Temperature	Thermometer in Data logger	°C
Environmental	Mean Radiant Temperature	Calculated from the dry bulb temperature, globe temperature and air speed measurements according to ISO:7726:1998 (ISO, 1998)	°C
Environmental	Relative Humidity	Hygrometer in Data logger	%
Environmental	Air Speed	Air speed sensor in Data logger	m/s
Personal	Corrected Metabolic Rate	Survey in Thermal Comfort Tablet – 'Describe your activity in the last 15 min in this space.'	Very relaxed activity = 1 MET Relaxed activity = 1.3 MET Light activity = 1.5 MET Moderate activity = 2.5 MET Active activity = 3.3 MET
Personal	Clothing	Survey in Thermal Comfort Tablet – 'How are you currently dressed?'	Very light = 1 Light = 2 Moderate = 3 Heavy = 4 Very heavy = 5
Personal	Health perception	Survey in Thermal Comfort Tablet – 'How would you describe your health and wellbeing at the moment?'	Very good = 1 Good = 2 Reasonable = 3 Poor = 4 Very poor = 5

6.3.3. Participant selection and characteristics

At the end the monitoring period, 10,787 survey votes were recorded from all 71 participants. Nonetheless, the classification task required that each participant voted at least 6 times in at least one of the three thermal preference classes, to allow a minimum of 5-fold cross-validation during model training, plus a minimum of 1 vote per category for testing. The cross-validation procedure is detailed in **Section**

6.3.5. Excluding the participants who did not meet this requirement resulted in 28 individual datasets selected for modelling.

It is important to highlight the level of diversity among participants selected, comprehending different older-age groups, weights, heights, health and frailty status, and climate zones of the dwelling locations, all of which can provide relevant insights on the influence of personal parameters in thermal response. **Table 6-2** presents each of the selected participants' personal characteristics.

Table 6-2 - Selected participants' personal characteristics, organised by ID number

ID[1]	Sex	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Frailty Score[2]	Climate Zone
1	F	71	157.0	78.9	31.9	Not Frail	*Csa*
2	M	86	179.5	86.4	26.8	Not Frail	*Csa*
3	F	79	156.5	64.6	26.4	Not Frail	*Csa*
4	F	81	163.0	58.2	21.9	Apparently vulnerable	*Csa*
5	F	79	161.0	97.6	37.6	Not Frail	*Csa*
6	M	76	175.5	88.5	28.7	Not Frail	*Csb*
7	F	76	149.5	75.1	33.6	Not Frail	*Csb*
8	M	82	174.0	89.9	29.7	Apparently vulnerable	*Csa*
10	F	86	151.0	110.4	48.4	Moderate Frailty	*BSk*
13	M	90	173.0	94.5	31.6	Not Frail	*Csb*
15	M	68	178.0	80.6	25.4	Not Frail	*BSk*
16	F	72	151.5	63.0	27.5	Not Frail	*Csb*
19	F	92	153.0	66.0	28.2	Not Frail	*Csb*
21	F	78	158.5	78.0	31.1	Not Frail	*Csb*
23	F	76	164.5	86.4	31.9	Apparently vulnerable	*Csb*
25	M	88	168.0	83.6	29.6	Not Frail	*Csb*
27	F	75-79[3]	[4]	[4]	[4]	Apparently vulnerable	*Csa*
32	F	82	145.0	64.0	30.4	Apparently vulnerable	*BSk*
33	M	80	171.5	109.1	37.1	Not Frail	*Csa*
35	M	73	160.0	119.0	46.5	Mild Frailty	*Csa*
36	F	74	160.5	95.4	37.0	Apparently vulnerable	*Csa*
38	F	82	166.0	71.9	26.1	Not Frail	*Csa*
40	M	86	175.0	85.9	28.0	Not Frail	*Csb*
42	F	75	156.5	75.9	31.0	Apparently vulnerable	*Csa*
46	F	66	166.5	117.0	42.2	Not Frail	*Csb*
50	F	81	162.0	60.0	22.8	Not Frail	*Csb*
51	F	72	150.5	64.6	28.5	Apparently vulnerable	*Csb*
62	F	76	158.0	85.5	34.2	Apparently vulnerable	Csa

[1] The IDs used in this chapter are the original used for the monitoring of the 71 participants.
[2] Assessed according to the Modified Reported Edmonton Scale (MRES) (Rose et al., 2018), on the scale 'Not frail', 'Apparently vulnerable', 'Mild frailty', 'Moderate frailty', 'Severe frailty'.
[3] Participant answered only her age group.
[4] Not assessed.

It should also be noted that the dwellings in this study represent a wide range of different construction typologies common in housing of older people in South Australia. These include double brick, brick veneer (also known as masonry veneer) or timber framed constructions (insulated and uninsulated); detached and semidetached layouts; 1 to more than 100 years old; and one or two stories high. Although building construction and design as well as natural ventilation and window orientation can have significant impacts on thermal preference, this correlation was out of the scope of this chapter and will be the subject of future publications.

6.3.4. Dataset balancing and pre-processing

The individual datasets exhibited unequal distributions between thermal preferences classes, as seen in **Figure 6-2**. Therefore, the datasets were randomly resampled to obtain classes with the exact same number of data points. This procedure, called undersampling, consisted of sizing all majority classes according to the size of the minority class, by removing examples from the dataset that belong to the majority class. Final individual dataset sizes can be seen in **Table 6-3**. Classes were also assigned a code from 0 to 2, where 0 corresponded to the 'preferring to be cooler' class, 1 the 'preferring no change' class and 2 the 'preferring to be warmer' class.

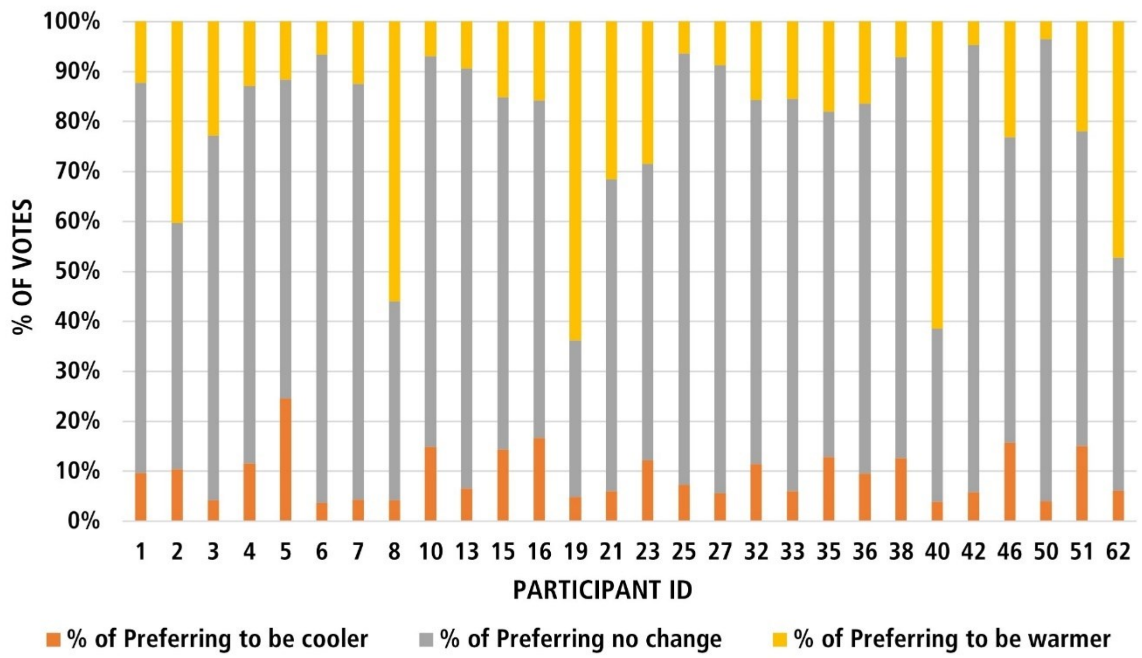

Figure 6-2 - Percentage of votes in each thermal preference class of each participant's original dataset

Finally, the input variables were normalised to a single range from 0 to 1, using min-max normalisation (Equation 1). The minimums and maximums used for normalisation are predefined and the same for all participants, to avoid information from the training sets to be leaked to the testing sets (i.e., data leakage). This created new values for the datapoints but maintained the general distribution and ratios in the original data, avoiding the negative influence of the different scales of each variable in the performance of the models.

$$x' = \frac{(x - \min)}{(\max - \min)} \qquad (16)$$

where x' is the normalised variable; $\min$ is the predefined minimum for the variable in question; and $\max$ is its predefined maximum.

6.3.5. Hyperparameters, model tuning, model selection and model evaluation

Deep learning algorithms have hyperparameters, which are settings used to control the model's behaviour and capacity. These settings cannot be directly estimated from the data and are not learned by the training process, but rather appropriately chosen by the model's developer while tuning different model options to select the best performing one.

To choose the best set of hyperparameters for a model, the first step was to divide the available dataset into three separate subsets, namely training set, validation set and test set. The training set is the subset of examples used for learning (i.e., fitting the internal coefficients or weights of the classifier). The validation set is the set of examples used to guide the selection of the hyperparameters of a classifier, a process also called model tuning. Lastly, the test set is an independent subset of examples used only to assess the performance of a fully trained classifier. The purpose of the test set is to simulate the model with data it has never seen before. This test performance is also called the generalisation performance (Ripley, 1996) .

These three subsets of data were split as follows. First, each participants' total datasets were randomly divided in two groups with at least 5 votes in each thermal preference class for training and at least 1 vote for each class for testing. The training set was then divided once again into two subsets to allow 5-fold cross validation, with at least 4 votes per class being used for the training set and at least 1 vote per class for the validation set. 5-fold cross-validation was chosen such that each train/validation group of data samples were large enough to be a representative of the total dataset, while small enough to allow modelling for participants with low vote counts. Cross-validation was repeated 5 times to reduce the noise in the estimated model performance between different cross validations splits. The subsets' splits were done in a stratified way, to maintain the balance of each subset, with the same number of data points for each classification category within the subsets.

Although deep learning algorithms have multiple hyperparameters to be tuned, this study selected 3 known to have a higher effect on the model's behaviour: (1) the learning rate of the optimisation algorithm, (2) the number of hidden neurons in the neural network and (3) the batch size of each iteration. The learning rate was varied from 0.001 to 0.01 to 0.1. The number of hidden neurons in the hidden layer of the model was varied between 4, 5 and 6. Lastly, the batch size varied between 2 and 8 data points. The varying ranges of the hyperparameters tuned were chosen according to common practice in computer science studies (Kuhn and Johnson, 2013; Goodfellow et al., 2016; Huang et al., 2019).

Considering the low complexity of task undertaken by the neural network, the number of the hidden layers in the models was kept to minimal of 1. Therefore, a feedforward neural network was implemented including an input layer, a hidden layer, and an output layer. In order to go from one layer to the sequential one, the neurons compute a weighted sum of their inputs from the previous layer (Equations 2 and 4) and pass the result through a non-linear function, called activation function (LeCun et al., 2015). The models in this study used Rectified Linear Unit (ReLU) (Agarap, 2018) as the activation function between the input layer and the hidden layer (Equation 3) and Softmax as the activation function between the hidden layer and the output layer (Equation 5). The mathematical expressions of the models can be written in the following form:

$$z_j = \sum_{i=1}^{7} w_{ij} \cdot x_i + b_j \quad (17)$$

$$y_j = f(z_j) = \max(0, z_j) \quad (18)$$

$$z_k = \sum_{j=1}^{N_J} w_{jk} \cdot y_j + b_k \quad (19)$$

$$f(\vec{z})_k = \frac{e^{z_k}}{\sum_{o=1}^{3} e^{z_o}} \quad (20)$$

where x_i are the normalised data of the input variables, w_{ij} are the weights between the input and hidden neurons, b_j are the bias values of the hidden neurons, and y_j the output values of the activation functions (ReLU) in the hidden layer; while w_{jk} are the weights between the hidden and output neurons, b_k are the bias values of the output neurons, N_J is the number of hidden neurons, and $f(\vec{z})_k$ are the outputs of the activation functions (Softmax) in the output layer.

Cross Entropy function was used to measure the loss (L_{CE}) – or error – of the classification rounds (Equation 6) and Stochastic Gradient Descent was used as the optimiser algorithm that aims to minimise the loss, with a learning momentum at 0.9. More details on the full optimiser algorithm can be found in Goodfellow et al. (2016).

$$L_{CE} = -\sum_{k=1}^{3} t_k \log f(\vec{z})_k \quad (21)$$

where t_k is the ground truth label, and $f(\vec{z})_k$ is the probability for the k^{th} class.

Figure 6-3 represents a simplified diagram of the neural network described.

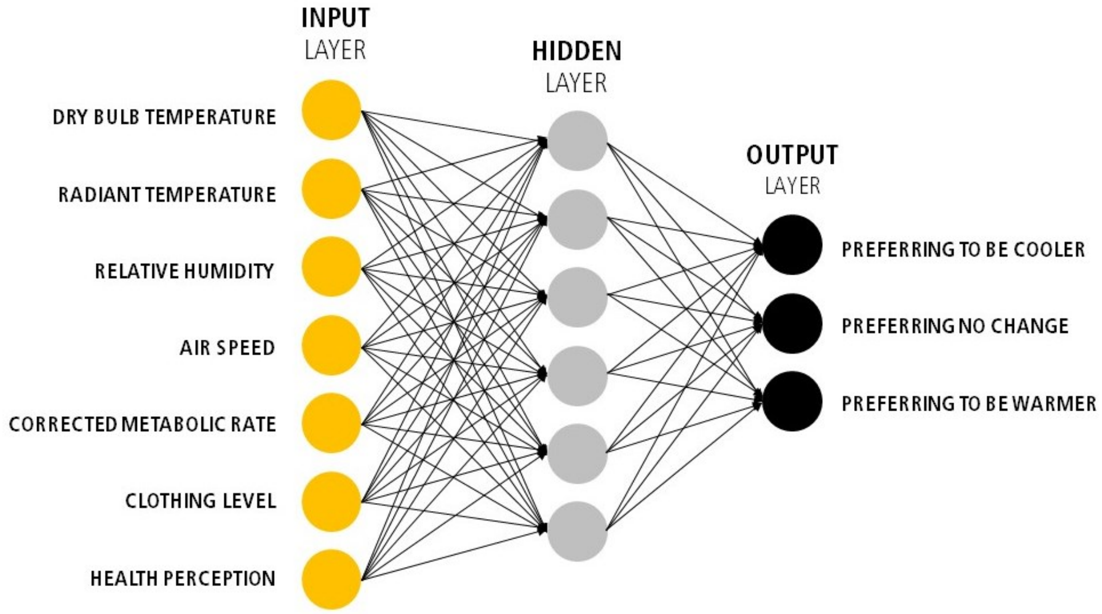

Figure 6-3 - Simplified diagram of the neural network used

The following steps, based on the framework detailed by Raschka (2018) and represented in **Figure 6-4**, were used for the model tuning, selection and evaluation process of this study.

- Step 1: Each participant's total dataset was divided into three subsets, a training set for model fitting, a validation set for model selection, and a test set for model evaluation.
- Step 2 (model tuning): The learning algorithm was then used for different hyperparameter settings to fit models to the training dataset.
- Step 3 (model selection): These models' performances were evaluated using the validation set. The performance estimates were then compared, and the hyperparameters settings associated with the best model performance were chosen. Each participant's best performing model and hyperparameters can differ between each other, depending on individuals' data sizes, personal patterns, and data quality.
- Step 4: To increase the dataset and enhance the models' performance, training and validation sets were then merged into one dataset and the best hyperparameter settings from the previous step were used to fit a new model to this larger dataset.

- Step 5 (model evaluation): Finally, the independent test set was used to estimate the generalisation performance of the model resulted from step 4.
- Step 6: The final model could then be trained with the use of all the dataset. This final step was not performed in this study because the main objective was to test the model selection and evaluation rather than preparing for model deployment.

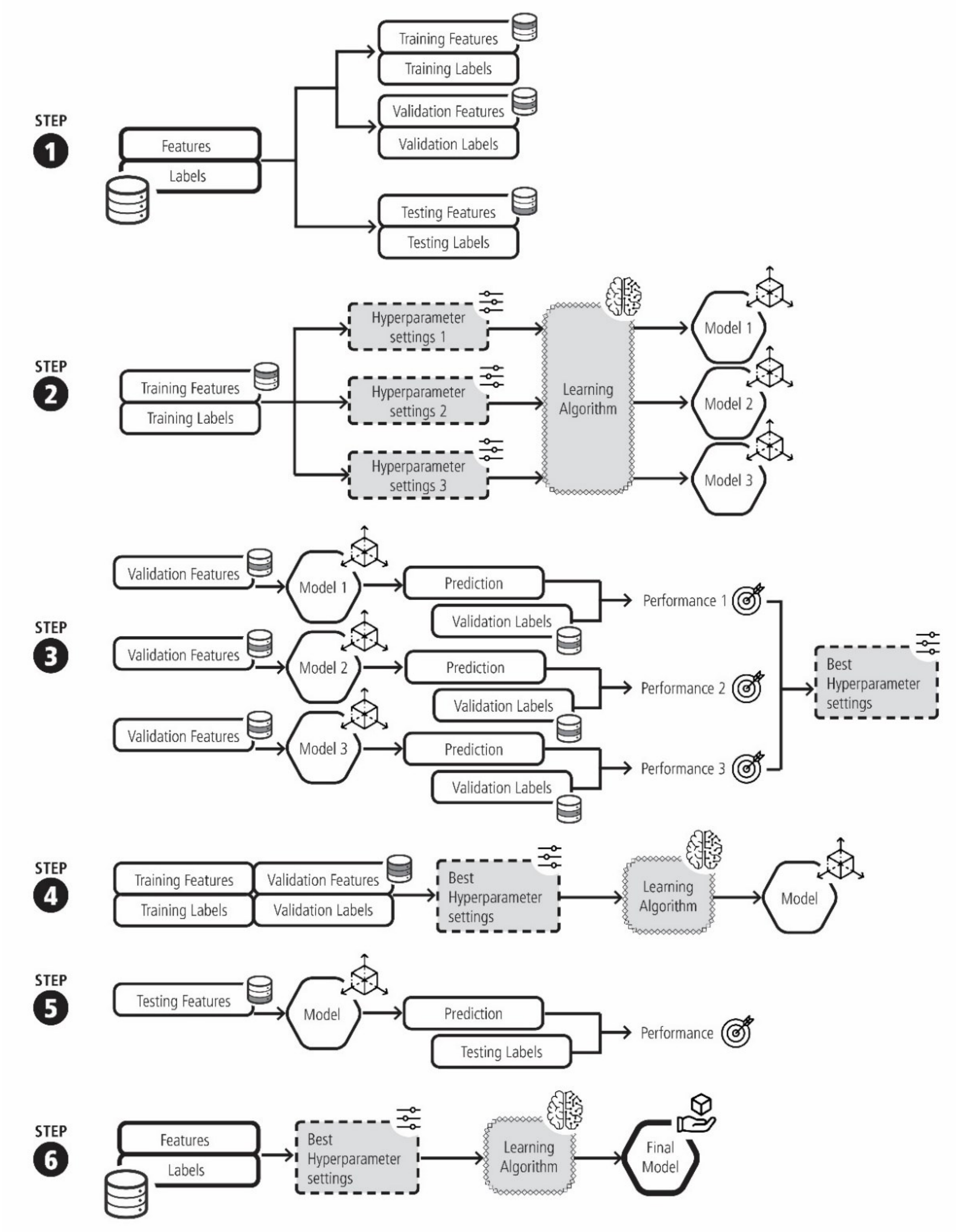

Figure 6-4 - Model tuning, selection, and evaluation process

6.3.6. Performance indicators

The performance indicators used in steps 3 and 5 of the modelling methodologies were the Accuracy, the Cohen's Kappa Coefficient, and the Area Under the Receiver Operating Characteristic Curve (AUC).

Accuracy was calculated as the percentage of correct predictions in relation to the total number of predictions. The Cohen's Kappa Coefficient (K) (Cohen, 1960) is a measure of reliability for two classifiers that are rating the same thing, corrected to exclude the frequency in which the classifiers may agree by random chance. It is defined by Equation 7:

$$\text{K} = \frac{(\mathrm{p}_o - \mathrm{p}_e)}{(1 - \mathrm{p}_e)} \quad (22)$$

where p_o is the relative agreement among classifiers, which is the same as the accuracy measure, and p_e is the hypothetical probability of a chance agreement.

The Cohen's Kappa Coefficient ranges from negative values to 1, where 1 means perfect agreement, 0 means no agreement among the classifiers other than what would be expected by chance, and negative values mean the agreement is worse than random. According to Cohen (1960), a Cohen's Kappa of 0.41 - 0.60 can be considered a moderate agreement between prediction and ground truth, 0.61 - 0.80 as substantial, and 0.81 - 1.00 as a perfect agreement.

The AUC is a measure frequently used in machine learning studies (Ben-David, 2008). First, the Receiver Operating Characteristic Curve (ROC) was built by plotting the probability of true positive rate (i.e., 'successes', also called sensitivity or recall) versus the probability of false positive rate (i.e., 'false alarms', also called fall-out) for all possible discrimination thresholds, for each of the three thermal preference classes using the 'one versus the rest' method. Equations 8 and 9 define true positive rate (TPR) and false positive rate (FPR):

$$TPR = \frac{TP}{TP+FN} \quad (23)$$

$$FPR = \frac{FP}{FP+TN} \quad (24)$$

where TP (true positive) is the number of positive class correctly predicted in a binary classification model; FP (false positive) is the number of positive class incorrectly predicted; TN (true negative) is the number of negative class correctly predicted; and FN (false negative) is the number of negative class incorrectly predicted.

Finally, the area under the ROC was computed for each of the classes and averaged to obtain a single numeric performance indicator of the thermal preference model. AUC can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement.

6.3.7. PMV scale conversion for comparison

PMV was calculated according to ANSI/ASHRAE (2020), using the environmental parameters measured during the field study and the corresponding clothing and metabolic rate according to participants survey answers. As the PMV uses a 7-point scale to predict thermal sensation, the results were converted into 3 thermal preference categories to enable a comparison, in the same scale, with the personal comfort models developed in this study. Therefore, when the PMV model predicted values between 0.5 and −0.5 (i.e., normally considered a 'neutral' sensation), the votes were labelled as 'no change'; when PMV > 0.5 (i.e., 'slightly warm', 'warm' and 'hot'), the votes were labelled as 'preferring to be cooler'; and when PMV < -0.5 (i.e., 'slightly cool', 'cool', 'cold'), the votes were labelled as 'preferring to be warmer'. These cut-offs were chosen to represent the recommended limits for a 10% Predicted Percentage of Dissatisfied (PPD). This conversion of the PMV model is referred in this chapter as 'Converted PMV' or PMV_C. The AUC of the PMV_C was calculated using a single pair of probability of true positive rate versus probability of false positive rate, since the model is not a probabilistic classifier and does not allow plotting different discrimination thresholds.

6.4. Results and discussion

Table 6-3 presents a summary of the performance of each selected participant's models in predicting thermal preference with and without the use of health perception as an input variable. The Accuracy, Cohen's Kappa Coefficient and AUC shown in the table correspond to the model evaluation step (i.e., step 5 in **Figure 6-4**) and represent the generalisation performance of the personalised models when using the merged training and validation sets for learning, and the 'never-before-seen' test set for assessment.

Table 6-3 - Performance of personal comfort models (PCM) and Converted Predicted Mean Vote (PMV_C)

	Dataset size		PMV_C			PCM without Health Perception			PCM with Health Perception		
ID[1]	Original	Balanced	Accuracy	Cohen's Kappa	AUC	Accuracy	Cohen's Kappa	AUC	Accuracy	Cohen's Kappa	AUC
1	114	30	53.33	0.30	0.65	73.33	0.60	0.89	73.33	0.60	0.94
2	77	24	55.56	0.33	0.67	66.67	0.50	0.73	66.67	0.50	0.84
3	189	24	55.56	0.33	0.67	66.67	0.50	0.83	77.78	0.67	0.89
4	78	27	58.33	0.38	0.69	83.33	0.75	0.82	75.00	0.63	0.86
5	215	75	46.67	0.20	0.60	60.00	0.40	0.64	60.00	0.40	0.67
6	242	27	58.33	0.38	0.69	58.33	0.38	0.76	91.67	0.88	0.92
7	274	30	46.67	0.20	0.60	66.67	0.50	0.91	66.67	0.50	0.83
8	234	30	40.00	0.10	0.55	66.67	0.50	0.78	80.00	0.70	0.91
10	101	21	33.33	0.00	0.50	33.33	0.00	0.50	33.33	0.00	0.50
13	107	21	50.00	0.25	0.63	100.0	1.00	1.00	100.00	1.00	1.00
15	139	60	73.33	0.60	0.80	80.00	0.70	0.94	73.33	0.60	0.97
16	108	51	66.67	0.50	0.75	76.19	0.64	0.85	61.90	0.43	0.81
19	185	27	41.67	0.13	0.56	75.00	0.63	0.90	75.00	0.63	0.80
21	149	27	58.33	0.38	0.69	66.67	0.50	0.66	66.67	0.50	0.80
23	204	75	46.67	0.20	0.60	86.67	0.80	0.91	86.67	0.80	0.91
25	190	30	40.00	0.10	0.55	46.67	0.20	0.65	46.67	0.20	0.51
27	196	30	26.67	-0.10	0.45	46.67	0.20	0.70	46.67	0.20	0.58
32	218	75	46.67	0.20	0.60	100.00	1.00	1.00	100.00	1.00	1.00
33	181	30	46.67	0.20	0.60	73.33	0.60	0.84	73.33	0.60	0.88
35	117	45	46.67	0.20	0.60	86.67	0.80	0.90	86.67	0.80	0.93
36	73	21	50.00	0.25	0.63	100.00	1.00	1.00	100.00	1.00	1.00
38	182	39	66.67	0.50	0.75	66.67	0.50	0.73	66.67	0.50	0.76
40	153	18	66.67	0.50	0.75	100.00	1.00	1.00	100.00	1.00	1.00
42	172	24	11.11	-0.33	0.33	66.67	0.50	0.78	66.67	0.50	0.69
46	285	135	60.00	0.40	0.70	66.67	0.50	0.74	76.67	0.65	0.86
50	174	18	33.33	0.00	0.50	100.00	1.00	1.00	100.00	1.00	1.00
51	146	66	47.62	0.21	0.61	71.43	0.57	0.83	61.90	0.43	0.78
62	163	30	60.00	0.40	0.70	66.67	0.50	0.76	66.67	0.50	0.75
Average			**49.52**	**0.24**	**0.62**	**72.87**	**0.59**	**0.82**	**73.98**	**0.61**	**0.83**

[1] The IDs used in this chapter are the original used for the monitoring of the 71 participants.

The generalisation accuracy of the personal comfort models (with health perception) ranges from 33.33 to 100%, with a mean of 73.98%; the Cohen's Kappa indicator ranges from 0.0 to 1.0, with a mean of 0.61; and the AUC ranges from 0.5 to 1.0, with a mean of 0.83. Although not optimal when considering individual performances of models such as ID 10 (33.33% accuracy, 0.0 Cohen's Kappa, 0.5 AUC), the personal comfort models developed still show an overall improvement in performance when compared to other similar studies in the field. Liu et al. (2019), for instance, reported an average Cohen's Kappa of 0.24 when analysing personal comfort models of 14 younger adults using different algorithms and input feature sets, in both indoor and outdoor environments. Likewise, Kim et al. (2018b) reported a median

AUC of 0.73, when considering the best performing algorithm from each of the 34 individual models developed for younger adults.

Table 6-3 also provides the prediction results of the PMV_C model for each of the selected participants. On average, PMV_C predicted individual preferences with an accuracy of 49.52%, a Cohen's Kappa indicator of 0.24, and an AUC of 0.62 (i.e., slightly better than random guessing). In comparison, on average, the personal comfort models' accuracy is 49% higher, the Cohen's Kappa Coefficient is 151% higher and the AUC is 34% than the respective PMV_C model's indicators. This shows a significant improvement in the predictive performance of the personalised models when compared to PMV_C model.

Additionally, the results suggest that the models' generalisation performance may vary among participants, even after individual hyperparameter tuning. ID 32, for instance, reached the highest predictive performance with an accuracy of 100%, and a Cohen's Kappa and an AUC of 1.0. ID 5, on the other hand, only reached an accuracy of 60%, a Cohen's Kappa of 0.4 and an AUC of 0.67, even after multiple rounds hyperparameter tuning. Likewise, ID 10 represents a personal comfort model with considerably low performance and that was not able to provide any improvement when compared to the PMV_C model. The poor performance of models such as these might have been a result of a low sample size for training, the presence of anomalous data points, or the absence of input features that might also be influencing this person's thermal preference. Furthermore, when considering diverse individuals such as older people, it is expected that these other intrinsic characteristics play different roles for each person in different intensities and frequencies. In addition, as pointed out by Liu et al. (2019) and Katić et al. (2020), it is reasonable to expect that some individuals might be harder to predict than others.

Figure 6-5 presents a visual representation of the confusion matrices of the personal comfort models (using health perception) for each of the participants selected. Each row of the matrices represents the true thermal preference votes in each class (i.e., participants' survey answers), while each column represents the corresponding predictions. Not only do the matrices allow the visualisation of the overall performance of the models, but they also indicate the models' performance in predicting each individual class. They are the basis for the calculation of the Cohen's Kappa Coefficient and the AUC. Models such as ID 13, 32, 36, 40 and 50, for instance, clearly show a perfect agreement between the ground truth and the predictions, with classes predicted equally correct, and consequently identified as darker colours in the main diagonal of the confusion matrices. ID 21's confusion matrix, in contrast, shows that this model was better at predicting classes 0 (i.e., preferring to be cooler) and 2 (i.e., preferring to be warmer) than class 1 (i.e., preferring no change). On the other hand, ID 42's model, although having the same accuracy as ID 21's model, predicts class 2 (i.e., preferring to be warmer) better than classes 0 (i.e., preferring to be cooler) and 1 (i.e., preferring no change).

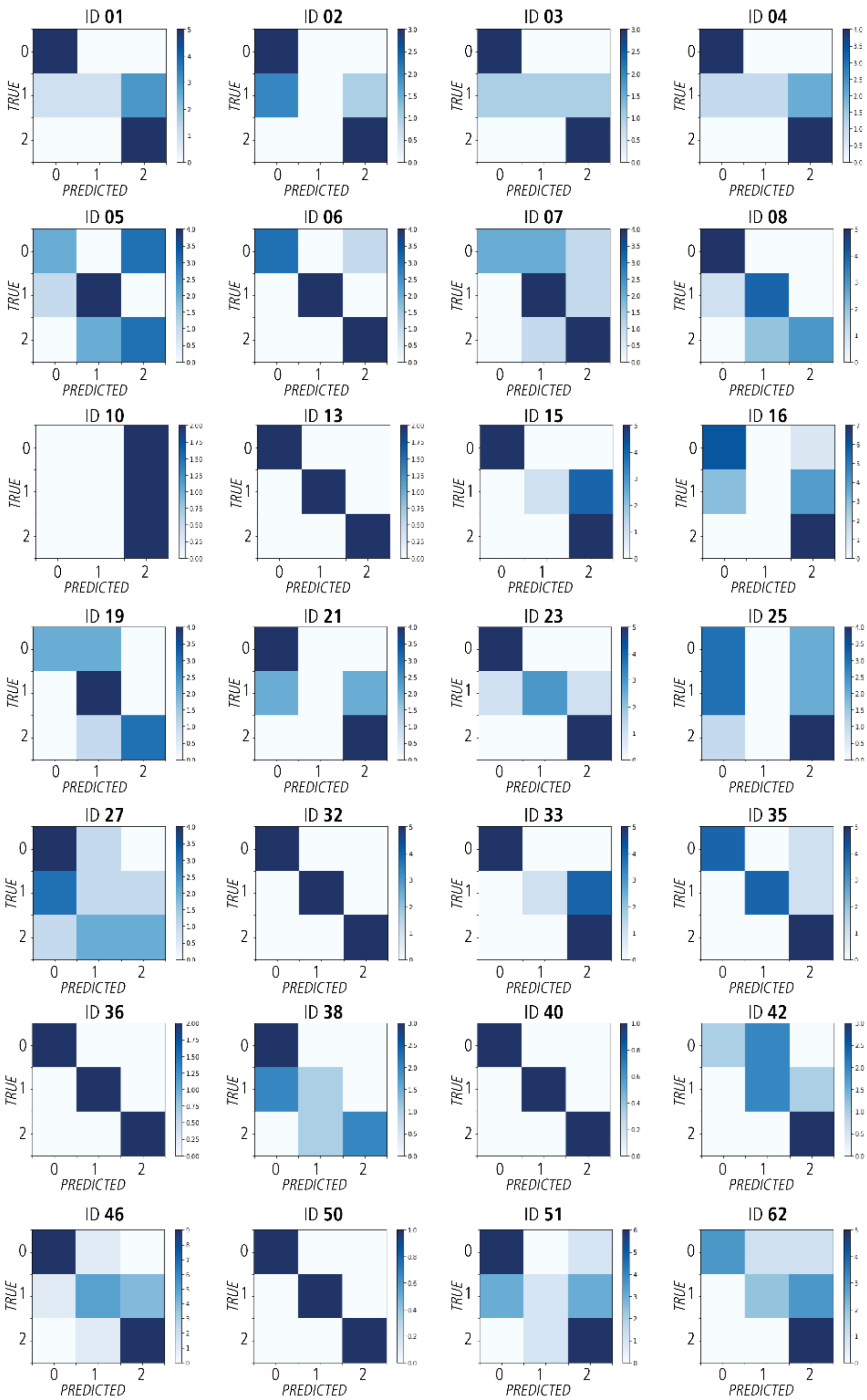

Figure 6-5 - Confusion matrix for PCMs with health perception, where 0 = preferring to be cooler, 1 = preferring no change, and 2 = preferring to be warmer

The Receiver Operating Curves (ROC) and respective Areas Under the Curve (AUC) can also help the visualisation of models' performance in predicting each individual class. **Figure 6-6** shows the ROC curve of each class, plotted using the 'one versus the other' method, for ID 46's model (using health perception). As seen in the curves, and confirmed by the confusion matrix, this model is slightly better at predicting 'preferring to be cooler' and 'preferring to be warmer' categories than 'preferring no change'.

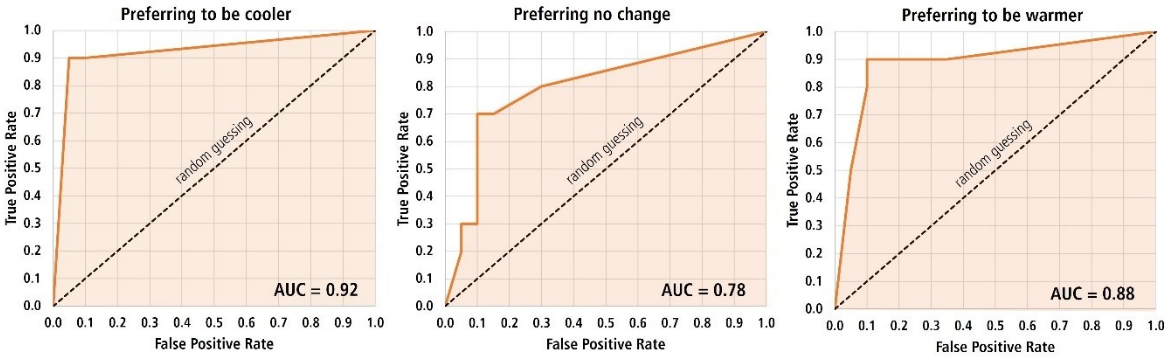

Figure 6-6 - Area Under the Receiver Operating Characteristic Curves of model for ID 46 (with health perception), for each thermal preference class, plotted using 'one versus the rest' method

The confusion matrixes are equally relevant to visualise and analyse the cost of misclassification. In the case of thermal preference models, where the classes represent ordinal intensities, classifying a 'preferring to be warmer' as a 'preferring to be cooler' (and vice-versa) is more problematic than classifying a 'preferring no change' as 'preferring to be cooler´ or 'preferring to be warmer' (and vice-versa). ID 5 and 42 are examples of models that have similar performance indicators but have different misclassification patterns that might incur different costs when deploying the model. While ID 42 incorrectly classifies 'preferring to be cooler' as 'preferring no change', ID 5 misclassifies it as 'preferring to be warmer'. If both models were deployed in real scenarios for automatic heating and cooling control, for instance, ID 5 would have her system activated in the opposite direction of the change expected, incurring higher energy use and lower comfort levels than ID 42's system, which would similarly not meet its demand, but would not cause higher energy use than it should either. Although not addressed in depth this study, the misclassification cost of personal thermal comfort categories is a relevant topic in the field and an interesting area for future research.

The lower performance of the models can also be explained by examining the model training and testing procedures. Overfitting, for instance, can be identified in some of the individual models. Observing the training learning curves of these models, which represent the training and testing loss by epoch (i.e., the number of passes of the entire dataset through the model), the gap between the training loss and the testing loss was significantly large in some cases. This means that the model has learned the training dataset too well, including errors in the data and possible statistical noise. As a result, the fit obtained was not able to produce accurate estimates on new observations that were not part of the original training dataset (James et al., 2013). **Figure 6-7** exemplifies this hypothesis. When observing the learning curve from ID 5 − who yielded a 60% accuracy, 0.4 Cohen's Kappa and an AUC of 0.67 −, the gap between the training and testing loss is vastly larger compared to ID 35's model − who reached an 86.67% accuracy, 0.8 Cohen's Kappa and a 0.93 AUC. Possible reasons for overfitting could be related to the small data size, the input features used, or the cross-validation procedure applied. Moreover, overfitting might be a result of using a test set that does not represent well the entire dataset. Although strategies for preventing overfitting were used in this study, such as early stopping, these models would still benefit from further explorations.

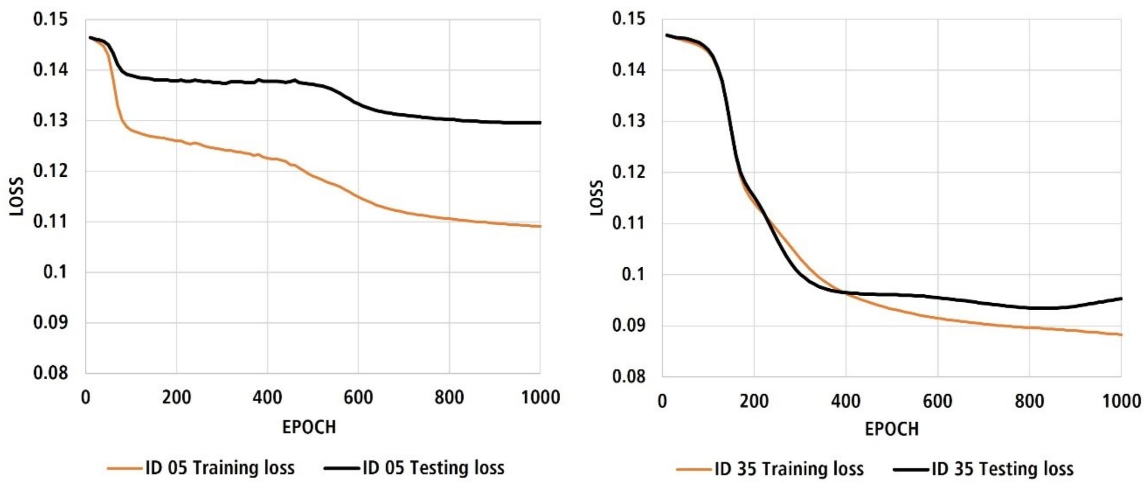

Figure 6-7 - Training learning curves for ID 5 and for ID 35

Furthermore, **Table 6-3** presents the performance of the models developed without health perception as one of the input variables. On average, the performance of models without the use of health perception as a predictor was slightly lower than the performance of the ones using this predictor. The difference between the two groups of results, however, was not statistically significant (i.e., $p > 0.05$) according to the independent-measures t-test.

Nevertheless, when examining individual models' results, it is still worth analysing the examples of models that performed better without the health perception indicator, such as ID 7, 16, 19, 25, 27, 42 and 51 are, as presented in **Figure 6-8**. In most of these cases, this could be a result of the low variability of the health perception input, which remained between 'good' and 'reasonable' regardless of the thermal preference or the other input variables. In other cases, where variability in health perception was indeed present, such as for ID 19, a possible cause for a lower performance might be the absence of clear correlation between health perception and thermal preference, as indicated by ID 19's box plots in **Figure 6-9**.

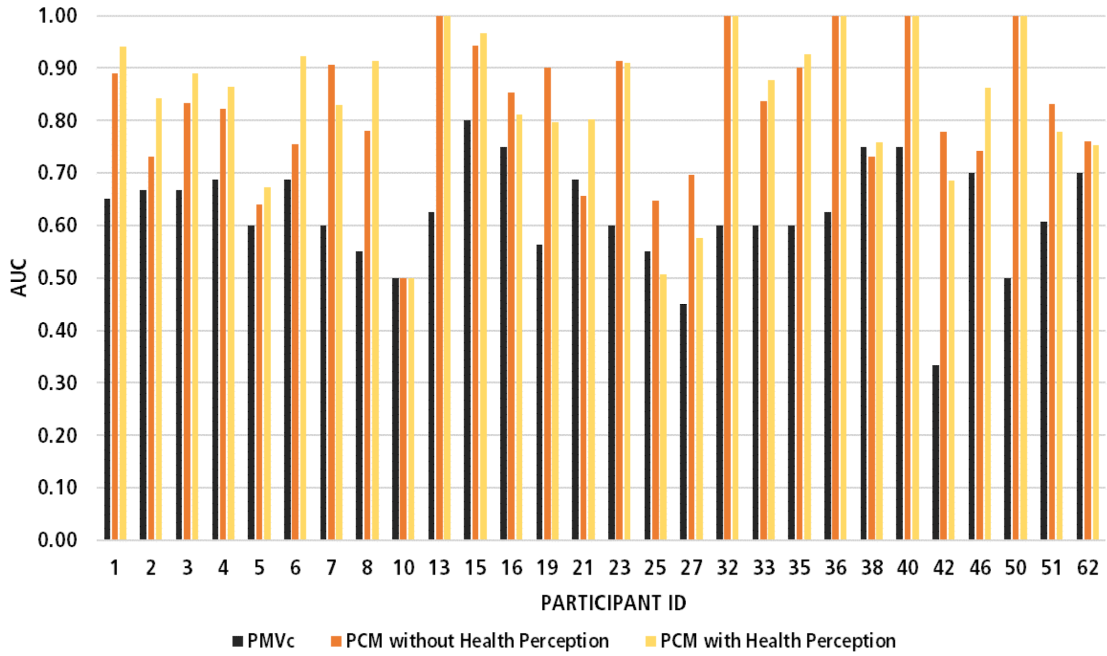

Figure 6-8 - AUC of PMV_C and PCM with and without health perception as one of the input variables

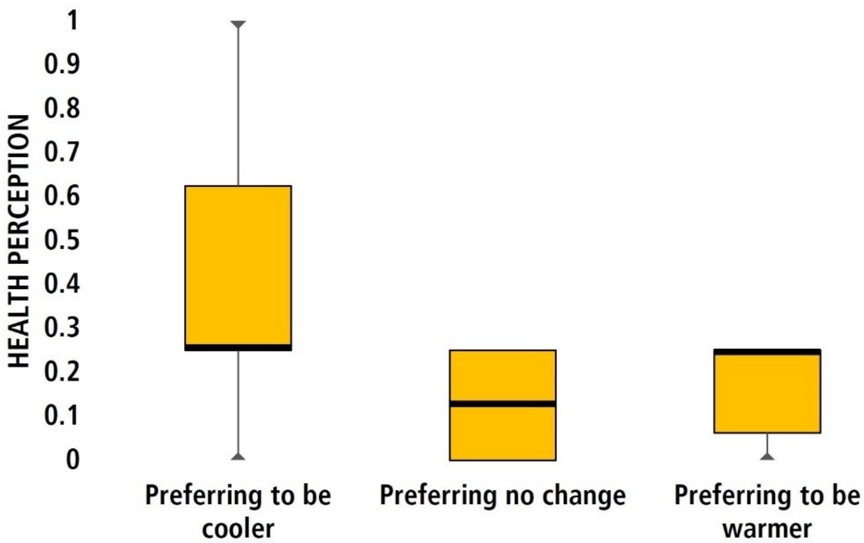

Figure 6-9 - Box plot of the health perception variable (normalised from 0 to 1, where 0 = 'very good' and 1 = 'very poor') according to the thermal preference classes, for ID 19

Similarly, **Figure 6-10** can indicate possible reasons why adding health perception as one of the input variables for ID 19 did not allow higher predictive performance to the personalised model. The figure shows the probability density of the distributions of the thermal preference classes depending on the seven input variables used, built using Kernel Density Estimation (KDE) (Zielinski et al., 2018). The overlapping areas of the three thermal preference classes could indicate that ID 19 is likely to prefer different thermal conditions while having the same health perception. This is also more evident for air speed and metabolic rate for ID 19. It is possible to imply, therefore, that adding these variables as predictors of thermal preference might not be ideal for this person and could potentially compromise models' predictive performance.

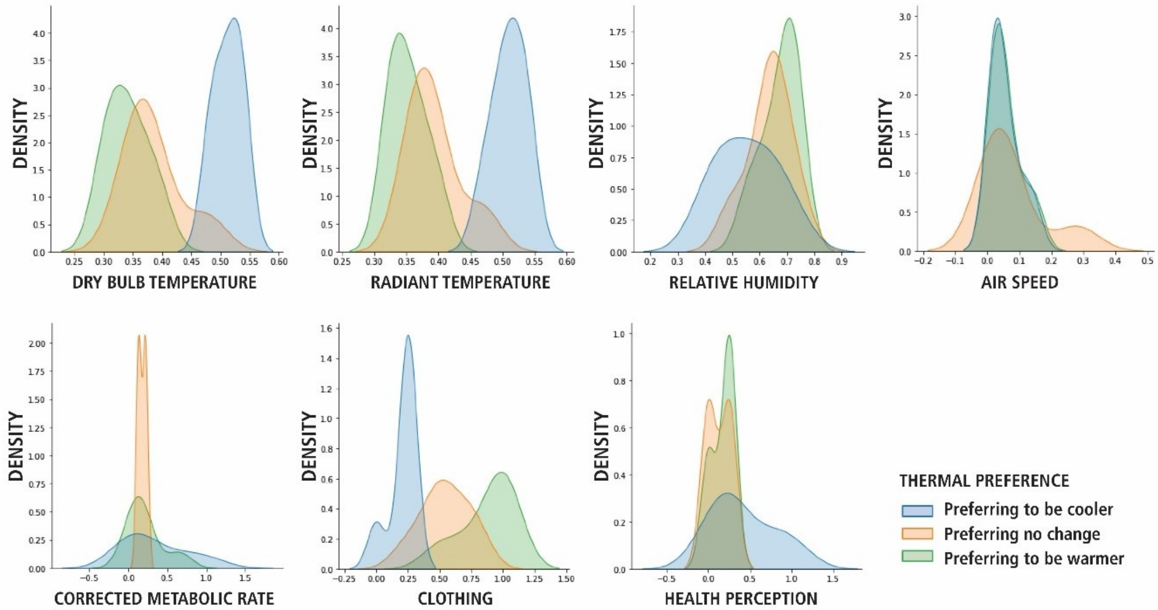

Figure 6-10 - Density plot of distributions of thermal preference votes against the seven input variables (normalised from 0 to 1) for ID 19

Although the minimum dataset size required for personal models to reach maximum predictive performance can vary for each participant, larger sample sizes might allow a better statistical representation of the data. The data collected in this study, however, were not sufficient to allow the testing of larger datasets. Nonetheless, other similar studies on personal thermal comfort models have calculated the predictive performances of individual models increasing training datasets incrementally. Most of them reported minimum datasets of 30 to 90 datapoints for maximum predictive performance (Daum et al., 2011; Jazizadeh et al., 2014a; Kim et al., 2018b; Lee et al., 2019; Li et al., 2017), which is in line with the average dataset sizes used in this study, as seen in **Table 6-3**.

6.5. Recommended applications

Three main implementation pathways are recommended through this study. The first, called automation pathway, uses the predictions yielded from personal comfort models for live control strategies of the HVAC temperature set points. Jung and Jazizadeh (2019a), for instance, proposed an HVAC agent that decided the optimal temperature set point according to different personalised thermal profiles, using 3 different strategies, namely thermal vote-based predictions, thermal preference-based and the thermal preference and sensitivity-based. Likewise, Auffenberg et al. (2018) developed an HVAC control algorithm using personalised models to retain user comfort while also minimising energy consumption. These models can also be integrated into personal comfort systems (PCS), allowing the conditioning of individuals in a more cost-effective scenario. Although control automation can benefit all individuals, personal models can be especially important as assistive tools for older adults with lower thermal sensitivity or with disabilities.

The second implementation pathway, called diagnostic pathway, relies on the use of the information gathered from personal datasets as a tool to quantify individual preferences, and identify possible design improvements to meet these preferences, especially considering buildings without air-conditioning. If, for instance, an individual model reveals that comfort preferences are more sensitive to air movement than indoor temperatures for a specific occupant, then investing on strategies related to ventilation would be more effective than investing in adding insulation materials only. This diagnostic information would aid not only designers but also older adults in the decision-making process to redesign their thermal environments to improve comfort satisfaction.

The third pathway, called public health pathway, is based on inserting individual models in regulations and standards to be used in a broader sense, without, however, disregarding personal preferences. Since extensive monitoring of new occupants may not be feasible for all settings, personal models from individuals with similar characteristics and preferences would be used to create a set of ‘profiles’ or ‘personas’ according to trends between their statistically significant variables, allowing them to be applied to other individuals, thus requiring a smaller set of relevant information and reduced or no monitoring period. Nevertheless, since this roadmap involves a broader application scenario, the consolidation of the individualised approach as a reliable and reproduceable technique needs to be further tested, and this depends on a collective research effort on the subject. A protocol will be required to prescribe the optimal data collection, processing, and management procedures and to guide the training, evaluation and reporting of models depending on the application. Finally, the standards should prescribe a set of initial models as common bases for each type of application, which can be used as a starting point for re-learning and updating for new and specific occupants and environments.

It is important to highlight that the modelling methodology, learning algorithms and input variables may differ depending on the complexity required for each sort of application envisioned. Using the models for HVAC control with live model-tuning when new data is available (i.e., automation pathway), for instance, may require less computational heavy models, lower training time and higher accuracy to provide immediate user satisfaction. On the other hand, models used in a more analytical sense, or when the relationship between features is more relevant than comfort predictions (i.e., diagnostic pathway), may require more transparent and interpretable modelling techniques rather than optimum performance.

6.6. Limitations

The current study presents the following limitations. Firstly, the use of undersampling as a strategy for balancing individual datasets has resulted in a reduction of the data size that can influence the model's predictive performance. In addition, undersampling can cause the loss of potentially useful data points. Possible alternatives are oversampling or SMOTE (Synthetic Minority Oversampling Technique) or increasing sample sizes with longer monitoring periods that allow more diverse thermal preference responses. Both strategies, however, have drawbacks. Oversampling can, on one hand, lead to model overfitting and an increase in learning time. Longer monitoring periods, on the other hand, can be intrusive for the participants, increase study cost and time, and add bias to participants' answers after repetitive tasks. The use of personal comfort systems is equally interesting to allow bigger sample sizes, since the system's control patterns can be collected continuously and later used as proxy for thermal comfort.

Secondly, the use of field studies instead of climate chamber experiments also poses challenges to dataset size and distribution. When monitoring real thermal environments, where conditions vary without the influence of researchers, extremes in thermal perception are naturally less often captured, making final imbalanced datasets almost unavoidable. Nevertheless, field studies provide an accurate representation of reality and its underlying conditions that controlled climate chamber experiments are rarely able to capture.

Thirdly, despite the study including 3 different climate zones, it is still limited to a specific climatic context of older people in South Australia. Future research is required to advance the knowledge on other scenarios and their related challenges. Likewise, although the older participants in this study represent a diverse cohort in terms of body composition, age, sex, health, frailty and living environment, other socio-cultural and economic factors that affect their thermal environments, as well as their thermal sensitivity and behaviour, still need to be addressed to build a more holistic image of their diversity.

Furthermore, this study is limited to the analysis of 7 features that might affect thermal preference for older people. Other potentially relevant input variables might include time of day and seasonal thermal expectation, physiological data, such as skin temperature or heart rate, and more accurate representations of metabolic rate, such as accelerometery measured with wearable sensors or activity captured using image recognition.

Finally, it is important to point out that the PMV conversion used in this study poses limitations in the comparisons. This is because thermal sensation and thermal preference scales cannot be considered interchangeable for all individuals. While several people might experience neutral sensation and thermal preference for no change at the same time, it is still necessary to account for preferred sensations other than neutral. Although not applicable to all participants in this study because of insufficient and highly unbalanced sample sizes, an alternative to this conversion would be analysing different conversion rules and cut-offs for each individual participant depending on their thermal sensation and thermal preference answers, instead of a single scale conversion method for all.

6.7. Conclusion

Responding accurately to older people's thermal preferences in their dwellings is essential to enable comfort and support healthy ageing. In this chapter, personal comfort models have been developed for 28 older people as an alternative to the traditional aggregate comfort modelling approaches used in the field that often disregard diversity in thermal preferences, living environments and health statuses.

Using deep learning as the modelling technique and both environmental and personal characteristics as model inputs, the study has demonstrated that:

- On average, the individualised models present an accuracy of 74%, a Cohen's Kappa Coefficient of 0.61 and an Area Under the Receiver Operating Characteristic Curve of 0.83, representing an overall improvement in performance when compared to other similar studies in the field and the PMV_C model.

- On average, the performance of models without the use of health perception as an input variable was slightly lower than the performance of the ones using this predictor, although the difference between the results was not statistically significant.

- The models' generalisation performance may vary among participants. Poor performance can be related to low sample sizes for training, the presence of anomalous data points, or the absence of input features that might also be influencing this person's thermal preference. Overfitting was also identified as a possible cause of low performance when testing the models.

- Personal comfort models for older adults are recommended as HVAC control automation strategies, as diagnostic tools for design decision-making, and as the basis for the development of thermal comfort profiles in the broader public health scenario.

The next step for this study includes expanding the models to take into account other physiological parameters such as skin temperatures, and testing the models' capabilities and feasibility by deploying them in real life scenarios.

Chapter 7. Personal thermal comfort models for older people using skin temperature and environmental, behavioural and health variables

Building on the findings of the personal comfort models presented in **Chapter 6**, this chapter provides further evidence of the exploration of 4 personal thermal comfort models for older adults using skin temperature data combined with previously used thermal comfort predictors. This chapter, therefore, similar to **Chapter 6**, aims to answer research questions C and D:

C. How will the accuracy of personal thermal comfort models be affected by individuals' particular variables?

D. How can the use of personal thermal comfort models lead to a more accurate prediction of older people's thermal preferences, in comparison with the prediction by a generalised model such as PMV?

These questions are related to ***Objective (2)****: Develop personal thermal comfort models for older people from the data collected, considering their personal and behavioural characteristics as well as the conditions of their thermal environments, and compare the results with the predictions by established models such as the PMV model*.

This chapter has been published as a journal article:

Arakawa Martins, L., Soebarto, V., Williamson, T (2022) "Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables", Journal of Building Engineering, Vol. 51, https://doi.org/10.1016/j.jobe.2022.104357

The paper is presented here in a reformatted version for consistency of the thesis presentation. The accepted manuscript can be found in **Appendix A**. Note that the original Participant's IDs were renumbered in this chapter to aid the manuscript readability when published as a stand-alone document:

Manuscript ID (as presented in this Chapter)	Original ID (as presented in Chapter 5, 6 and 8)
1	5
2	35

3	33
4	46
5	47
6	8
7	38
8	39
9	51
10	52
11	4

Statement of Authorship

Title of Paper	Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables
Publication Status	■ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Arakawa Martins, L., Soebarto, V., Williamson, T. (2022) "Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables", Journal of Building Engineering, Vol. 51, https://doi.org/10.1016/j.jobe.2022.104357

Principal Author

Name of Principal Author (Candidate)	Larissa Arakawa Martins		
Contribution to the Paper	Study design and concept, data acquisition, data analysis and interpretation, manuscript preparation, manuscript editing, and corresponding author		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	24/02/2022

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

vii. the candidate's stated contribution to the publication is accurate (as detailed above);

viii. permission is granted for the candidate in include the publication in the thesis; and

ix. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Veronica Soebarto		
Contribution to the Paper	Study design and concept, data acquisition, manuscript editing		
Signature		Date	24/02/2022

Name of Co-Author	Terence Williamson		
Contribution to the Paper	Study design and concept, data acquisition, manuscript editing		
Signature		Date	24/02/2022

Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables

Authors and affiliations:

Larissa Arakawa Martins[a], Veronica Soebarto[a], Terence Williamson[a]

[a] School of Architecture and Built Environment, The University of Adelaide, 5000, Australia

Abstract: Personal thermal comfort models hold the promise of a more accurate way to predict thermal comfort and therefore a more reliable approach for managing indoor thermal environments. They can be especially relevant as an assistive tool for people with lower thermal sensitivity or with limitations to thermal management and adaptation, such as older people. Nonetheless, although in constant development, studies on personal comfort models continue to focus on office environments and younger adults. This paper explores the development of personal comfort models to predict older people's thermal needs in their homes and evaluates the models' predictive performances in comparison with conventional generalised approaches. Machine learning and environmental, behavioural, health and skin temperature measurements were used to develop individual models for a set of older adults in South Australia. The results show that, on average, the personal thermal comfort models using all studied inputs, except for health perception, presented an optimal accuracy of 66.72%, a Cohen's Kappa of 50.08% and AUC of 0.77, a superior performance when compared with generalised approaches. Results have also highlighted the need for further research on combining physiological sensing, individualised predictive modelling and wearable comfort systems, as well as on defining thermal preference misclassification costs in the context of older people.

Keywords: Thermal comfort, personal comfort model, skin temperature, older people, machine learning

7.1. Introduction

Over the last two decades, the field of thermal comfort modelling has been going through an important paradigm shift. Studies on thermal comfort that focus on aggregated responses from a group of people, such as the PMV (Predictive Mean Vote) (Fanger, 1970) and adaptive models (Humphreys et al., 2016; de Dear and Brager, 1998), are being called into question by individualised and occupant-centric modelling alternatives (Kim et al., 2018a; Čulić et al., 2021; Xie et al., 2020; André et al., 2020; Arakawa Martins et al., 2022a). To predict specific comfort requirements more accurately, instead of an average condition calculated from the responses of a group of people, the new personalised approach relies solely on thermal assessments from a single person. By absorbing individual diversity into thermal comfort management, this new modelling approach offers the potential to increase both occupant acceptability and related energy benefits in the built environment. As discussed in works by Kim et al. (2018a) and Arakawa Martins et al. (2022a), by using the individual as the unit of analysis, personal comfort models help unmask and quantify the differences between individuals in an environment, enabling a better understanding of specific comfort needs and requirements, such as acceptable temperature limits for a given space, and collecting diagnostic information to identify problems. This information, in turn, aids the decision-making process involved in optimizing thermal environments to improve both comfort and energy efficiency. If, for instance, the acceptable temperature limits diagnosed are greater than the default HVAC (Heating, Ventilation and Air Conditioning) temperature set point ranges, energy savings can be expected by widening the set point temperatures. If HVAC systems are used in shared spaces and individual control is not possible, personal comfort models can still be used as the basis for consensus-based solutions (Jazizadeh et al., 2014b), or the development of thermal comfort profiles for general use (Kim et al., 2018a; Arakawa Martins et al., 2022c). In single-occupant spaces where individual control is possible, personal comfort models can help automate any type of conditioning systems with higher precision. Although automatic control might not be a priority for some individuals, the automation provided by personal comfort models can be especially relevant as assistive tools for people with lower thermal sensitivity, such as older people, for those with more limitations to thermal management and adaptation, such as people with disabilities, or for those with less means to afford the cost of HVAC fuel consumption. Examples of energy savings resulting from the use of individualised thermal comfort models were experimentally demonstrated by Jazizadeh et al. (2014b) and Ghahramani et al. (2014).

Personalised models have been the subject of multiple recent research studies. They have been developed through a plurality of frameworks, varying data collection approaches, model inputs and output variables and the modelling algorithms used (Arakawa Martins et al., 2022a). When analysing the models' input variables specifically, environmental factors, such as indoor air temperature (Shan et al., 2018; Konis and Annavaram, 2017; Ghahramani et al., 2015b; Daum et al., 2011; Pazhoohesh and Zhang, 2018; Aguilera et al., 2019), relative humidity (Zhao et al., 2014a), air speed (Liu et al., 2007), mean radiant temperature (Zhao et al., 2014b) and outdoor air temperature (Kim, 2018b; Fay et al., 2017), are most frequently used as single or combined predictors in these studies. There is, however, an increasing body of research focusing on personal comfort models driven by physiological variables, such as skin temperature or heart rate (Aryal and Becerik-Gerber, 2019; Aryal and Becerik-Gerber, 2020; Jung et al., 2019; Katić et al., 2020; Li et al., 2017; Li et al., 2018; Li et al., 2020; Liu et al., 2019; Lu et al., 2019; Sim et al., 2016). Powered by the recent development of wearable devices and the Internet of Things (IoT), this area of research is advancing towards novel ways to monitor and predict individual thermal responses in increasingly more accurate and less intrusive ways.

Nonetheless, although in constant development, studies on personal comfort models continue to focus on office environments and younger adults. While the literature contains multiple studies on thermal comfort for older adults (Jiao et al., 2017; Yang et al., 2016; Bills et al., 2016; Wong et al., 2009; Childs et al., 2020) and age-related differences in thermal sensation and preferences (Soebarto et al., 2019b; Schellen et al., 2010; Hwang and Chen, 2010), the studies focus on generalised conclusions in specific contexts. Studies on the development of personal comfort models that focus on older people, their specific physiological responses, and their living environments are still absent in the current literature (Arakawa Martins et al., 2022a). This is despite the fact that the proportion of older people (i.e., those aged 65 years old and over) worldwide is increasing rapidly, projected to grow from 9% in 2019 to 16% by 2050, due to historically low birth rates combined with increased life expectancy (United Nations Department of Economic and Social Affairs Population Division, 2019a). Furthermore, this research gap is especially relevant because heterogeneity in personal capabilities and needs tends to be greater in older than younger people, as older adults have likely experienced a greater range of cumulative social and environmental factors during their individual lifetime (World Health Organization, 2015b). Using a generalised thermal comfort model for older adults could result in a great proportion of them being exposed to unacceptable indoor thermal environments. Such thermal exposures can, in turn, interact with multiple comorbidities, leading to adverse health outcomes (Hansen et al., 2011; Nitschke et al., 2011; Hajat et al., 2007) and possibly premature institutional care. Personal comfort models thus hold the promise of a much more accurate approach to thermal environment management, which could potentially prevent both heat and cold related illnesses across a more diverse and vulnerable population. Furthermore, the human-in-the-loop (HITL) (Jung and Jazizadeh, 2019b) automation enabled by the integration of these models with heating and cooling control systems may be especially relevant as an assistive tool for people with lower thermal sensitivity or for those with more limitations to thermal management and adaptation, such as people with disabilities.

Therefore, this chapter explores the development of personal comfort models, using different combinations of environmental, behavioural, health and physiological (i.e., hand skin temperature) input variables, to predict older South Australians' thermal needs in their homes, and evaluates the models' predictive performances in comparison with conventional generalised approaches. Considering that approximately 80% of households in Australia have heating devices and 74% have cooling devices (Australian Bureau of Statistics, 2014), the opportunities for the use of personal thermal comfort models for possible HVAC or personal comfort systems automation in the Australian context become especially relevant.

The structure of the chapter is organized as follows. The following **Subsection 7.1.1** presents related works on personal thermal comfort models using both environmental and physiological features. **Section 7.2** details the field study process and tools used for data collection, as well as the two modelling methodologies applied, a conventional generalised approach and a new personalised alternative. **Section 7.3** explores the performance results of the two models while **Section 7.4** discusses the main topics highlighted by the study's outcomes. **Section 7.5** presents the study's limitations as well as future study opportunities, and **Section 7.6** concludes this chapter.

7.1.1. Related literature on personal comfort models using environmental and physiological input variables

The recent literature on personal comfort models employing environmental and physiological variables as predictors for thermal comfort indicates that the models' predictive performance increases when a combination of both types of inputs are used. Aryal and Becerik-Gerber (2019), for instance, monitored 20 participants, in their late teens to mid-thirties, through experimental sessions in an office building, and compared the accuracy of individual models using both environmental measurements and wrist and face skin temperatures. According to these researchers, using data from the environmental sensors for predicting thermal comfort resulted in a higher accuracy compared with using physiological data alone. However, combining data from both environmental and physiological sensors led to a slightly increased accuracy (3% - 4%) over using environmental sensors alone. A further study from the same authors (Aryal and Becerik-Gerber, 2020), involving 15 participants in their late teens to mid-twenties, also in experimental sessions in an office environment, confirmed similar results.

Jung et al. (2019) indicated a much greater increase in prediction performance when including physiological features as input parameters for personal thermal preference models. In a climate chamber study involving 18 participants, the research used skin heat exchange via a heat flux gauge, skin temperature, indoor temperatures and humidity to infer personal thermal preferences. According to their results, the use of the heat exchange rate from the skin resulted in higher performance indicators than using skin temperature and indoor temperature as factors. The study's best performing modelling algorithm presented a median accuracy of 71% when using air temperature as a sole feature, 93% with the addition of skin temperature and 97% with the addition of heat flux, highlighting that the best performance was observed when skin temperature and heat flux were used along with ambient temperature.

Likewise, Lu et al. (2019) conducted experimental sessions in an open-plan office with 2 healthy participants in their mid-twenties. The personal models predicted thermal sensations using three different feature sets, involving both environmental and physiological parameters. The models were trained using linear kernel Support Vector Machine, and the recall score (i.e., the proportion of all actual positive cases that were correctly predicted as positive), the precision score (i.e., the ratio between true positives and all predicted positives) and the F1 score (i.e., the harmonic mean of recall and precision) were used as the performance indicators (Lu et al., 2019). The combination of indoor air temperature, relative humidity, skin temperature and clothing surface temperature achieved a 100% recall, precision and F1 score for the female subject and a 96.1%, 97.5% and 95% recall, precision and F1 score, respectively, for the male subject.

Li et al. (2017) also reported that the combination of both environmental and human data (i.e., activity level, clothing, heart rate, skin temperature) can significantly improve the performance of personalised comfort prediction models. Through two field studies, involving 3 and 7 participants in both office and residential environments, their research showed that the combined feature set achieved approximately 80% accuracy, improving the classification accuracy by 24% and 39% when compared with the use of environmental features only and physiological factors only, respectively. A subsequent study by the same authors (Li et al., 2018) explored personal comfort modelling using skin temperatures collected from different facial regions using thermal cameras. Through a series of experiments in an office environment with 12 participants in their early to mid-twenties, the researchers not only indicated that ears, nose, and cheeks skin temperatures are most indicative of thermal comfort, but also that their proposed framework can achieve an average accuracy of 85%. Building on these previous works, Li et al. (2020) proposed the Human Embodied Autonomous Thermostat (HEAT) tool, where facial skin temperature and room air temperature were used to directly communicate with and control HVAC operations in multi-occupancy spaces.

Similarly, Liu et al. (2019) collected physiological responses including skin temperature and heart rate, as well as environmental parameters such as air temperature and relative humidity, of 14 participants, through a series of wearable sensors, in both indoors and outdoors environments. Through the use of 14 different machine learning algorithms, the personal thermal comfort models presented a median Cohen's Kappa indicator of 24%, accuracy of 78% and Area Under the Receiver Operating Characteristic Curve of 0.79 (details on these performance indicators are presented in **Section 7.2.7** of this chapter). These results showed a significant improvement of predictive performance when compared with the PMV and adaptive models. A follow-up study by the same research group (Das et al., 2021) used deep learning to develop personal thermal preference models for 7 of the original 14 participants, successfully testing transfer learning techniques in order to decrease data collection periods and test the generalisation of the models to other building occupants.

A recent study by Jung et al. (2022) also explored the use of deep learning algorithms to optimize both thermal comfort and energy consumption of 4 young individuals in climate chamber experiments. Both environmental and physiological data were used as inputs. The results showed that the proposed optimization system could reduce by 10.9% the thermal discomfort of the occupants while maintaining their respective energy consumptions.

The literature review, however, confirms a lack of studies where older adults are involved, as well as a limited amount of research in residential settings. Furthermore, as pointed out by Arakawa Martins et al. (2022a), although a general idea of trends in outcomes can be extracted from previous studies, a direct comparison of different physiological sensing and modelling approaches among these studies is difficult. As seen above, multiple performance indicators (e.g., accuracy, recall, Cohen's Kappa and Area Under the Receiver Operating Characteristic Curve) and different experimental settings (e.g., climate chambers or field experiments, different body parts being monitored, and multiple types of sensing equipment) are used, making immediate conclusions on predictive performance difficult to draw. This study, therefore, aims to investigate an individualised modelling approach for older adults and their living environments, as well as a reproduceable modelling and evaluation methodology.

7.2. Study design and methodology

7.2.1. Data collection periods

The dataset used in this study is derived from two separate data collection periods, involving 11 participants (6 males and 5 females) who lived in 8 households located in 3 climate zones (hot dry (BSk), warm temperate (Csa) and cool temperate (Csb), according to the Köppen–Geiger Climate Classification System) in South Australia. The participants were volunteers who met the following criteria: (1) be 65 years old or over; (2) live independently, and (3) be able to communicate in English. These participants were part of a larger research project that investigated the thermal qualities of older adults' living environments (Soebarto et al., 2021). While this research project involved 71 participants in 57 households, only 11 participants agreed to be involved in the further data collection, which involved measuring their skin temperature, as explained below. The study received approval from The University of Adelaide Human Research Ethics Committee (approval number H-2018-042).

In the first data collection period, indoor environment data were collected simultaneously in all houses, across a period of 9 months, from mid-January to mid-October in 2019. The sensors and data loggers were placed in each house's main living room and main bedroom and a portable electronic tablet was left for participants to answer a point-in-time survey about their thermal environment and their preferences and sensations at least twice a week. The indoor environment loggers recorded data from measurements of dry bulb temperature, globe temperature, air speed, and relative humidity, at 30-minute intervals and when a participant completed a survey. Mean radiant temperature was later calculated from the measured dry bulb temperature, globe temperature and air speed measurements applying the method from ISO 7726:1998 (ISO, 1998). Participants were able to choose whether to answer the surveys in the living room or the bedroom, since the tablet was portable and could be carried between the rooms. The survey's first question asked participants to indicate in which room the survey was being conducted and the loggers' measurements were later sorted to match the corresponding rooms.

While the indoor environmental parameters were being recorded, each participant was asked to periodically respond to a thermal comfort survey through an electronic tablet. The survey comprised of questions about participants' clothing level, activity level, health/wellbeing perception (for which the answer scales are further detailed in **Table 7-2**), thermal sensation (TSV) and thermal preference (TPV). TSV was assessed using the question 'How do you feel right now?' with possible responses being 'Cold', 'Cool', 'Slightly cool', 'Neutral', 'Slightly warm', 'Warm' or 'Hot'. TPV was assessed using the question 'Would you prefer to be...' with possible responses being 'Cooler', 'No change' or 'Warmer'. Details of the loggers and thermal comfort survey tablet have been reported by Soebarto et al. (2020).

A questionnaire about sociodemographic information and an open-ended interview about house details were administered at the start of the monitoring period. Furthermore, frailty status (using the Modified Reported Edmonton Scale (MRES) (Rose et al., 2018)) and participants' height, weight and body mass index (BMI) (using a Tanita Inner Scan RD-953 scale (Tanita Corporation, 2016)) were assessed at the end of the monitoring period.

After the conclusion of the first data collection period, a preliminary analysis of the data and further literature investigations highlighted a lack of physiological factors being investigated in the first stage of the study. Therefore, a second data collection was conducted with the same participants. Each house was monitored across 2 consecutive weeks, one house after the other, between the months of September 2020 and February 2021.

In this second data collection, the survey tablet, as detailed below, was modified to include a non-contact infra-red temperature sensor to measure the skin temperature of the back of participants' non-dominant hand after they completed each point-in-time survey. The other environmental measurements and the comfort survey questions remained the same as for the first collection period. Frailty and body composition assessments were redone and, after analysis, variations between the two data collection periods were considered minimal (i.e., maximum 1 unit change in the frailty score and a weight change under 5 kg). In addition, through new photographic documentation and interviews with participants, researchers ensured that the environments had not undergone major changes that could compromise the merging of the two collected datasets.

7.2.2. Hand skin temperature measurement tool

Human hands are known to contain a high number of arteriovenous anastomoses (AVAs), valves that regulate vasoconstriction and vasodilatation, and therefore influence heat loss by changing the peripheral blood flow (Hales, 1985). This makes the skin temperatures of hands a possible indicator of a person's thermal state (Wang et al., 2007). The skin temperature of the back of the hand (i.e., dorsal side of the hand) was chosen for this study in line with previous research that correlated thermal sensation to this specific body part (Soebarto et al., 2019b; Wang et al., 2007; Katić et al., 2020; Childs et al., 2020) and according to ISO:9886:2004 (ISO, 2004). The measurement of the back of hand also reduced the intrusiveness of the method since this skin surface is more frequently exposed to the environment than other body parts. In addition, the use of the dorsal side of the hand, in combination with the space and position available for the new sensors in the original tablet enclosure, allowed the most comfortable position for older participants to take the measurements whilst seated. The non-dominant hand was chosen to minimize the effect of frequent hand movements in the skin temperature measurements.

To include skin temperature measurements in the study, the original tablet and logger were modified to record and store data from a non-contact infra-red temperature sensor (model MLX90614-DCC). The sensor has a ±0.5°C precision of temperature measurement and a field of view (FOV) of 35 degrees. To measure a spot with a radius of approximately 1 cm on the back of participants' non-dominant hand, participants positioned their hands at a maximum distance of 1.5 cm from the sensor.

An Arduino line trace sensor (model LB-LR0005) was also included in the modified version of the equipment, serving as a proximity sensor to allow measurements only when the participants' hand was close enough to the infra-red sensor. In addition, a dark coloured upright partition was attached in front of the sensors to avoid accidental measurements triggered by surrounding reflective surfaces, and to guide participants' hand positioning. A buzzer was also included as an audible indication that a measurement had been taken by the skin temperature sensor and recorded by the tablet. Recorded measurements, however, could contain irregularities that were later analysed individually, as described in the next sections of this chapter. The modified equipment and skin temperature measurement procedure was tested with 3 people (in their late fifties to mid-seventies) before deployment to ensure suitability for the cohort involved in the study. The accuracy of the setup was compared with a medical grade infra-red temperature device, presenting a ±0.5°C error range.

Figure 7-1 shows the indoor environmental data logger and thermal comfort survey tablet with infra-red skin temperature sensor used in the second data collection period and demonstrates how the skin temperature measurements were taken.

Figure 7-1 - Thermal comfort survey tablet with infra-red skin temperature sensor and indoor environment data logger (left), and back of hand skin temperature measurement being taken (right).

7.2.3. Participants and datasets

Table 7-1 presents the characteristics of the 11 participants. The exploration presented in this chapter is divided in two parts, the first comprising of a conventional generalised modelling method (detailed in **Section 7.2.4**) and the second contemplating a new individualised modelling approach using machine learning (detailed in **Section 7.2.5**). The first exploration was developed from the full dataset from the second data collection period of the 11 participants. The second exploration is based on the individual datasets of 4 of the 11 participants involved. Only 4 participants were evaluated individually because the modelling methodology required that each participant voted at least 6 times in at least one of the three thermal preference (TPV) classes, to allow a minimum of 5-fold cross-validation during model training, plus a minimum of 1 vote per category for testing. Seven participants did not meet these criteria and therefore were excluded from the second exploration. The cross-validation procedure is based on common practice in the field of machine learning (Raschka, 2018) and on similar thermal comfort studies (Aryal and Becerik-Gerber, 2020; Katić et al., 2020; Jiang and Yao, 2016; Liu et al., 2019).It is further detailed in **Section 2.5.2**. Since dealing with individual datasets reduced the dataset sizes for modelling, records from the first and second collection periods were merged to increase the number of data points for each of the 4 participants. In this case, k-Nearest-Neighbours technique was used to impute the missing values of skin temperature in the first data collection set. These 4 participants are highlighted in bold in **Table 7-1**.

Table 7-1 - Participants' characteristics. Participants whose personal thermal comfort models were developed are highlighted in bold.

ID	Climate Zone	Sex (Female or Male)	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m²)	Frailty Score (MRES scale)
1	**Csa**	**Female**	**80**	**161.0**	**103.4**	**39.9**	**Not Frail**
2	Csa	Male	74	160.0	120.6	47.1	Mild Frailty
3	Csa	Male	81	171.5	111.1	37.8	Not Frail
4	**Csb**	**Female**	**67**	**166.5**	**115.6**	**41.7**	**Not Frail**
5	Csb	Male	66	183.0	68.3	20.4	Not Frail
6	Csa	Male	83	174.0	92.35	30.5	Apparently vulnerable
7	Csa	Female	83	166.0	72.85	26.4	Not Frail
8	Csa	Male	85	173.0	98.95	33.1	Not Frail
9	**Csb**	**Female**	**73**	**150.5**	**62.95**	**27.8**	**Apparently vulnerable**
10	Csb	Male	77	180.0	69.15	21.3	Not Frail
11	**Csa**	**Female**	**82**	**163.0**	**61.5**	**23.2**	**Apparently vulnerable**

It is important to note that, in the case of personal thermal comfort modelling, the number of data points for each participant (i.e., the number of thermal preference votes in each individual dataset) is more relevant for each model's robustness than the total number of participants involved in the overall study, as already pointed out by Li et al. (2020). In addition, the range and number of votes in each of the thermal preference categories is of great importance for model's predictive performance and reliability, especially when dealing with highly unbalanced datasets such as the ones commonly produced by field studies.

7.2.4. First exploration method: weighted least squares regression model

One of the most common methods to calculate thermal comfort predictions is through weighted regression models (Wang et al., 2018). Therefore, the first exploration in this study is based on the following steps.

From 565 survey answers and environmental and skin temperature measurements derived from all 11 participants, 500 contained valid data for skin temperature (i.e., no measurement error or missing values). This valid dataset was first analysed for outlier detection in the skin temperature measurements, which may have been the result of issues such as accidental triggering of the sensor or moisture on the back of the hand. Outliers were considered as any data value that lay outside the range between the 3rd quartile plus 1.5 times the interquartile range and the 1st quartile minus 1.5 times the interquartile range. The outliers were then excluded from the dataset, resulting in a final dataset of 470 datapoints.

Next, the skin temperature measurements (i.e., the independent variable) were binned in 0.5°C increments. The mean of the skin temperatures and corresponding thermal preference votes (i.e., the dependent variable) were then calculated for each bin. With binning, the ordinal thermal preference vote (TPV), assuming equal intervals, may be considered an interval variable and therefore amenable to inferential statistical analysis. A linear regression model was then fitted to the binned data points, weighted by the number of votes in each bin, using the weighted least squares regression method, which is widely used in thermal comfort field studies (Wang, 2006; Nakano et al., 2002; de Dear and Fountain, 1994; Wang et al., 2018).

Further relationships between skin temperature and the other environmental (i.e., dry bulb temperature, radiant temperature, air speed, and relative humidity) and behavioural/physiological measurements (i.e., clothing level, health perception and metabolic rate) were also analysed, using a similar method, with skin temperature as the dependent variable and the other factors as independent variables. In this case, dry bulb and radiant temperatures were binned in 0.5°C increments, air speed in 0.1m/s increments, relative humidity in 5% increments, metabolic rates in 0.1 MET increments and clothing level and health perception in their original 1 increment categories. This analysis was developed using IBM SPSS Version 27.0.0 (IBM Corp., 2020).

7.2.5. Second exploration method: personal thermal comfort model

The second exploration conducted in this study investigates thermal preference predictions at an individualised level, using personal thermal comfort models. In this case, instead of the single dataset containing the thermal preference votes for all participants involved, individual datasets were used to develop personal models targeted for each participant.

Artificial neural networks (ANN), also known as deep learning (Goodfellow et al., 2016), were used to develop these personalised comfort models. Although other high-performance machine learning techniques could have been used (e.g., Random Forests or Support Vector Machine) for thermal preference prediction, an extensive review of personal thermal comfort models highlighted a lack of exploration of artificial neural networks (Arakawa Martins et al., 2022a). Furthermore, ANNs have the advantage of not imposing prior assumptions about data distribution before learning, unlike other conventional techniques, which significantly leverages the use of ANNs in different applications (Thach et al., 2021).

The models were developed to perform a multiclass classification task of occupants' TPV on a 3-category-scale (i.e., 'prefer to be cooler', 'prefer no change' or 'prefer to be warmer'). The survey's TPV were used as the ground truth to train the models and were later compared to the predicted values. It is important to highlight that, TPV was deemed more appropriate than TSV — which is commonly used in thermal comfort studies — because, as pointed out by Kim et al. (2018b), the thermal preference scale not only represents the ideal condition desired by each person, but also suggests in which direction a change may be desired.

In total, 8 input variables were used, 4 of which represented the environmental conditions of the participant's room (i.e., dry bulb temperature, radiant temperature, relative humidity, and air speed) and 4 of which represented the participant's personal, physiological, or behavioural characteristics (i.e., corrected metabolic rate, clothing level, self-reported health perception and hand skin temperature). These 8 variables were selected to cover factors known in the architectural science, medicine, and public health fields to influence thermal responses (Arakawa Martins et al., 2020; Bluyssen, 2019). Table 2 shows each input's data collection tool and unit or scale.

Participants' activity answers in the survey were converted to MET values according to the Compendium of Physical Activities (Ainsworth et al., 2011), and later corrected based on participants' sex, height, weight and age, according to Byrne et al. (2005) and Kozey et al. (2010). **Table 7-2** shows the activity scale points and corresponding MET values.

Table 7-2 - Input variables used

Type	Input variable	Data collection tool	Unit or scale	Min and max used in normalization
Environmental	Dry Bulb Temperature	Thermometer in Data logger	°C	Min 5°C Max 45°C
Environmental	Mean Radiant Temperature	Calculated from globe thermometer, thermometer, and air speed sensor measurements in Data logger	°C	Min 5°C Max 45°C
Environmental	Relative Humidity	Hygrometer in Data logger	%	Min 0% Max 100%
Environmental	Air Speed	Air speed sensor in Data logger	m/s	Min 0 m/s Max 4m/s
Personal	Skin Temperature	Infra-red temperature sensor in Thermal Comfort Tablet	°C	Min 20°C Max 40°C
Personal	Metabolic Rate	Survey in Thermal Comfort Tablet – 'Describe your activity in the last 15 min in this space.'	Very relaxed activity = 1 MET Relaxed activity = 1.3 MET Light activity = 1.5 MET Moderate activity = 2.5 MET Active activity = 3.3 MET	Min 1 Max 3.3
Personal	Clothing Level	Survey in Thermal Comfort Tablet – 'How are you currently dressed?'	Very light = 1 Light = 2 Moderate = 3 Heavy = 4 Very heavy = 5	Min 1 Max 5

Personal	Health Perception	Survey in Thermal Comfort Tablet – 'How would you describe your health and wellbeing at the moment?'	Very good = 1 Good = 2 Reasonable = 3 Poor = 4 Very poor = 5	Min 1 Max 5

To compare the impact of different types of input on models' predictive performance, three different combinations of input variables were tested:

(1) Skin temperature;

(2) Skin temperature plus the "6PMV" variables, namely dry bulb temperature, radiant temperature, relative humidity, air speed, clothing and metabolic rate;

(3) Skin temperature plus the "6PMV" variables plus the participant's perception about their health.

The modelling process involved the following stages: (A) dataset pre-processing and balancing and (B) model tuning, selection, and evaluation. Anaconda version 2019.3 (Anaconda, 2019) was used as the package manager to script and run all models using Python version 3.7 and PyTorch tensor library (Paszke et al., 2017).

7.2.5.1. Dataset pre-processing and balancing

In the 4 individual datasets, the middle category (i.e., 'prefer no change') was more frequently voted for than the extreme categories, resulting in highly imbalanced thermal preference distributions, as seen in **Figure 7-2**. Therefore, undersampling was conducted, by randomly removing votes from the majority classes until reaching the size of the minority class. Final individual dataset sizes can be seen in Table 3. The use of undersampling as a balancing strategy has resulted in a reduction of the datasets' sizes. Although other balancing strategies such as oversampling or SMOTE (Synthetic Minority Oversampling Technique) (Mishra, 2017) could have avoided the decrease in sample size, they are more likely to lead to model overfitting (Branco et al., 2015), and were, therefore, not chosen in the current study.

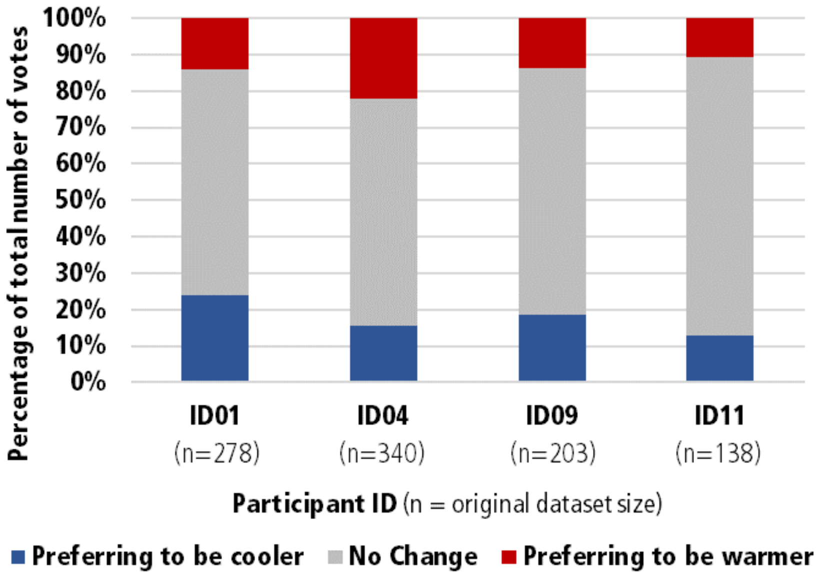

Figure 7-2 - Percentage of total number of votes of each thermal preference category, for each participant's original dataset

Nevertheless, although larger sample sizes might allow a better statistical representation of the data, other similar studies on personal thermal comfort models using machine learning techniques have reported minimum datasets of 30 to 90 datapoints for maximum predictive performance (Daum et al., 2011; Jazizadeh et al., 2014a; Kim et al., 2018b; Lee et al., 2019; Li et al., 2017), which is in line with the average dataset sizes used in this study, as seen in **Table 7-3**. Considering personal models using ANNs specifically, Shan et al. (2018) reported an average accuracy of 89.2%, and an average MSE (Mean Standard Error) of 0.06 using 150 datapoints per model, while Kim (2018b) reported an average MSE of 0.0029 using 26 to 133 datapoints per model, supporting the data sizes of the current study. Furthermore, k-fold cross validation, detailed in the next section, was used to avoid the drawbacks due to limited sample sizes.

The categories were also coded from 0 to 2, where 0 corresponded to the 'prefer to be cooler' class, 1 the 'prefer no change' class and 2 the 'prefer to be warmer' class. Finally, the input variables were normalized to a single range from 0 to 1, using minimum and maximum values according to **Table 7-2**.

7.2.5.2. Model tuning, selection, and evaluation

Hyperparameters are settings used to control the model's behaviour and capacity (Goodfellow et al., 2016). To choose the optimal set of hyperparameters, model tuning was conducted. The first step of model tuning consisted of dividing the datasets into three separate subsets. The training set is the subset of data points used for learning (i.e., fitting the internal coefficients of the classifier). The validation set is the dataset used to guide the selection of the hyperparameters. The testing set is an independent subset of examples used to assess the performance of a fully trained model, evaluating the model with data it has never seen before (Ripley, 1996) .

First, each participant's total datasets were randomly split into training and testing sets, with at least 5 votes in each thermal preference class for training and at least 1 vote for each class for testing. The training set was then divided into two subsets to allow 5-fold cross validation, with at least 4 votes per class for the training set and at least 1 vote per class for the validation set. Five-fold cross-validation was chosen such that each training/validation group of data samples were large enough to be a representative of the total dataset, while small enough to allow modelling for participants with low vote counts. Stratified cross-validation was repeated 5 times to reduce the noise in the model performance between different cross validation splits.

After the validation-train-test split, the next step involved the imputation of missing values for skin temperature. This involved inputting values to substitute outliers and measurement errors from the second data collection period as well as missing values from the first data collection period. The K-Nearest-Neighbours technique was used due to its low complexity, robustness and frequent use in machine learning related approaches (Kuhn and Johnson, 2013; Beretta and Santaniello, 2016). An optimal value of k=5 was used for the imputation.

The next step of model tuning involved training the models, varying three main hyperparameters according to common practice in machine learning studies (Kuhn and Johnson, 2013). The learning rate was varied from 0.001 to 0.01 to 0.1. The number of hidden neurons in the hidden layer of the model was varied between 4, 5 and 6. Lastly, the batch size was varied between 2 and 8 data points.

The models were trained using an input layer, a single hidden layer, and an output layer. In order to go from one layer to the next, the neurons compute a weighted sum of their inputs from the previous layer (Equations 1 and 3) and pass the result through a non-linear function, called the activation function (LeCun et al., 2015). The models in this study used Rectified Linear Unit (ReLU) (Agarap, 2018) as the activation function between the input layer and the hidden layer (Equation 2) and Softmax as the activation function between the hidden layer and the output layer (Equation 4). The mathematical expressions of the models can be written in the following form:

$$z_j = \sum_{i=1}^{8} w_{ij} \cdot x_i + b_j \qquad (25)$$

$$y_j = f(z_j) = \max(0, z_j) \qquad (26)$$

$$z_k = \sum_{j=1}^{N_J} w_{jk} \cdot y_j + b_k \qquad (27)$$

$$f(\vec{z})_k = \frac{e^{z_k}}{\sum_{o=1}^{3} e^{z_o}} \qquad (28)$$

where x_i are the normalised data of the input variables, w_{ij} are the weights between the input and hidden neurons, b_j are the bias values of the hidden neurons, and y_j the output values of the activation functions (ReLU) in the hidden layer; while w_{jk} are the weights between the hidden and output neurons, b_k are the bias values of the output neurons, N_J is the number of hidden neurons, and $f(\vec{z})_k$ are the outputs of the activation functions (Softmax) in the output layer (as probability distributions from 0 to 1 for each class).

The Cross Entropy function was used to measure the error (L_{CE}) of each classification rounds (Equation 5):

$$L_{CE} = -\sum_{k=1}^{3} t_k \log f(\vec{z})_k \qquad (29)$$

where t_k is the target probability for each class, and $f(\vec{z})_k$ is the predicted probability for each class.

Stochastic Gradient Descent was used as the optimizer algorithm to minimize L_{CE}, with a momentum at 0.9 (Goodfellow et al., 2016).

After each training round, the models' performances were evaluated using the validation set. The performance indicators (detailed in **Section 7.2.7**) were then compared, and the hyperparameters associated with the best model performance were chosen (model selection). Next, training and validation sets were merged into one dataset and the best hyperparameter settings from the previous step were used to fit a new model to this larger dataset. Finally, the test set was used to estimate the generalization performance of the model resulted from the previous step (model evaluation) (Raschka, 2018). More details of the modelling methodology used have been previously published (Arakawa Martins et al., 2022b).

7.2.6. Conversion of the PMV model for comparison

To allow a further comparison between generalised and individualised models, the PMV index was calculated according to ASHRAE Standard 55-2020 (ANSI/ASHRAE, 2020) using each participants' testing set. The PMV predictions on a thermal sensation 7-point-scale were transformed to a 3-point thermal preference scale to enable a direct comparison with the personal thermal preference models.

When PMV < -0.5 (i.e., less than 'slightly cool' to 'cold'), the votes were labelled as 'preferring to be warmer'; when -0.5 < PMV < 0.5 (i.e., 'neutral'), the votes were labelled as 'no change'; and when PMV > 0.5 (i.e., more than 'slightly warm' to 'hot'), the votes were labelled as 'preferring to be cooler'. The ±0.5 cut-offs represent the recommended limits for a 10% Predicted Percentage of Dissatisfied (PPD), as prescribed by ASHRAE Standard 55-2020 (ANSI/ASHRAE, 2020). The transformed PMV index is referred to in this chapter as PMV_C.

7.2.7. Performance indicators

The performance indicators used during the personal comfort models' tuning and evaluation, as well as when comparing them with the weighted linear regression model and the PMV_C model, were the Accuracy, the Cohen's Kappa Coefficient, and the Area Under the Receiver Operating Characteristic Curve (AUC).

Accuracy was calculated by dividing the number of correct predictions by the total number of predictions. The Cohen's Kappa Coefficient (K) (Cohen, 1960) was calculated using Equation 6 and compensates the measurement of accuracy, by taking into account the agreements that can be attributed to random chance. It ranges from negative values to 1, where 1 means perfect agreement, 0 means no agreement other than what would be expected by chance, and negative values mean the agreement is worse than random. In this chapter, the accuracy and the Cohen's Kappa Coefficients are presented in percentages.

$$\mathrm{K} = \frac{(\mathrm{p}_o - \mathrm{p}_e)}{(1 - \mathrm{p}_e)} \qquad (30)$$

where p_o is the accuracy measure, and p_e is the hypothetical probability of a chance agreement.

To calculate the AUC, first, the Receiver Operating Characteristic Curve (ROC) was built by plotting the probability of a true positive versus the probability of a false positive rate for all possible discrimination thresholds, for each of the three thermal preference classes using the 'one versus the rest' method. Equations 7 and 8 define the true positive rate (TPR) and the false positive rate (FPR):

$$TPR = \frac{TP}{TP+FN} \qquad (31)$$

$$FPR = \frac{FP}{FP+TN} \qquad (32)$$

where TP (true positive) is the number of positive class correctly predicted in a binary classification model; FP (false positive) is the number of positive class incorrectly predicted; TN (true negative) is the number of negative class correctly predicted; and FN (false negative) is the number of negative class incorrectly predicted.

Then, the area under the ROC was computed for each of the classes and averaged to obtain a single performance indicator. AUC is a measure frequently used in machine learning studies (Ben-David, 2008) and can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement. It is important to highlight, however, that the AUC for the weighted linear regression model and for the PMV_C model was calculated using a single pair of probability of true positive rate versus probability of false positive rate, since these models are not probabilistic classifiers and do not allow plotting of more than one discrimination threshold.

The differences between the models' performance, for each model type, were tested for statistical significance using Independent Samples t-tests. The level of statistical significance was set at $p < 0.05$.

7.3. Results

7.3.1. Weighted least squares regression analysis

Figure 7-3 presents the histogram of hand skin temperature measurements collected during the second monitoring period of the 11 participants. Data outliers were found to be lower than or equal to 22.10°C, and the mean hand skin temperature after the outliers were removed was 30.58°C.

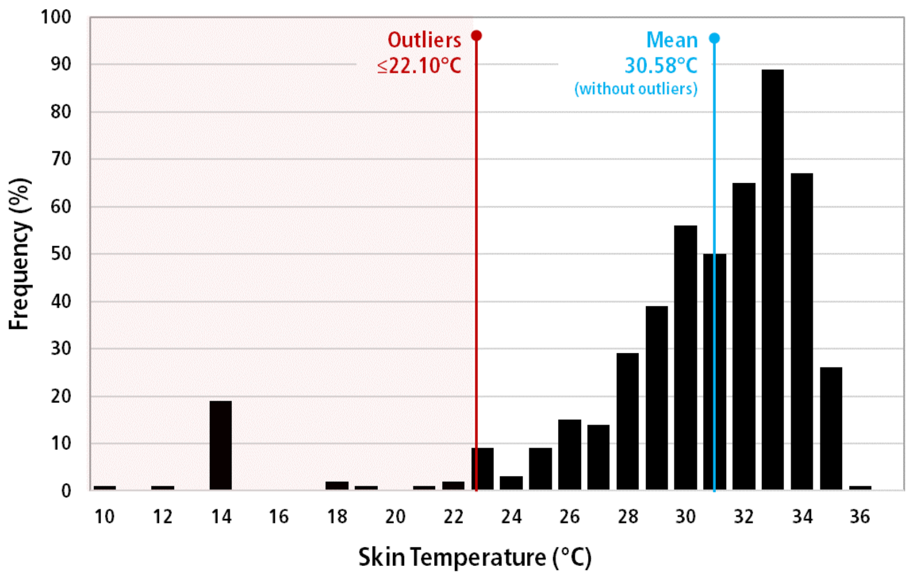

Figure 7-3 - Histogram of skin temperature measurements with indication of outliers identified

According to the regression analysis, among the independent variables tested against skin temperature as the dependent variable, significant relationships were identified between skin temperature and dry bulb temperature, radiant temperature, clothing level and health perception. This was indicated by higher R-squared values (i.e., the coefficient of determination, indicating the percentage of the skin temperature variance that the independent variable explains), statistically significant independent variable coefficients (i.e., $p < 0.05$) and a general visual indication in the raw data scatter plots. The R-squared values, p-values, and raw data scatters, as well as the binned means and corresponding weighted linear regression lines and equations for each analysis are shown in **Figure 7-4**. The variance (R-squared values) of the binned data have increased (because they are now based on the bin-mean values) but still serve as an indicator of comparison between models for exploratory analysis.

When fitting a weighted least squares linear regression model for thermal preference prediction using skin temperature as the predictor, the independent variable coefficient remained statistically significant ($p = 0.001$), validating the model for further analysis. **Figure 7-5** presents the model fit. The performance of this model in predicting individuals' thermal preferences using the selected participants' testing datasets is presented in **Section 7.3.2**.

The box plot of skin temperatures for each of the thermal preference categories, presented in **Figure 7-6**, illustrates the same relationship between skin temperature and thermal preference for the general sample of 11 participants. Nevertheless, when analysing participants' individual box plots, presented in **Figure 7-7**, not only does this relationship differ among individuals, but it is also less evident than the case of the general sample, suggesting that an individualised analysis is required. Among the participants selected for the personal comfort models' analysis, highlighted in grey in **Figure 7-7**, ID11 presents the most evident correlation between skin temperature and thermal preference. This is indicated by skin temperature medians and means for each thermal preference category at distinctively different levels and in a linear descending order from 'prefer to be cooler' through to 'prefer to be warmer'. The plots also show considerable range variations in skin temperatures across participants, emphasizing once again a need for a more individualised level of analysis.

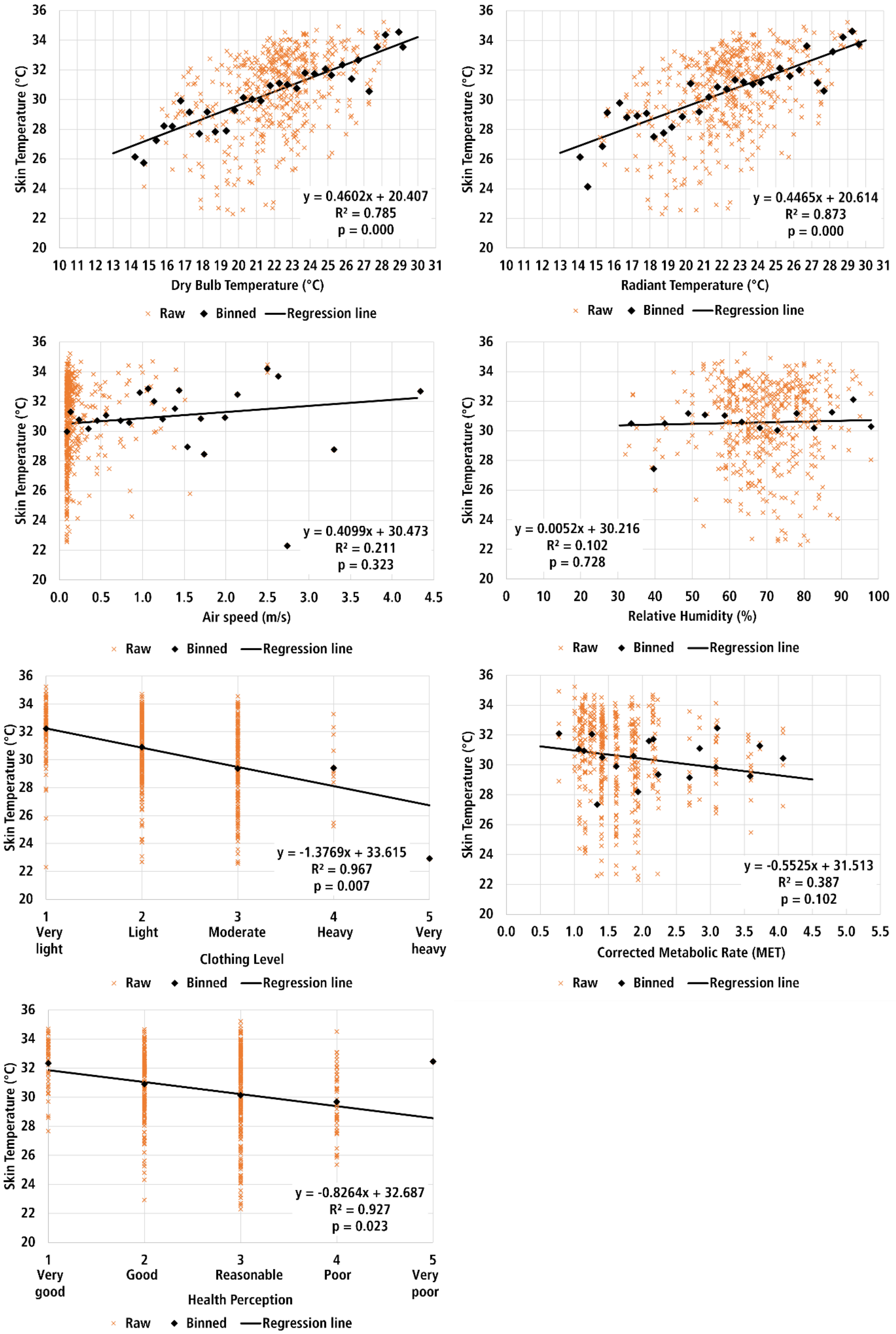

Figure 7-4. Regression analysis between skin temperature and dry bulb temperature, radiant temperature, air speed, relative humidity, clothing level, corrected metabolic rate and health perception

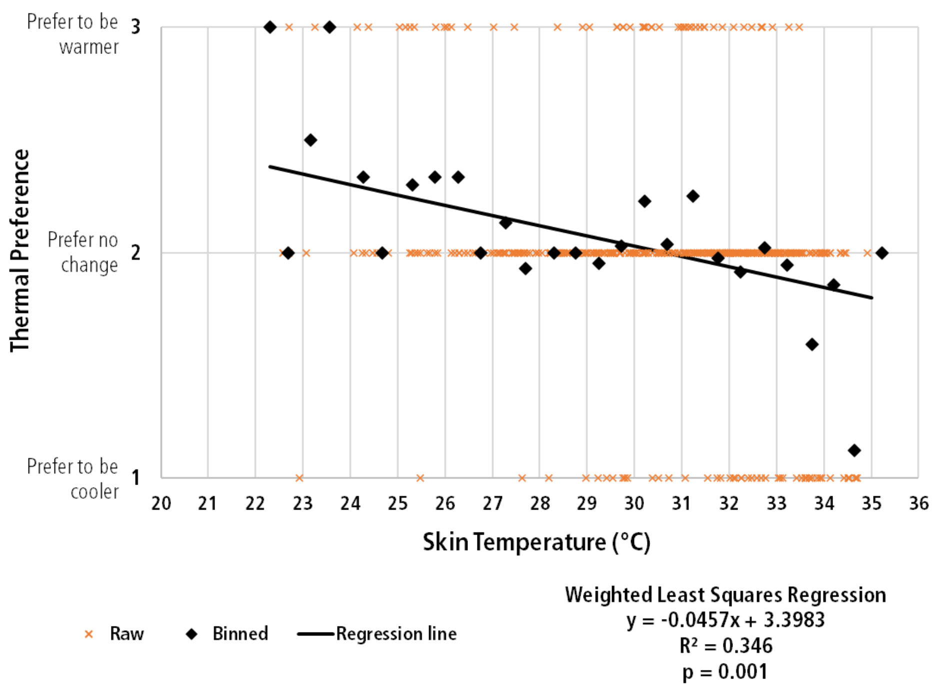

Figure 7-5 - Weighted Least Squares Regression model for thermal preference prediction using skin temperature

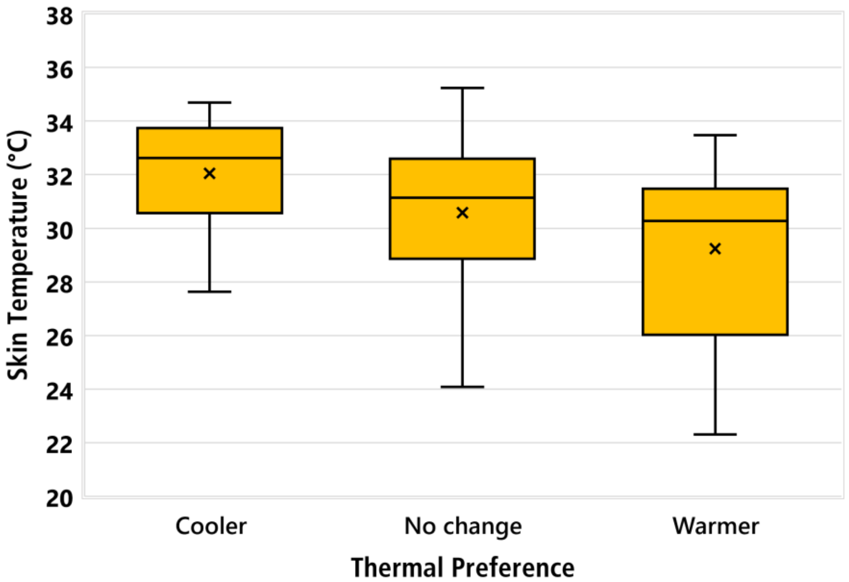

Figure 7-6 - Box plot of skin temperature for each thermal preference category, for all participants (n=470)

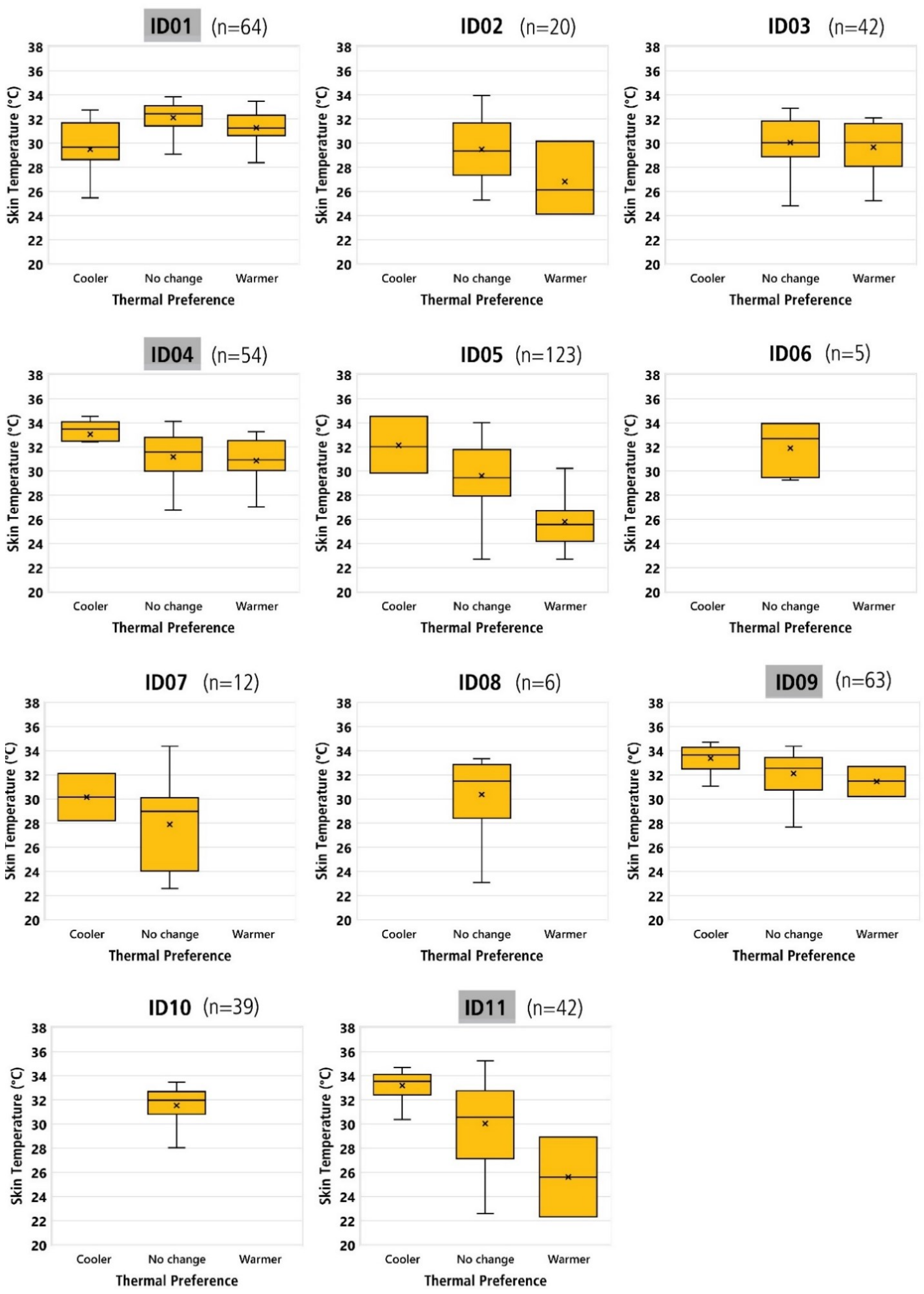

Figure 7-7 - Box plots of skin temperatures for each thermal preference category, for each individual participant. Selected participants for personal thermal comfort modelling are highlighted in grey

7.3.2. Personal thermal comfort models and comparison between approaches

Table 7-3 presents a summary of the predictive performance of the weighted least squares regression model (WLS), the converted predicted mean vote model (PMV_C) and the personal comfort models (PCM) using the 3 different input combinations. The predictive performance is presented as the Accuracy, Cohen's Kappa Coefficient and AUC for the testing dataset (i.e., the 'never-before-seen' dataset) of each participant.

Table 7-3 - Predictive performance of Weighted Least Squares Regression (WLS), Converted Predicted Mean Vote (PMV_C) and Personal Comfort Models (PCM) with different input variables. The best AUCs (Area Under the Receiver Operating Characteristic Curve) for each participant across model types are highlighted in bold.

	Dataset size (balanced)			WLS*			PMV_C *			PCM*								
				Input variables: Skin Temp.			Input variables: 6PMV*			Input variables: Skin Temp.			Input variables: 6PMV* + Skin Temp.			Input variables: 6PMV* + Health + Skin Temp.		
ID	Training	Testing	Total	Acc* (%)	Cohen's Kappa (%)	AUC*	Acc* (%)	Cohen's Kappa (%)	AUC*	Acc* (%)	Cohen's Kappa (%)	AUC*	Acc* (%)	Cohen's Kappa (%)	AUC*	Acc* (%)	Cohen's Kappa (%)	AUC*
1	90	27	117	33.33	00.00	0.50	48.15	22.22	0.61	55.56	33.33	**0.71**	59.26	38.89	0.69	48.15	22.22	0.69
4	120	39	159	43.59	15.38	0.58	53.85	30.77	0.65	43.59	15.38	0.50	71.79	57.69	**0.87**	74.36	61.54	0.84
9	60	24	84	33.33	00.00	0.50	50.00	25.00	0.63	33.33	00.00	0.50	62.50	43.75	**0.72**	54.17	31.25	0.71
11	30	15	45	46.67	20.00	0.60	53.33	30.00	0.65	66.67	50.00	0.75	73.33	60.00	**0.79**	73.33	60.00	0.77
	Mean			39.23	8.85	0.54	51.33	27.00	0.63	49.79	24.68	0.62	66.72	50.08	0.77	62.50	43.75	0.75

* WLS = Weighted Least Squares Regression; PMVC = Converted Predicted Mean Vote; PCM = Personal Comfort Model; 6PMV = dry bulb temperature, radiant temperature, relative humidity, air speed, metabolic rate, and clothing level; Acc = accuracy; AUC = Area Under the Receiver Operating Characteristic Curve.

The accuracy of the personal thermal comfort models using skin temperature alone as the single predictor ranged from 33.33% to 66.67%, with a mean of 49.79%. The Cohen's Kappa indicator ranged from 0.00% to 50.00%, with a mean of 24.68%, and the AUC ranged from 0.5 to 0.75, with a mean of 0.62. These indicators suggest a relatively low performance, especially when considering individual AUC performances lower than 0.5 (i.e., worse than random guessing).

When adding dry bulb temperature, radiant temperature, relative humidity, and air speed (i.e., environmental factors) and the metabolic rate and clothing level (i.e., behavioural factors) − the combination called in this chapter the 6PMV variables −, the individual models' performance increased, especially for ID04 and ID09, but not for ID01. The average accuracy increased to 66.72%, the average Cohen's Kappa to 50.08% and the average AUC to 0.77. These results are also similar to related studies, such as the work of Liu et al. (2019), which reported an average Cohen's Kappa indicator of 24%, accuracy of 78% and AUC of 0.79 among a set personal models using physiological and environmental data.

Including health perception produces a slight decline in the average and individual models' performance indicators. This difference in averages, however, is not statistically significant ($p > 0.05$). With the inclusion of health perception as a predictor, the personal comfort models presented an average accuracy of 62.50%, an average Cohen's Kappa Coefficient of 43.75% and an average AUC of 0.75. From these results, the best performing personal thermal comfort models were the ones using physiological, environmental, and behavioural input variables.

When analysing the generalised models, on average, the PMV_C model predicted individual thermal preferences with an accuracy of 51.33%, a Cohen's Kappa indicator of 27.00%, and an AUC of 0.63. The WLS model presented an even lower performance, with a mean accuracy of 39.23%, a mean Cohen's Kappa of 8.85%, and a mean AUC of 0.54 (i.e., slightly better than random guessing). On average, therefore, this represents a superior predictive performance of the individualised models using both environmental and personal variables when compared with the generalised approaches, as represented by **Figure 7-8**. These differences in mean predictive performance are statistically significant ($p < 0.05$).

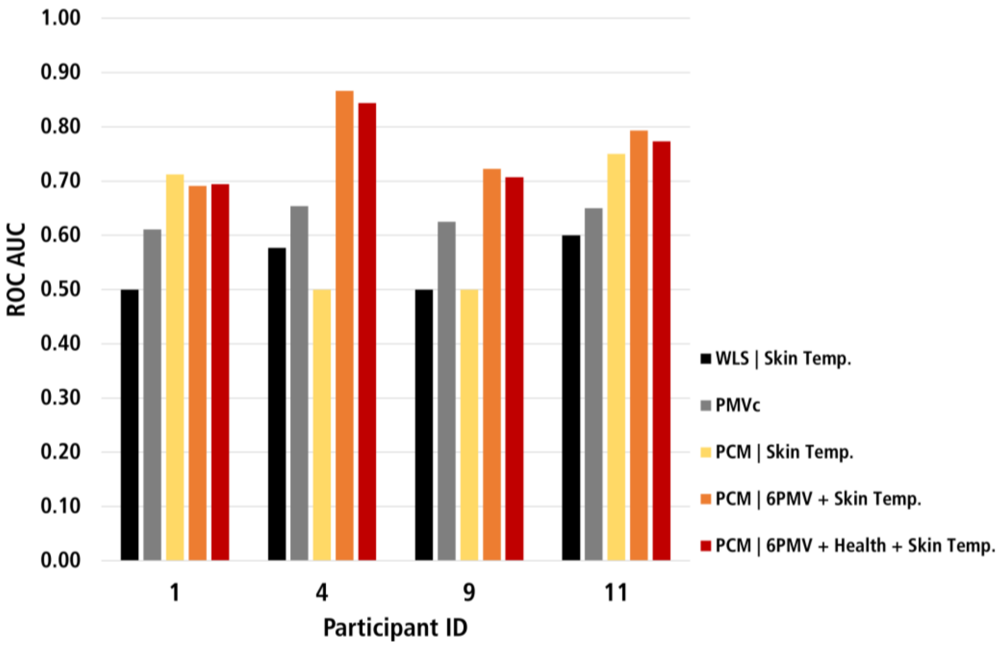

Figure 7-8 - Comparison between AUC for different models

It is also evident in **Figure 7-8** that ID04 and ID09's personal thermal models using only skin temperature underperformed, even when compared with the generalised models. Exploring in more detail these lower performances, Figure 7-9 shows the probability density of the distributions of the thermal preference categories depending on the 8 input variables involved in the study, built using Kernel Density Estimation (KDE) (Zielinski et al., 2018). When thermal preference categories have overlapping areas in these density plots, it suggests a participant is likely to prefer different thermal conditions when experiencing the same environmental conditions or having the same skin temperatures. Therefore, overlapping areas can represent the presence of events that are harder for the models to distinguish and predict. When analysing the density plots for skin temperature for ID04 and ID09, it is evident from the overlapping areas that adding this single variable as a predictor of thermal preference might not be ideal for them and could potentially compromise the models' predictive performance. ID11, on the other hand, has many fewer overlapping density regions for skin temperature, which could explain the higher performance of the personal model using this predictor. The skin temperature influence on thermal preference for ID11 has already been indicated by the box plot in **Figure 7-7**.

The density plots can also help explain the relatively low impact that the health perception variable had on all individual models. Furthermore, it is noted that the four participants analysed in detail, although having varying health perception throughout the monitoring study, were either not frail or had low levels of frailty (as presented in **Table 7-1**), which could have limited the range and variability of the data collected related to health and wellbeing perception. The quality of data could also have been affected by the self-reported nature of the health assessment. Finally, although health perception could have impacted these participants' thermal preference, the weight of the other input variables certainly prevailed. This is evident for ID04 and ID09, for which the environmental factors played a much more distinguishable role in the models. In addition, it is possible to extract from the plots the reason for the higher impact that adding environmental factors such as dry bulb and radiant temperatures had for ID04 and ID09 than it had for ID01.

When analysing how well the personal comfort models and generalised alternatives predict each of the three thermal preference categories, shown in **Figure 7-10**, the results suggest different misclassification patterns for each modelling method. The personal comfort models tended to present a higher predictive performance for 'prefer to be cooler' and 'prefer to be warmer' than for 'prefer to be neutral'. This meant that a preference for no change was being misclassified as preferring change more frequently than other possible misclassification options, which, in real scenarios where the models are used to control cooling and heating systems, would mean increasing the probability of unnecessarily cooling or heating the occupant's space. The generalised WLS model, however, presented the opposite tendency. This model's power for predicting the central category ('prefer no change') was generally better than its power for predicting the extremity classes ('prefer to be cooler' and 'prefer to be warmer'). This meant that a preference for change was misclassified as either preferring no change or preferring change in the wrong direction, more frequently than other possible misclassification options, which, in real scenarios, would mean leaving occupants either unattended during extreme events, or even more dissatisfied.

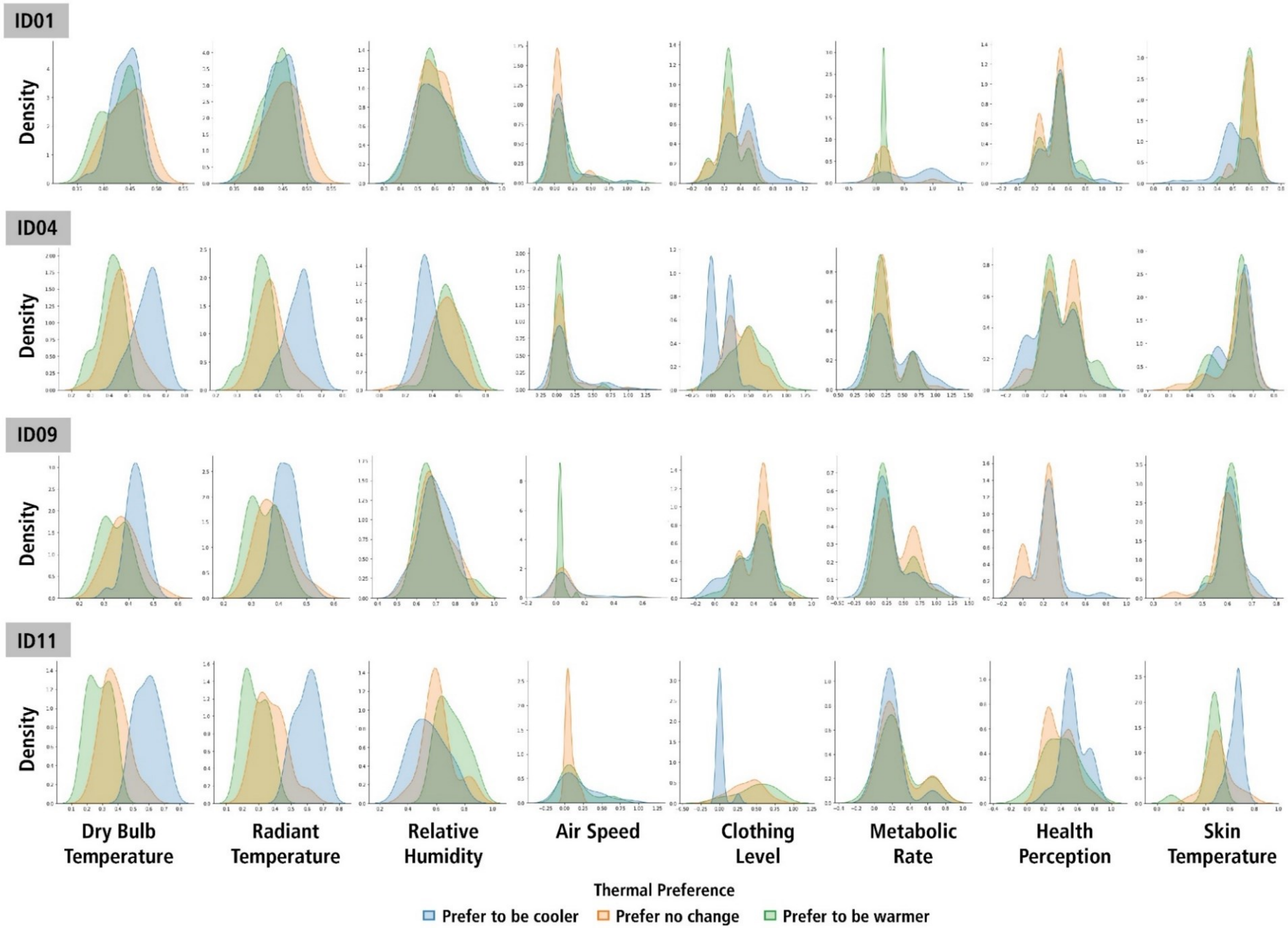

Figure 7-9 - Density plots for input variables used, for each thermal preference category, for each participant. Variables are normalized from 0 to 1, according to maximums and minimums presented in **Table 7-2**.

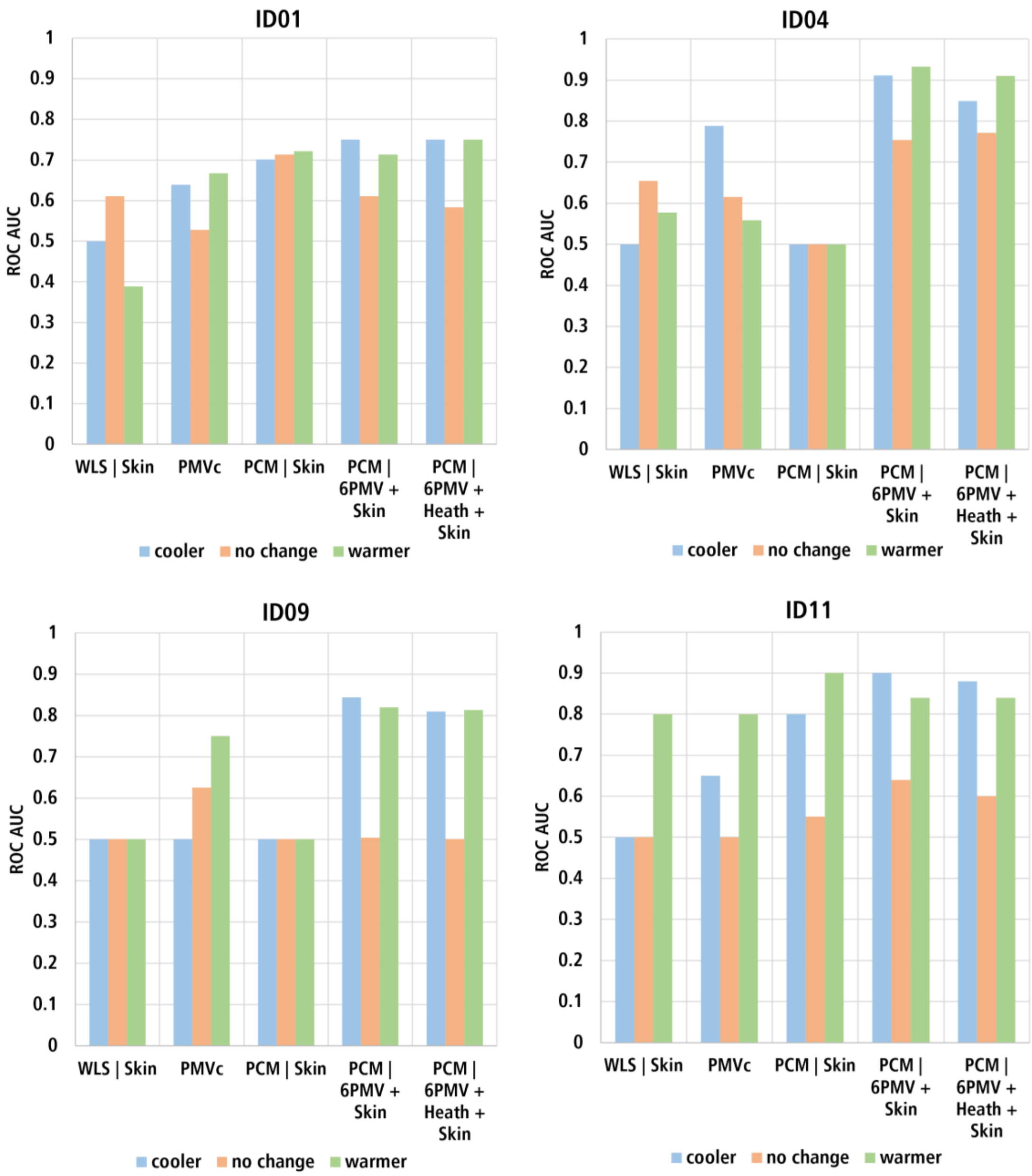

Figure 7-10 - Models' predictive performance for each thermal preference category, for each participant

7.4. Discussion

The results of this study show that personal thermal comfort models can be considered appropriate tools to predict older people's thermal preferences, outperforming generalised approaches such as the PMV_C or a weighted regression model driven by skin temperature. It is also evident that, although to different degrees for each individual, hand skin temperature can be an indicator of thermal preferences for the cohort analysed. In addition, combining this physiological measurement with other environmental factors, especially air temperature and radiant temperature, along with behavioural factors, such as clothing level, has been proven to be beneficial for the model's predictive performance, although the best predictor combination may differ across individual older adults.

The key next step would be merging the following elements:

(1) physiological sensing technologies for **data collection**;

(2) individualised predicting models for **evaluation and decision-making**;

(3) and wearable comfort systems for **autonomous and automatic action**.

As physiological sensing could collect real-time proxy for comfort without the need for occupant feedback, individualised models could use this real-time proxy to allow more reliable predictions for change, and pass them to wearable actuators, which, in turn, could enable direct conditioning without the need for any manual activation. Although it could be beneficial for all ages, this automation process would particularly be relevant for older adults, enabling thermal comfort management without reliance on others, which is key for older people maintaining independence in their own homes.

Physiological sensing devices have been researched extensively over the last decades, with a wide range already available on the market. Sensors mounted on smart watches are one of the main solutions for physiological and environmental sensing in real time (Reeder and David, 2016; Sim et al., 2018). On the other hand, heated clothing (e.g., gloves, socks, vests), neck and shoulder fans (also called wearable air-conditioning) (Knecht et al., 2016), or heating or cooling wrist-bands (Lopez et al., 2016) are common options for wearable actuators. Nevertheless, although hypothesized (Liu et al., 2019), combining the 3 facets, i.e., wearable sensing (data collection), prediction (evaluation) and conditioning (autonomous and automatic action), in a single solution is yet to be explored. In addition, these independent products tend to target a general and relatively homogeneous population, without considering the specific thermal comfort requirements and associated physiological responses of older people.

Nevertheless, it is important to highlight that the use of personal thermal comfort models, using not only physiological variables but also any type of input variable, requires non-interrupted and ideally infinite data collection, as well as constant update and re-learning to maintain accuracy and relevance through time for each individual. Furthermore, a wide range of thermal and situational conditions are essential to create enough deviations in the data collected to allow a balanced dataset and a statistically accurate and reliable analysis. Although real-time thermal comfort proxy data collection is currently being explored in studies involving personal comfort systems (PCS) (Kim et al., 2018b), these requirements involving data size and structure, related directly to how data is collected, remain the main challenge of personal comfort models. Further efforts on solving these data collection requirements are needed in order to move personal comfort models from a mere research methodology paradigm to a real practical solution, feasible to be deployed.

Another point of consideration is that the monitoring of physiological factors, either through the use of wearable devices or non-contact sensors such as the ones used in this study, poses additional cost and data privacy concerns in comparison with stand-alone environmental sensors, as already highlighted by Aryal and Becerik-Gerber (2019). Choosing the best combination of inputs for the personal models relies, therefore, not only on the type of measurements' impact on predictive performance, but also on individuals' capability to afford the sensing and privacy costs. In addition, despite recent efforts to decrease the intrusiveness of sensor data collection by using wearable devices or PCS (Katić et al., 2020; Kim et al., 2018b; Liu et al., 2019), personalised modelling would still require initial occupant feedback on their thermal preferences to allow minimum model training. Although the disruptions caused by monitoring would be an issue for all age cohorts, they may introduce additional barriers for frailer older adults' participation.

Furthermore, this study highlighted an important modelling limitation, still not entirely explored by studies on personal thermal comfort, which is the misclassification cost of thermal preference in general and specifically for older adults. The misclassification of each thermal preference category may represent different application consequences in real scenarios. While unnecessarily cooling or heating an occupant's space by misclassifying a preference for no change may result in an increase in energy use, leaving occupants unattended during extreme events by misclassifying a preference for change could result in heat related illnesses. In this context, not only are these misclassification costs complex to estimate, but they also involve different domains (e.g., energy use costs versus health costs). Applying different weights for each type of misclassification is potentially a more appropriate way to measure thermal preference models' performance than any of the indicators used so far (e.g., accuracy, Cohen's Kappa Coefficient or AUC). Lee et al. (2019), for instance, have presented an alternative for generic metrics. Although they did not determine the exact cost for each case of misclassification, they estimated the cost ratio between cases. By assessing three cost matrices, a thermal satisfaction oriented, an energy-saving oriented and an equally weighted cost matrix, the authors explored different domains of cost (i.e., energy cost versus comfort cost) and highlighted that, apart from predictive performances, selecting the optimal model would depend on the intended application. The principles applied by the authors are in line with a sub-field of machine learning called cost-sensitive learning (Elkan, 2001), and could be further investigated in future studies to deal with the un-even costs of thermal preference misclassification. Moreover, further studies should analyse whether the thermal preference misclassification costs differ between younger and older adults, considering the health, living and financial arrangements of each cohort.

7.5. Limitations and future studies

It is important to highlight that this study has limitations. Firstly, the data collection involving skin temperature was conducted between the months of September and February, covering only a warm and hot season in South Australia. Further data collection periods in cool and cold seasons are required to allow a broader understanding of the effects of thermal exposures on the skin temperature of older adults.

Secondly, although field studies provide a more accurate representation of reality than controlled climate chamber experiments, their use in this study also posed challenges to dataset sizes and distributions. Monitoring real thermal environments, where conditions vary without the influence of researchers, naturally resulted in imbalanced datasets, impacting the dataset sizes available for modelling, especially once undersampling was conducted. The authors, therefore, acknowledge the relevance of exploring the development of personal thermal comfort models under imbalanced dataset scenarios, especially considering the likelihood of these scenarios in thermal comfort field research. Furthermore, future studies by the authors plan to address other balancing strategies and overfitting reduction (e.g., dropout or batch regularization) in order to investigate the effectiveness of different sampling techniques in this specific context.

It is also noteworthy that the first data collection period was concluded in October 2019, before the declaration of COVID-19 as a pandemic in March 2020, and was not affected by the pandemic. The second data collection period, on the other hand, happened between September 2020 and February 2021. During this period, however, the State of South Australia implemented a strict response plan, which resulted in a relative low number of reported COVID-19 cases. In addition, none of the participants reported contracting the disease during or before this data collection. Normal activities, including research visits within the State were largely unaffected. Hence, the impacts of the pandemic on the data size or quality (especially related to health perception) were considered minimal by the authors. Nevertheless, an in-depth analysis of the effects of the pandemic on the cohort could be part of the scope of future studies.

Furthermore, although the older participants involved in this study represent a diverse cohort in terms of body composition, health and living environment, other socio-cultural and economic factors need to be addressed to build a more holistic image of their diversity. Moreover, the four participants whose individual dataset sizes allowed the development of personal thermal comfort models happened to be all female. The development of individual models for males is, therefore, required in future studies. In addition, although the models involve different environmental and personal inputs, other relevant input variables could be explored, such as seasonal thermal expectations or other physiological data, such as heart rates. Moreover, given the nature of the study, only self-reported health perceptions were used as inputs, which might lack the accuracy of records from healthcare providers.

Regarding the modelling methodology, it is important to highlight that the binning approach used for continuous variables in the weighted regression estimation can result in loss of information, depending on the granularity of the increments chosen. In addition, the use of k-Nearest-Neighbours for missing value imputation can impact the overall data structure and further studies are required to analyse the risk of distorting estimates despite an apparent optimal performance on other quality metrics. The impact of missing value imputation using data across two separate collection periods, although considered minimal in this study, should also be further analysed. Furthermore, other normalization techniques and standardization techniques could have been applied to determine the central tendency of the ordinal (and discrete) variables used in the models. Further studies will be developed by the authors to comprise not only different pre-processing techniques according to variable type, but also other methods for ordinal variable encoding.

Finally, the PMV scale conversion conducted in this study poses limitations in the comparisons, since thermal sensation and thermal preference scales cannot be considered interchangeable for all individuals. While neutral sensation and thermal preference for no change can be experienced simultaneously, it is still necessary to account for preferred sensations other than neutral. An alternative could be analysing different conversion rules for each individual participant, depending on their thermal sensation and thermal preference answers.

7.6. Conclusion

This chapter presents an individualised modelling approach to predict older adults' thermal preferences in their living environments, based on environmental, physiological, and behavioural data, comparing the models' predictive performance with conventional aggregate modelling methods. From the analysis conducted, the study has pointed to the following findings and future pathways:

- When analysing the aggregate dataset, strong relationships were identified between skin temperature and dry bulb temperature, radiant temperature, clothing level and health perception for the older adults involved.

- Fitting a weighted least squares regression model for thermal preference prediction using skin temperature as the single predictor resulted in a R-squared value of 0.346 and a statistically significant independent variable coefficient ($p = 0.001$).

- On average, the PMV_C model predicted individual thermal preferences with an accuracy of 51.33%, a Cohen's Kappa indicator of 27.00%, and an AUC of 0.63. The WLS model presented a lower performance, with a mean accuracy of 39.23%, a mean Cohen's Kappa of 8.85%, and a mean AUC of 0.54.

- On average, the personal thermal comfort models using skin temperature as the single predictor showed an accuracy of 49.79%, a Cohen's Kappa indicator of 24.68%, an AUC of 0.62.

- When skin temperature data are combined with dry bulb temperature, radiant temperature, relative humidity, air speed (i.e., environmental factors), metabolic rate and clothing level (i.e., behavioural factors), the average accuracy of the prediction increased to 66.72%, the average Cohen's Kappa to 50.08% and the average AUC to 0.77. This represents a superior predictive performance of the individualised models, using both environmental and personal variables, when compared with the generalised approaches.

- Including health perception as an input variable represents a slight decline in the average model's performance, but this difference is not statistically significant ($p > 0.05$).

- The results suggested different misclassification patterns for each modelling method and require further investigation into thermal preference misclassification costs in the context of older adults.

The key next step would be to combine physiological sensing technologies, individualised predicting models and wearable comfort systems. Although it would be beneficial for all ages, this automation process could be particularly relevant to assist older adults to maintain independence in their own homes.

Chapter 8. Applications of personal thermal comfort models for older people

8.1. Introduction

By analysing datasets at the individual level, personal thermal comfort models help to unmask the differences between individuals in an environment, enabling a better understanding of specific comfort needs and collecting diagnostic information to identify user acceptability problems, as already highlighted in **Chapter 3**. This information, in turn, can be applied in the decision-making process involved in designing and optimising thermal environments to improve comfort satisfaction and energy efficiency.

Therefore, drawing from the exploration on personal comfort models conducted in **Chapters 6 and 7**, the next and final natural step of this research was to investigate possible application opportunities and their benefits in older people's contexts and real settings. Hence, this chapter aims to answer research questions E and F:

E. Can personal comfort models for older people be used to determine heating and cooling set points more accurately?

F. How can personal comfort models for older people be used to aid the control and adaptation of older people's environments to increase comfort and health and wellbeing?

These questions are related to ***Objective (3)****: Investigate the application of personal thermal comfort models in managing the thermal environment of older people's dwellings and the health and wellbeing of older people in general*.

Two types of application for the personal thermal comfort models developed in this thesis are explored in this chapter. The first exploration assesses the possibility of using the models to predict a set of new personal temperature thermostat set points for HVAC systems, in order to predict energy loads more accurately than pre-determined assumptions commonly used in the field of building performance simulation. The second investigation explores the use of the models in a web-based smart device tool, that allows the automatic calculation of thermal preferences for older individuals, aimed at aiding their control and adaptation for older people's environments, to increase levels of comfort. The app is destined to be used by designers, caregivers or health care professionals, and was developed using, as references, a series of user-interfaces and smart device apps in the related fields. The methodology used in each application, as well as the corresponding results and limitations are described in detail below.

8.2. Building Simulation application

Two participants and their respective houses were selected (based on the quality of information about their houses and other details) to assess whether new heating and cooling temperature set points (i.e., HVAC thermostat settings) calculated from their personal thermal comfort models could accurately represent their real preferences. To conduct this evaluation, a comparison was made between the simulated energy loads[11] for heating and cooling using the new personal temperature set points and the actual energy loads for heating and cooling of the participants' households, based on actual energy use records.

Participant ID27, who lived in House 08 located in the Adelaide Metropolitan Area, and participant ID32, who lived in House 53 located in Whyalla, were selected to represent not only different thermal preferences, but also different house types, climate zones and HVAC system types. The participants' full personal characteristics are presented in **Chapter 5**.

Design Builder/Energy Plus Version 7.0.0.088 Design Builder Software Ltd (2021) was used to model, calibrate and simulate the buildings.

8.2.1. Building simulation model calibration method

To ensure that the simulation models reflected the actual houses and thus could be used to explore the heating and cooling energy loads in an accurate way, the first step was to calibrate the simulation models. The calibration procedure included the following steps:

(1) initial model development according to building drawings and site visits;

(2) actual 2019 weather data acquisition from the nearest Australian Bureau of Meteorology station;

[11] The term "energy load" is used in this thesis as the amount of energy needing to be added or extracted from a building's space, in order to maintain its indoor temperature within a pre-defined range. The heating energy load is the amount of energy that would need to be added to a space, and the cooling load is the amount of energy that would need to be removed from a space.

(3) compilation of the actual measured hourly indoor temperatures in the selected houses from the monitoring stage of the project, for at least 14 consecutive days (during the hot/warm season and the cool/cold season), during which cooling and/or heating was not in use;

(4) initial simulation (using actual weather data) and comparison between simulated and measured indoor temperatures using graphical tools and the Coefficient of Variance of the Root Mean Square Error (CV(RMSE)) and the Normalised Mean Bias Error (NMBE); and

(5) iterative revision of the simulation input parameters to minimise the CV(RMSE) and the NMBE between the simulated and measured indoor temperatures.

Three types of input parameters were considered during calibration, based on the methodology by Soebarto (1997). The first one, called "basic data", included the parameters confirmed through building drawings and visits, such as the building orientation, dimensions of all envelope surfaces, position of openings and shading devices. The second, "estimated data", included parameters only determined by estimation, namely the thickness of envelope material layers, the materials' thermal properties, and the building infiltration rates. The third, "measured data", included parameters obtained through the monitoring and survey of participants, such as occupancy and building operation levels and schedules.

Among the three types of inputs, however, the basic data and the measured data were not revised during calibration, as they were based on specific information collected from the participants, on-site measurements, and the architectural drawings (construction drawings were not available). The iterative revision of the simulation parameters involved individually adjusting, in successive increments, the estimated data until acceptable CV(RMSE) and NMBE were achieved. All adjustments were made within a likely or credible range of values. Firstly, the thickness of each layer in the external walls, roof, ceiling, and floor was adjusted one by one, followed by adjusting the materials' thermal properties (thermal conductivity, specific heat, and density) until acceptable matches were achieved. Finally, the building infiltration rates were incrementally revised, when necessary. All adjustment increments and directions were determined according to expert knowledge and common practice in the field (Roberti et al., 2015; Spitz et al., 2012; Abrahams et al., 2020).

The International Performance Measurement and Verification Protocol (Efficiency Valuation Organization, 2012) and the ASHRAE Guideline 14 (ASHRAE, 2002) define the acceptance criteria for the CV(RMSE) and the NMBE indicators in terms of energy consumption (i.e., NMBE within ±10% and CV(RMSE) lower than 30% for hourly calibration data). There are, however, no standards that determine the adequate acceptance criteria for these indicators for models calibrated using indoor air temperatures

(Roberti et al., 2015). This study, therefore, determined the acceptance criteria as NMBE within ±10% and CV(RMSE) lower than 10%. This was based on other studies that used indoor temperatures in degrees Celsius to calibrate simulation models, such as the work of Royapoor and Roskilly (2015) (which observed a CV(RMSE) of 1.96% and an MBE of 0.74%), Saleh (2015) (who reported a CV(RMSE) lower than the 30% and NMBE lower than the 10%) and Abrahams et al. (2020) (which reported a CV(RMSE) of 3% and an MBE of -1%).

8.2.2. Energy disaggregation method

In order to assess whether the new heating and cooling set points calculated from the personal thermal comfort models accurately represented participants' real preferences, the study conducted a comparison between the simulated energy use for heating and cooling using the new personal set points and the actual energy consumption for heating and cooling of the participants' households. Actual household energy consumption for at least a 3-year period was obtained for each house from the bills provided from their appropriate electricity retailers. This data included details on the total electricity consumption, date of issue, bill period, units used, and off-peak units used, where applicable.

The actual energy consumption data, however, represented the total energy consumption regardless of type of use and thus did not allow direct comparison with the isolated heating and cooling energy simulation results. Therefore, the next step consisted of disaggregating the actual total energy use into 3 components: (1) actual energy used for heating, (2) actual energy used for cooling and (3) actual energy used for all other appliances and lighting.

Following the work by Williamson et al. (2006), heating and cooling related energy consumption was disaggregated from total consumption data using a least squares methodology. For a household where electricity supplies both heating and cooling energy, the following overdetermined system of equations (i.e., sets of equations in which there are more equations than unknowns), was written:

$$a_1 x + b_1\, y + c_1\, z = \, d_1 \qquad (1)$$

$$a_2 x + b_2\, y + c_2\, z = \, d_2 \qquad (2)$$

$$a_3 x + b_3\, y + c_3\, z = \, d_3 \qquad (3)$$

...

$$a_i x + b_i\, y + c_i\, z = \, d_i \qquad (x)$$

where x is the total consumption for the household attributable to heating over all periods of analysis; y is the total consumption for the household attributable to cooling over all periods of analysis; z is the total other household electricity consumption (e.g., lighting, appliances) over all periods of analysis; a, b and c are the coefficients expressing the fraction of the relevant components x, y and z for each individual bill period; and d is the total electricity consumption for individual bill periods.

To estimate the coefficients a and b, it was assumed that the heating and cooling use of the building is climate dependent and a function of the heating degree-days and cooling degree-days, respectively. The mean outdoor temperatures for each day for each billing period (i.e., around 90 days), collected from the Australian Bureau of Meteorology database for the corresponding locations, were used to calculate the heating and cooling degree-days as the sum of the differences between the outdoor temperature and different possible base temperatures over the specified time period (CIBSE, 2006). The beforementioned overdetermined system of equations formed from this data was then reduced to a defined set of normal equations with three variables (i.e., x, y and z) by least squares best fit (Rao et al., 2008).

A range of possible heating and cooling base temperatures were tested with the chosen values being the combination that provided the highest R^2 solution. The solution values of x, y and z were then converted to annual values of energy consumption by multiplying them by 365 days and dividing them by the total number of days in all periods of analysis.

For the buildings with photovoltaic panels installed, the standard South Australian energy retailers only measure and provide the amount of solar energy fed back into the grid system (i.e., net value), which means that the solar energy produced and used in the buildings is not reported in the occupants' bills. Therefore, it was necessary to first calculate the total solar energy production, considering the area of the panels installed, a 15% system efficiency and the daily solar radiation, extracted from the Australian Bureau of Meteorology databases, at the location for each billing period. The actual solar energy consumption was then calculated by subtracting the feed-in energy from the total produced. This was then added to the total energy consumption of the bill.

Details on the consumption of other non-metered fuels used for heating, such as bottled LPG (liquefied petroleum gas), were also collected from participants through interviews and added to the final annual heating energy consumption. The heating and cooling energy consumption were then converted to energy loads by multiplying them by the COP (Coefficient of Performance) and EER (Energy Efficiency Ratio), respectively, of the actual HVAC systems installed in each house. The COPs and EERs of the systems were obtained according to each manufacturer's information and assumptions according to the Australia Greenhouse and Energy Minimum Standards Registration Database (Greenhouse and Energy Minimal Standards Regulator, 2021) and the Australian Gas Association Certified Products (The Australian Gas Association, 2021).

8.2.3. HVAC set point calculation method using personal thermal comfort models

The next step consisted of calculating the heating and cooling temperature set points for each participant using their personalised thermal comfort model, developed, and detailed in Chapter 5 of this thesis (with dry bulb temperature, mean radiant temperature, relative humidity, air speed, clothing level and corrected metabolic rate as input variables).

The personal models developed in this study are probabilistic models. Unlike deterministic models, which give a single exact outcome for a prediction, probabilistic models provide a solution as a probability distribution to account for uncertainty in the events analysed. As discussed in Chapter 3, probabilistic methods are especially relevant when analysing systems that are inherently stochastic and/or highly uncertain due to insufficient data (Ghahramani, 2015; Murphy, 2012; Goodfellow et al., 2016), which is in line with the nature of thermal comfort modelling in general.

Therefore, the set points were determined considering the model's probability prediction for each thermal preference category (i.e., "preferring to be cooler", "preferring no change", "preferring to be warmer"). The cooling temperature set point was determined as the indoor dry bulb temperature at which the probability of "preferring to be cooler" equalled 50%, representing the exact moment when a participant's thermal preference moves from "preferring no change" to "preferring to be cooler". Likewise, the heating temperature set point was determined as the indoor dry bulb temperature in which the probability of "preferring to be warmer" equalled 50%, representing the moment when a participant's thermal preference moves from "preferring no change" to "preferring to be warmer".

Microsoft Excel (Microsoft Corporation, 2021) Iterative Solver add-in was used, with the Generalized Reduced Gradient (GRG) solving method, to achieve these probabilities by changing the dry bulb temperature variable. In these calculations, the mean radiant temperature was assumed to be equal to the dry bulb temperature in order to simplify the calculations. The other variables were kept constant. For the cooling set point calculation, the relative humidity variable was kept constant at the average measured indoor relative humidity plus 1 standard deviation in the hot/warm months (i.e., from January to March) at the specific person's house, to account for 85% of the cases. Note that relative humidity was normally distributed. Likewise, for the heating set point calculation, the relative humidity variable was kept constant at the average measured indoor relative humidity minus 1 standard deviation in the cold/cool months (i.e., from June to August) at the specific person's house. The air speed was assumed constant at 0.1 m/s, in accordance with common practice in the field to represent a stand still air velocity (CIBSE, 2017; CIBSE, 2013). The clothing level was kept constant at the specific person's average monitored clothing levels when "preferring to be cooler" and when "preferring to be warmer", for cooling and heating set points calculations respectively. Similarly, the corrected metabolic rate was kept constant at the specific person's average monitored corrected metabolic rates when "preferring to be cooler" and when "preferring to be warmer", for cooling and heating set points calculations respectively.

Once the personal heating and cooling temperature set points were determined, they were inserted as inputs in the building energy simulation models to predict the HVAC energy loads to achieve and maintain such temperatures throughout the year. The energy loads were then compared with the actual disaggregated HVAC energy loads to assess the accuracy of the personal set points. In addition, the simulated HVAC energy loads derived from the personal set points were compared with the simulated energy loads resulting from using a 21°C set point for heating and a 24°C set point for cooling. These temperatures not only represent common set point approximations used in building simulation studies (Chen, 2016), but also represent a theoretical range of temperatures calculated by a previous study by Bills (2018) and recommended as beneficial to minimize the presence of health symptoms for older people living at home. This exploration, therefore, aims to investigate whether this recommended range, derived from an aggregate and generalised calculation approach, remains the best solution when assuming occupants' set points in building simulations.

8.2.4. Results: House 08 – Participant ID27

House 08 (**Figure 8-1**) is a traditional brick-veneer house, 10 to 20 years old, semi-detached, in a long, narrow layout. Calibration was conducted using the data from the main living area of the house where the logger was placed, highlighted in red in **Figure 8-1**. **Figure 8-1** also shows the surrounding buildings and shading devices.

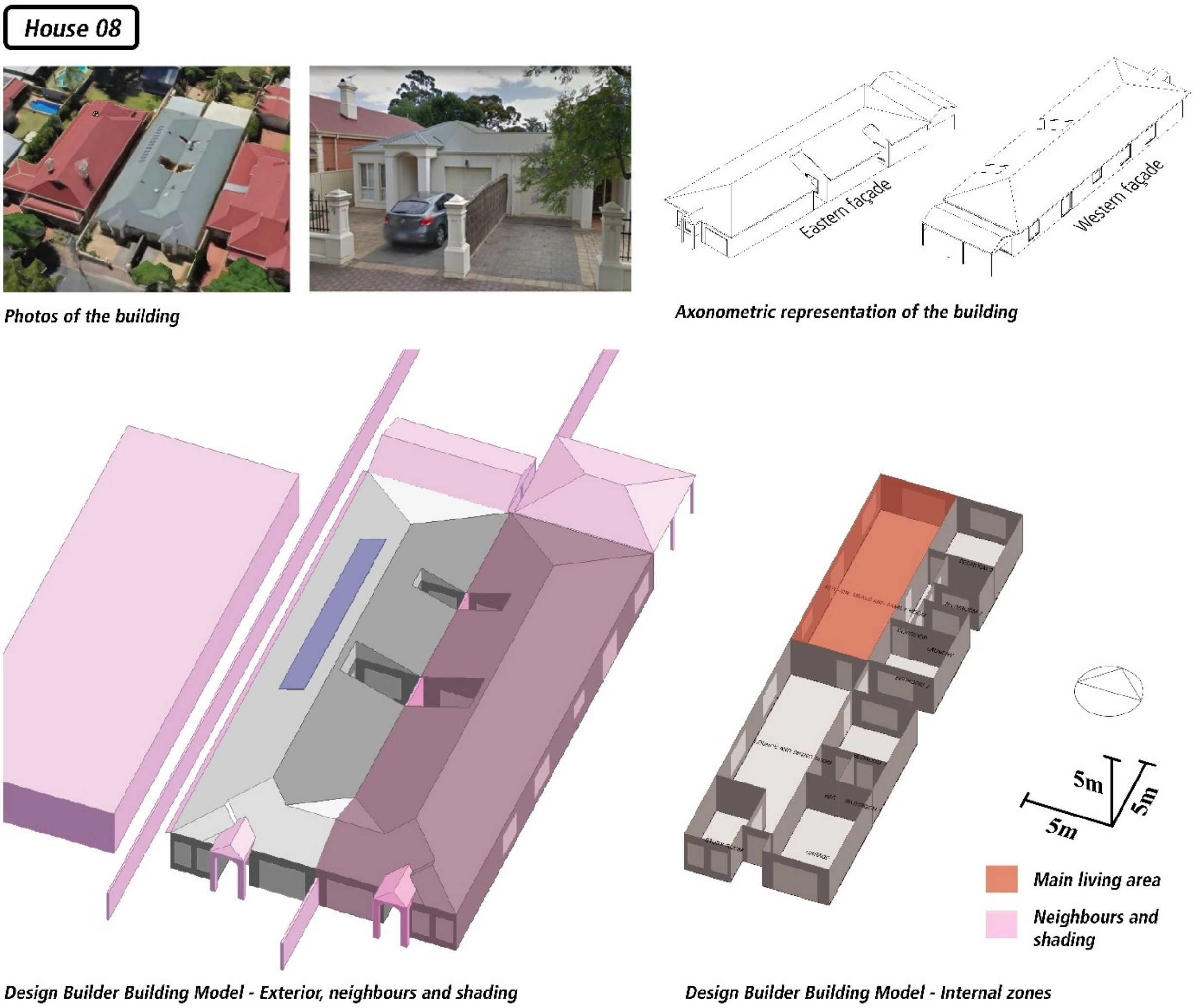

Figure 8-1 - House 08's photo, axonometric representation and Design Builder building model

8.2.4.1. Building simulation model calibration results

Figure 8-2 shows the comparison between the simulated and measured indoor temperatures in House 08 (Participant ID27) and the corresponding CV(RMSE) and NMBE, for the calibration period. House 8 was only calibrated for the hot/warm season because it did not have any consecutive days during which heating was not in use in the cool/cold season.

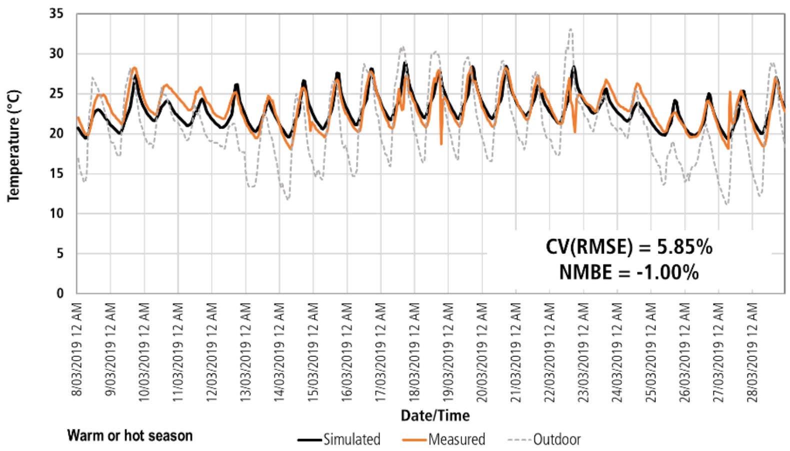

Figure 8-2 - Calibration Results for House 08 – ID27

Table 8-1 presents the calibrated houses' characteristics in more detail. The initial thermophysical properties of the building materials were obtained from Design Builder/Energy Plus databases (Design Builder Software Ltd, 2021). *Table* **8-2** presents the other relevant building simulation inputs for House 08, according to the specificities of the building and its occupants. The distance between the building and chosen weather station was less than 10km. The impact of appliances and equipment as internal heat sources was considered minimal for the specific building (no heavy use of computers or inefficient equipment), and thus not included in the simulation models.

Table 8-1 - House 08's characteristics

	Construction layers	**R-value (U-value)[1]**
Floor Material (outside to inside)	120 mm concrete slab-on-ground, 10 mm timber flooring	0.388 (2.580)
Internal Wall Material	10 mm plasterboard, 100 mm air gap, 10 mm plasterboard	0.482 (2.075)
External Wall Material (outside to inside)	110 mm brickwork, 40 mm air gap, 90 mm glass fibre board, 10 mm plasterboard	3.021 (0.331)
Ceiling Material (inside to outside)	12 mm plasterboard	0.322 (3.106)
Roof Material (inside to outside)	90 mm glass fibre batt Metal roofing	2.661 (0.376)
Window Material	single clear glazing (3 mm)	(5.894)
Total Floor Area (m²)	230.60	
Main Living Area External Wall Orientations	North and West	
Main Living Area Window-floor Ratio	0.26	

[1] R-value in $m^2.K/W$ and U-value in $W/m^2.K$

Table 8-2 - Other building simulation inputs for House 08

Parameters	**Assumptions**
Number of occupants	2
Occupancy schedule in the living area	7 am to 10 pm
Lighting schedule in the living area	5 pm to 10 pm
Lighting in the living area	$1W/m^2$ – 100 lux
Mechanical ventilation	None
Natural ventilation	None (windows closed)
Heating and Cooling schedule	on 24/7 according to set points
Weather file	Calibration – Adelaide Airport weather station, year 2019 Energy assessment – Adelaide Airport weather station, year 2018, 2017 and 2016

8.2.4.2. Energy disaggregation results

The energy consumption data from House 08 comprised the period between 24th of September 2016 and 17th of December 2018. Through the energy disaggregation method described in **Section 8.2.2**, the total annual energy consumption was broken down into heating, cooling and other uses, as shown in **Table 8-3**. It is important to highlight that this building was operated using auxiliary solar energy input from photovoltaic panels, with approximate total area of 16.3 m^2. The effect of the panels on energy consumption was taken into consideration, using the methodology detailed in **Section 8.2.2**.

Table 8-3 - House 08's disaggregated annual energy use (electricity)

	Annual Energy Use (kWh)
Total	10383.6
Other	4093.9
Heating	3401.7
Cooling	2888.1

House 08 is equipped with a ducted reverse cycle air-conditioning system, which has an assumed heating COP of 3.5 and a cooling EER of 2.7, according to the manufacturer's information (Temperzone Limited, 2005) and assumptions according to the Australian Greenhouse and Energy Minimum Standards Registration Database (Greenhouse and Energy Minimal Standards Regulator, 2021). The conditioned zones include the kitchen/meal area (i.e., main living area), all bedrooms, the corridor, the lounge/dining room and a study room, accounting for 82% of the building's total area. **Figure 8-3** presents the photos of the outdoor unit of the system and the controls located in the building's main living area. The annual energy loads for heating and cooling were then calculated by multiplying the actual heating and cooling energy use by the corresponding COP/EERs of the system. As presented in **Table 8-4**, this resulted in a total actual annual energy load for heating of 11905.8 kWh and a total actual annual energy load for cooling of 7797.8 kWh.

Figure 8-3 - House 08's HVAC system and controls. Source: Photographed by the author.

Table 8-4 - House 08's heating and cooling energy use and load (electricity)

	HVAC System type/model	Annual Energy Use (kWh)	COP/EER	Annual Energy Load (kWh)
Heating	Ducted Reverse Cycle Temperzone ISD181Q/OSA181R	**3401.7**	3.5	**11905.8**
Cooling	Ducted Reverse Cycle Temperzone ISD181Q/OSA181R	**2888.1**	2.7	**7797.8**

8.2.4.3. HVAC set point determination using the Personal Comfort Model

Using the personal thermal comfort model developed for ID27 (presented in **Chapter 6**) and the methodology described in **Section 8.2.3**, the set points for heating and cooling for House 08 were determined. **Table 8-5** presents the inputs used to reach the dry-bulb temperature threshold that represents a 50% probability of "preferring to be warmer", resulting in the heating temperature set point, and the inputs used to reach the dry-bulb temperature threshold that represents a 50% probability of "preferring to be cooler", resulting in the cooling temperature set point. Therefore, the resulting set points are: 22.8°C for heating and 23.8°C for cooling.

Table 8-5 - Personal comfort model inputs used to determine the heating and cooling set points for Participant ID27

	Dry bulb temperature (°C) = Mean radiant temperature (°C)	Relative Humidity (%)	Air speed (m/s)	Metabolic Rate (MET)	Clothing level
Heating	22.8	41	0.1	1.0	3
Cooling	23.8	55	0.1	1.0	2

8.2.4.4. Comparison between real and simulated HVAC energy load

Using the beforementioned set points, the buildings were simulated. Three simulation runs were conducted utilising the weather data from the years of 2016, 2017 and 2018, as these were the years covered by the actual energy data provided by the occupant. As seen in **Table 8-6**, the difference between the actual and simulated heating loads (i.e., the error) ranged from 12.3% to 19.1% of the actual energy load, which can be seen as acceptable considering the limitations of the methodology proposed (discussed further in **Section 8.2.7**). The errors for cooling loads, however, were higher and ranged from -44.1% to -54.9%. Although the individual heating and cooling results are not optimal, the differences between the actual and simulated total loads are relatively lower, between -8.0% and -10.2%.

Table 8-6 - Energy loads' comparison for House 08 - ID27, using new personal set points

			2016 weather file			**2017 weather file**			**2018 weather file**		
Set point (°C)		Actual (kWh)	Simulated (kWh)	Error (kWh)	Error (%)	Simulated (kWh)	Error (kWh)	Error (%)	Simulated (kWh)	Error (kWh)	Error (%)
22.8	Heating Load	11905.8	14182.1	2276.3	**19.1%**	13758.0	1852.2	**15.6%**	13364.5	1458.7	**12.3%**
23.8	Cooling Load	7797.8	3514.4	-4283.4	**-54.9%**	4365.8	-3432.0	**-44.0%**	4356.0	-3441.7	**-44.1%**
	Total load	19703.6	17696.5	-2007.1	**-10.2%**	18123.7	-1579.8	**-8.0%**	17720.5	-1983.1	**-10.1%**

When simulating House 08, assuming a 21°C set point for heating and a 24°C for cooling, the difference between actual and simulated energy loads is larger than when using the new preferred set points, as presented in **Table 8-7**.

Table 8-7 - Energy loads' comparison for House 08 - ID27, using 21-24°C set points

			2016 weather file			**2017 weather file**			**2018 weather file**		
Set point (°C)		Actual (kWh)	Simulated (kWh)	Error (kWh)	Error (%)	Simulated (kWh)	Error (kWh)	Error (%)	Simulated (kWh)	Error (kWh)	Error (%)
21.0	Heating Load	11905.8	7587.6	-4318.2	**-36.3%**	7478.7	-4427.1	**-37.2%**	7157.2	-4748.7	**-39.9%**
24.0	Cooling Load	7797.8	3022.7	-4775.1	**-61.2%**	3840.2	-3957.6	**-50.8%**	3829.1	-3968.6	**-50.9%**

Total load	19703.6	10610.3	-9093.3	**-46.2%**	11318.9	-8384.7	**-42.6%**	10986.3	-8717.3	**-44.2%**

8.2.5. Results: House 53 – Participant ID32

House 53 (**Figure 8-4**) is an example of an older house, semi-detached, with double-brick external walls. Calibration was conducted using the data from the main living area of the house where the logger was placed, highlighted in red in **Figure 8-4**. **Figure 8-4** also shows the surrounding buildings, shading devices, and vegetation.

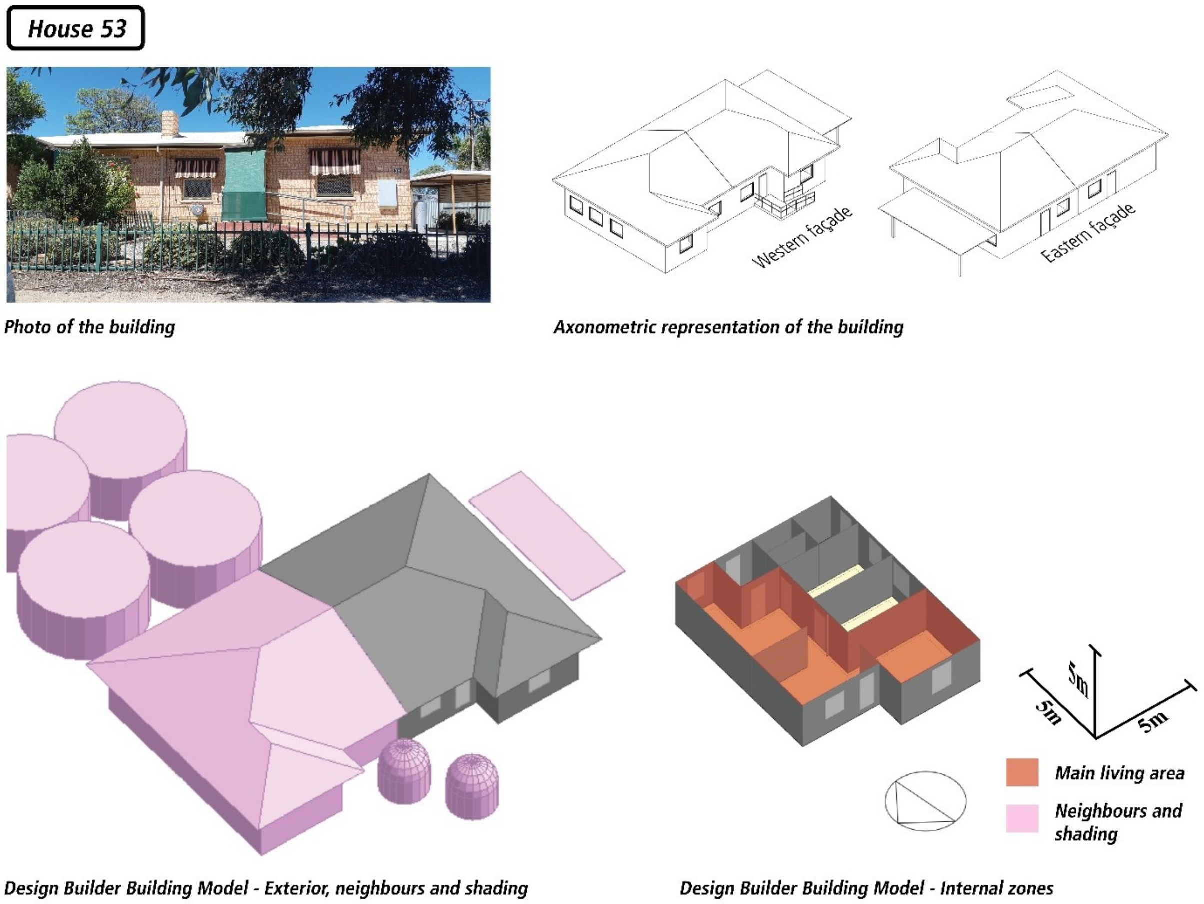

Figure 8-4 - House 53's photo, axonometric representation and Design Builder building model

8.2.5.1. Building simulation model calibration results

Figure 8-5 shows the comparison between the simulated and measured indoor temperatures in House 53 (Participant ID32) and the corresponding CV(RMSE) and NMBE, for the calibration periods (warm/hot season and cool/cold season).

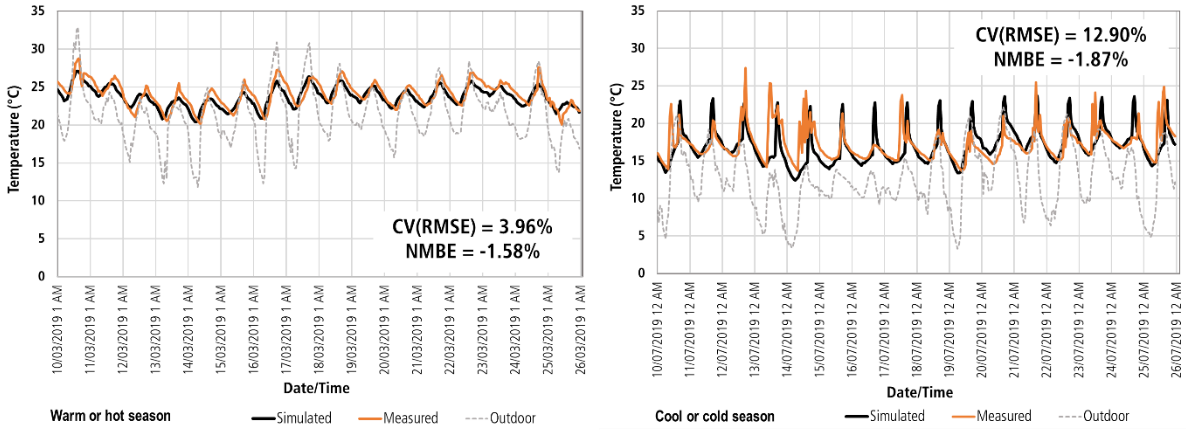

Figure 8-5 - Calibration Results for House 53 – ID32

Table 8-8 presents the calibrated house's characteristics in more detail. Similar to House 08, the initial thermophysical properties of the building materials of House 53 were obtained from Design Builder/Energy Plus databases (Design Builder Software Ltd, 2021). **Table 8-9** presents the other relevant building simulation inputs for House 53, according to the specificities of the building and the occupant. The distance between the building and chosen weather station was less than 10km. The impact of appliances and equipment as internal heat sources was considered minimal for the specific building (no heavy use of computers or inefficient equipment), and thus not included in the simulation models.

Table 8-8 - House 53's characteristics

	Construction layers	**R-value (U-value)[1]**
Floor Material (outside to inside)	400 mm ventilated cavity, 20 mm timber flooring, 3 mm linoleum	2.384 (0.420)
Internal Wall Material	15 mm plasterboard, 110 mm brickwork, 10 mm air gap, 110 mm brickwork, 15 mm plasterboard	0.838 (1.193)
External Wall Material (outside to inside)	110 mm brickwork, 50 mm air gap, 110 mm brickwork, 13 mm plasterboard	0.740 (1.351)
Ceiling Material (inside to outside)	13 mm plasterboard, 200 mm glass-fibre board	4.843 (0.206)
Roof Material (inside to outside)	Metal roofing	0.140 (7.117)
Window Material	single clear glazing (3 mm)	(5.894)
Total Floor Area (m²)	81.95	
Main Living Area External Wall Orientations	East and West	
Main Living Area Window-floor Ratio	0.082	

[1] R-value in m².K/W and U-value in W/m².K

Table 8-9 - Other building simulation inputs for House 53

Parameters	Assumptions
Number of occupants	1
Occupancy schedule in the living area	7 am to 10 pm
Lighting schedule in the living area	5 pm to 10 pm
Lighting in the living area	1W/m^2 – 100 lux
Mechanical ventilation	None
Natural ventilation	None (windows closed)
Heating and Cooling schedule	on 24/7 according to set points
Weather file	Calibration – Whyalla weather station, year 2019 Energy assessment – Whyalla weather station, year 2018, 2017 and 2016

8.2.5.2. Energy disaggregation results

The energy consumption data from House 53 comprised the period between 29th of September 2016 and 19th of December 2018. Through the energy disaggregation method described in **Section 8.2.2**, the total annual energy consumption was broken down into heating, cooling and other uses, as shown in **Table 8-10**.

Table 8-10 - House 53's disaggregated annual energy (electricity) use

	Annual Energy Use (kWh)
Total	2375.0
Other appliances	1833.0
Heating	**113.8**
Cooling	**428.2**

House 53 is equipped with a split reverse cycle air-conditioning system, which has an assumed heating COP of 3.55 and a cooling EER of 3.63, according to the manufacturer's information (Mitsubishi Electric, 2021). The only conditioned zone of the house is the main living area. **Figure 8-6** presents the photos of the outdoor and indoor units of the system. Apart from the split system, the building has a gas heater fuelled by bottled LPG, as seen in **Figure 8-7**. The occupant reported using 1.5 LPG bottles per year for heating, which corresponds to 67.5 kg of gas, and a total of 918.0 kWh of energy. The COP of the gas heater was estimated as 0.9, considering the model's Energy Star Rating (i.e., 6) reported in the Directory of the Australian Gas Association Certified Products (The Australian Gas Association, 2021).

The annual energy loads for heating and cooling were then calculated by multiplying the actual heating and cooling energy use by the corresponding COP/EERs of the systems. As presented in **Table 8-11**, this resulted in a total actual annual energy load for heating of 1230.2 kWh and a total actual annual energy load for cooling of 1554.4 kWh.

Figure 8-6 - House 53's Split Reverse Cycle system. Source: Photographed by the author

Figure 8-7 - House 53's LPG heater and LPG tank. Source: Photographed by the author

Table 8-11 - House 53's heating and cooling energy use and energy load (electricity and LPG)

	HVAC System type/model	Annual Energy Use (kWh)		COP/EER	Annual Energy Load (kWh)	
Heating	LPG Flued Radiant/Convection Heater Lancer Everdure 15MJ	918.0	**1031.8**	0.90	826.2	**1230.2**
	Split Reverse Cycle Mitsubishi MSZ-GE50VA-A1	113.8		3.55	404.0	
Cooling	Split Reverse Cycle Mitsubishi MSZ-GE50VA-A1	**428.2**		3.63	**1554.4**	

8.2.5.3. HVAC set point determination using Personal Comfort Model

Using the personal thermal comfort model developed for ID32 (presented in **Chapter 6**) and the methodology described in **Section 8.2.3**, the set points for heating and cooling for House 53 were determined. **Table 8-12** presents the inputs used to reach the dry-bulb temperature threshold that represents a 50% probability of "preferring to be warmer", resulting in the heating temperature set point, and the inputs used to reach the dry-bulb temperature threshold that represents a 50% probability of "preferring to be cooler", resulting in the cooling temperature set point. Therefore, the resulting set points are: 18.4°C for heating and 23.3°C for cooling.

Table 8-12 - Personal comfort model inputs used to determine the heating and cooling set points for Participant ID32

	Dry bulb temperature (°C) = Mean radiant temperature (°C)	Relative Humidity (%)	Air speed (m/s)	Metabolic Rate (MET)	Clothing level
Heating	18.4	52	0.1	2.0	4
Cooling	23.3	66	0.1	1.3	3

8.2.5.4. Comparison between real and simulated HVAC energy use

The results of the simulations using the new preferred heating and cooling set points for ID32 in House 53 are presented in **Table 8-13**. Similar to the exploration for ID27 in House 08, three simulation runs were conducted using the weather files from the years 2016, 2017 and 2018, since these cover the analysis periods used for the actual energy consumption disaggregation. The results show a good agreement between the actual and simulated energy loads, for both heating and cooling. The cooling load errors across the three simulations ranged from -4.5% to 16.4% of the actual energy load, while the heating load errors ranged from 4.8% to 26.5%. The total loads represent an even greater agreement, with errors ranging from -2.0% to 11.6%.

Table 8-13 - Energy loads' comparison for House 53 - ID32, using new personal set points

			2016 weather file			**2017 weather file**			**2018 weather file**		
Set point (°C)		Actual (kWh)	Simulated (kWh)	Error (kWh)	**Error (%)**	Simulated (kWh)	Error (kWh)	**Error (%)**	Simulated (kWh)	Error (kWh)	**Error (%)**
18.4	Heating Load	1230.2	1101.3	-128.9	**-10.5%**	1174.9	-55.3	**-4.5%**	1028.6	-201.6	**-16.4%**
23.3	Cooling Load	1554.4	1628.5	74.1	**4.8%**	1933.7	379.3	**24.4%**	1965.7	411.2	**26.5%**
	Total load	2784.7	2729.8	-54.9	**-2.0%**	3108.6	324.0	**11.6%**	2994.3	209.6	**7.5%**

Comparing these error ratios with the ones resulting from simulations assuming a 21°C set point for heating and a 24°C for cooling, a considerable increase in the errors is observed. As seen in **Table 8-14**, the heating loads are overestimated by as much as 106.4%, in the case of the year 2017. Although cooling loads estimation errors are lower than when using the preferred personal thermostat settings, the total load error remains higher.

Table 8-14 - Energy loads' comparison for House 53 – ID32, using 21-24°C set points

			2016 weather file			**2017 weather file**			**2018 weather file**		
Set point (°C)		Actual (kWh)	Simulated (kWh)	Error (kWh)	**Error (%)**	Simulated (kWh)	Error (kWh)	**Error (%)**	Simulated (kWh)	Error (kWh)	**Error (%)**
21.0	Heating Load	1230.2	2530.8	1300.6	**105.7%**	2539.0	1308.8	**106.4%**	2383.8	1153.6	**93.8%**
24.0	Cooling Load	1554.4	1274.5	-279.9	**-18.0%**	1536.8	-17.6	**-1.1%**	1586.1	31.6	**2.0%**
	Total load	2784.7	3805.4	1020.7	**36.7%**	4075.8	1291.1	**46.4%**	3969.9	1185.2	**42.6%**

8.2.6. Discussion

This section of the study aimed to explore opportunities for application of the personal thermal comfort models developed in this thesis. Through the analysis of two case studies, the exploration demonstrates how the models can be used to calculate preferred HVAC thermostat settings, which can subsequently be used as inputs in building performance simulations to predict heating and cooling energy use more accurately.

Given the uncertainties surrounding these analyses (highlighted in **Section 8.2.7.**), overall, the set points based on the personal comfort models provide a better estimate of energy use compared with the "standard" inputs. Further work, not within the scope of this research, involving sensitivity analysis could be employed to improve the accuracy of estimates based on the comfort model derived set points.

A number of studies have investigated different ways to determine thermostat set points for HVAC systems in building simulations, not only considering daily changes in weather conditions, but also different potential occupant behavioural tendencies. In a recent study by Han et al. (2019), for instance, a derivation method was explored to calculate the optimal cooling set point temperature of a HVAC system in an office environment. Through the use of measured indoor and outdoor temperatures, sky types (cloud cover), and time data as inputs, the authors proposed a new daily set point temperature equation shown to improve thermal comfort by 38.5% in building simulation results. The study, however, did not evaluate thermal comfort through real occupant feedback, and the analysis of comfort was conducted at the generalised level, using the PMV model as the basis for possible occupants' thermal sensation and acceptability.

Ouf et al. (2020), on the other hand, explored a different approach to estimate an office's optimal thermostat set point and its potential to decrease energy use. Their building simulation model was integrated into logistic regression models that predicted the probability of a set point decrease or increase based on the indoor temperature in the next simulation timestep and potential occupants' behavioural tendencies (i.e., sensitive or tolerant behaviour). Similar to the exploration in this thesis, the authors observed significant variations in the proposed control performance under different occupant behaviours and tendencies. Nevertheless, although promising, the study was limited to synthetic occupant behaviour models (i.e., not real occupant feedback), in which the assumptions of tolerant and sensitive behaviours were arbitrarily assigned to represent extreme scenarios, as pointed out by the authors. The use of real participant feedback, as highlighted in this thesis' simulation exploration, becomes essential to validate actual behaviours and energy consumptions. In addition, the studies have so far relied on younger potential occupants in an office environment and are yet to investigate different scenarios, such buildings designed for older people.

It is also important to consider that, although increasing cooling set points and decreasing heating set points can be beneficial for energy savings (Hoyt et al., 2015; Ghahramani et al., 2015a), the assumption that thermal comfort levels can be maintained by widening temperature set point ranges cannot be considered universal. While an individual might prefer or tolerate wider ranges, such as participant ID32 in this study, others could experience considerable discomfort, as would be the case for participant ID27. The exploration presented in this chapter, therefore, reiterates the importance of analysis at an individual level, especially when considering residential settings and heterogeneous cohorts.

8.2.7. Limitations and future research opportunities

The investigation presented in this chapter, nonetheless, presented shortcomings. The results for the validation of the preferred set points of participant ID27 (House 08), as highlighted previously, showed limited agreement with real scenarios. This can be explained, firstly, by this individual's personal thermal comfort model predictive performance. As presented in **Chapter 6**, this model presented an accuracy of 46.67%, a Cohen's Kappa Coefficient of 0.2, and an AUC of 0.7, which, although higher than the PMV_C results, are not optimal. This lower performance could have impacted the model's ability to provide accurate preferred set points, which, in turn, compromised the heating and cooling energy loads agreement between simulated and actual values. In addition, it is noteworthy that participant ID27 lives in House 08 with her partner, who, despite having a similar socio-economic background and age, has a different sex, body composition, as well as different frailty and health status. These different personal characteristics could result in each occupant controlling the heating and cooling set points of the house differently throughout the year, which means that the actual energy consumption of this house is not solely dependent on ID27's preference, but also on her partner's preference. Future investigations are necessary to analyse validation scenarios in shared spaces where occupants differ in thermal preferences and behaviours.

Other general limitations of the present exploration should be noted. The energy disaggregation method used in this study is based on the assumption that the heating and cooling use intensity of the building is solely climate dependent. The drivers of heating and cooling use intensity in buildings, however, can also be related to the number of occupants living in the households or their socio-demographic and contextual scenarios. Other energy load disaggregation methods such as extraction of appliance level data from energy signals and smart meters, however, were beyond the scope of this study. It is also important to highlight that the energy data used in the disaggregation process was limited to a 2.5-year period for both case studies (i.e., the middle of 2016 until the end of 2018). A higher data sample of energy consumption could have increased the reliability of the method. In addition, the use of non-metered energy fuel, such bottled gas in House 53, meant adding further inaccuracies to the actual energy estimation, related to approximations reported by the occupant.

Regarding the building energy simulation methods used in this study, other points should be considered. The calibration methodology used in this study relied on manually identifying the most influential model parameters and correcting discrepancies according to expert knowledge and related references in the field. Although valid, the methodology could have been conducted using automated optimization algorithms (Roberti et al., 2015). Furthermore, it is important to highlight that the data used for calibration was measured in a single point in each participant's living area, which could have relevant spatial temperature variations. A weighted average of multiple points could better represent the spaces for calibration. Furthermore, other assumptions related to the HVAC system's COP, static occupancy and HVAC operation schedules, and static clothing and activity levels in the set point calculations should also be considered as potential causes of inaccuracies in the final results.

Nevertheless, the current study has created important opportunities for future research. Apart from personal seasonal set points, daily set point calculation strategies can potentially generate better solutions for accurate energy use prediction. This could be achieved through incorporating personal comfort models in the building simulation workflow, using components such as the Energy Management System (EMS) object within EnergyPlus (Gunay et al., 2015) or co-simulation methods (Kontes et al., 2018; Peng and Hsieh, 2017). This would enable a dynamic calculation of personal thermal preferences and instant HVAC control that can more realistically represent occupant behaviour and reduce model inaccuracies due to static assumptions, thus enhancing overall model reliability.

8.3. Smart device application

A smart device application was explored as a second opportunity for the implementation of the personal thermal comfort models developed in this thesis. The aim was to provide an online user interface for personal thermal comfort prediction, as well as a catalogue of text-based strategies related to personal actions, technology, building operation and design, which could aid control and adaptation for each individual older person's environment to increase their comfort. Although potentially useful for other demographics, the personalised apps can be especially relevant for designers, caregivers and health professionals.

8.3.1. Similar tools

A number of applications and interfaces have been developed with similar concepts. Considering interfaces on thermal comfort predictions specifically, the *Center for the Built Environment (CBE) Thermal Comfort Tool* (available at https://comfort.cbe.berkeley.edu/), for instance, is a free online tool that allows the calculation and evaluation of thermal comfort according to the ASHRAE Standard 55 (Tartarini et al., 2020). It includes models such as the PMV and the adaptive comfort model, as well as visualization features involving psychrometric and temperature-humidity charts. The developers aimed to address the field's lack of tools that could be used to calculate thermal comfort indices without prior coding skills. The tool's end users comprise of engineers, architects, researchers, educators, facility managers and policy makers (Schiavon et al., 2013). Applying a simple and accessible interface, users can input their own measured or simulated data and automatically visualise outcomes in the same browser screen, as seen in **Figure 8-8**.

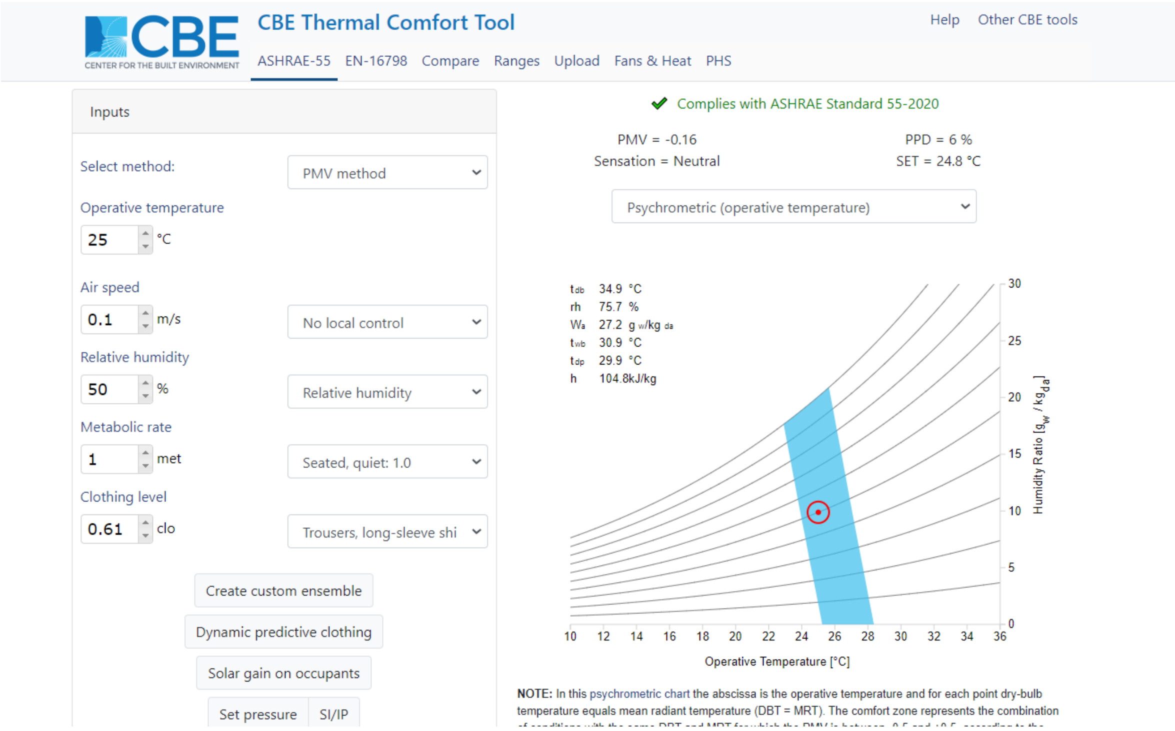

Figure 8-8 - The CBE Thermal Comfort Tool. Source: https://comfort.cbe.berkeley.edu/

The *Arup Advanced Comfort Tool* (available at https://comfort.arup.com/) is a similar free web-based interface that allows the prediction of thermal comfort under changing and non-uniform thermal environmental conditions, including stratification, radiant asymmetry, and effects of personal environmental controls. Based on human psychophysiological models, the tool also provides the option of individual thermal comfort calculation based on personal characteristics such as sex, age, and body fat percentile values, displaying the comfort indices on a thermal sensation timeline, as shown in **Figure 8-9** (Jones et al., 2021; Jones et al., 2020).

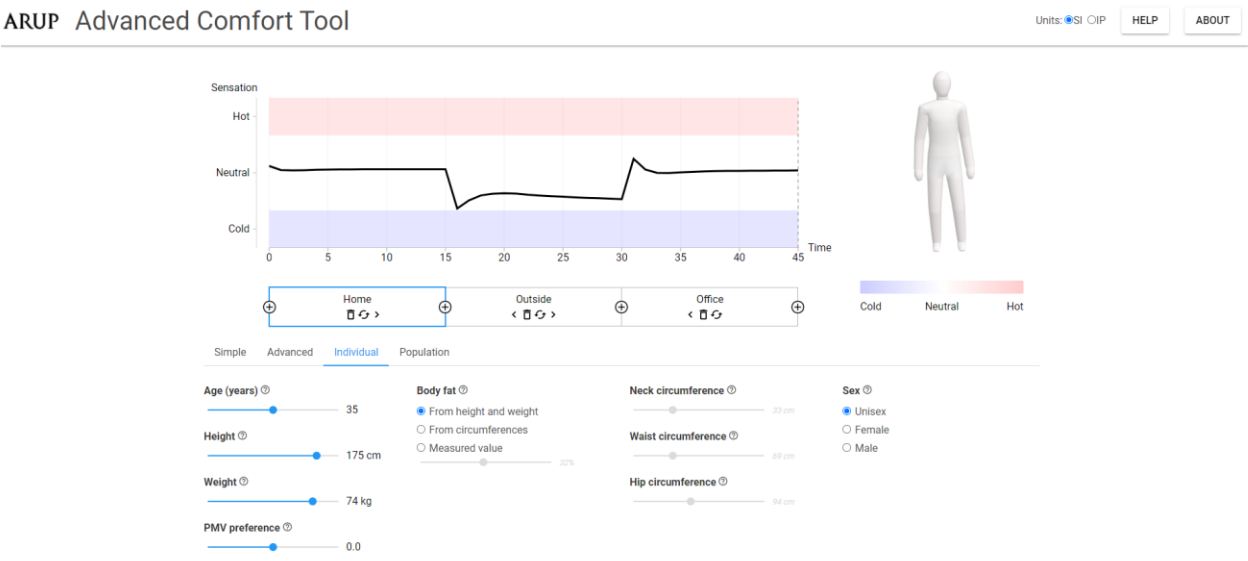

Figure 8-9 - Arup Advanced Comfort Tool. Source: https://comfort.arup.com/

In the context of older people's health, several other interfaces are aimed at caregivers and health professionals to provide them with information and strategies to increase health and wellbeing, as well as to monitor vitals and symptoms of specific diseases. For caregivers, for instance, a review by Wozney et al. (2018) gathered references for eight commercially-available apps addressing Alzheimer's disease or other related dementias (ADRD) caregivers. The apps are generally static, providing text-based informational resources to understand and deal with older adults' symptoms or specific behaviours. Two examples are the *Dementia Caregiver Solutions* app (**Figure 8-10**) (Personalized Dementia Solutions Inc., 2021) and the *Alzheimer's Daily Companion* app (**Figure 8-11**) (Home Instead Senior Care, 2021). Resources and tools for caregivers to manage thermal comfort of older adults in the form of smart device applications are, however, non-existent in the market today.

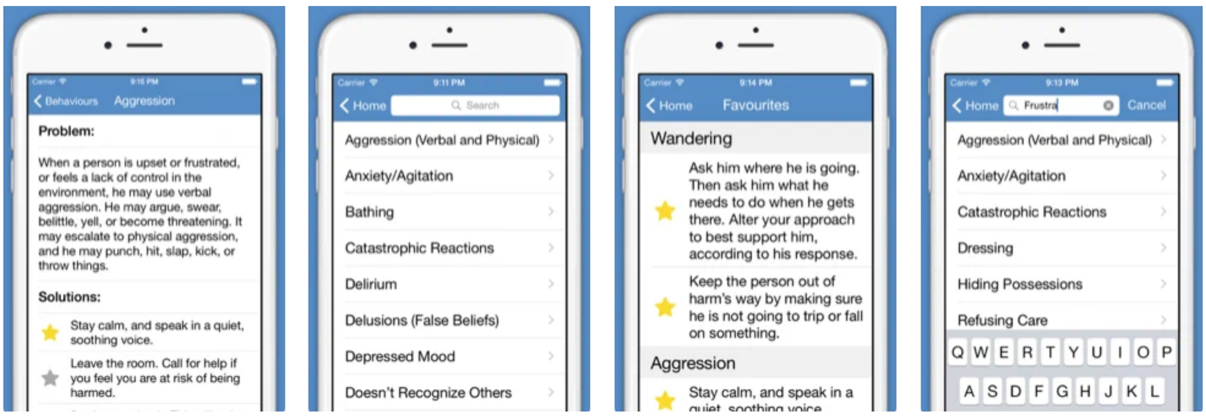

Figure 8-10 - Dementia Caregiver Solutions app. Source: Personalized Dementia Solutions Inc. (2021)

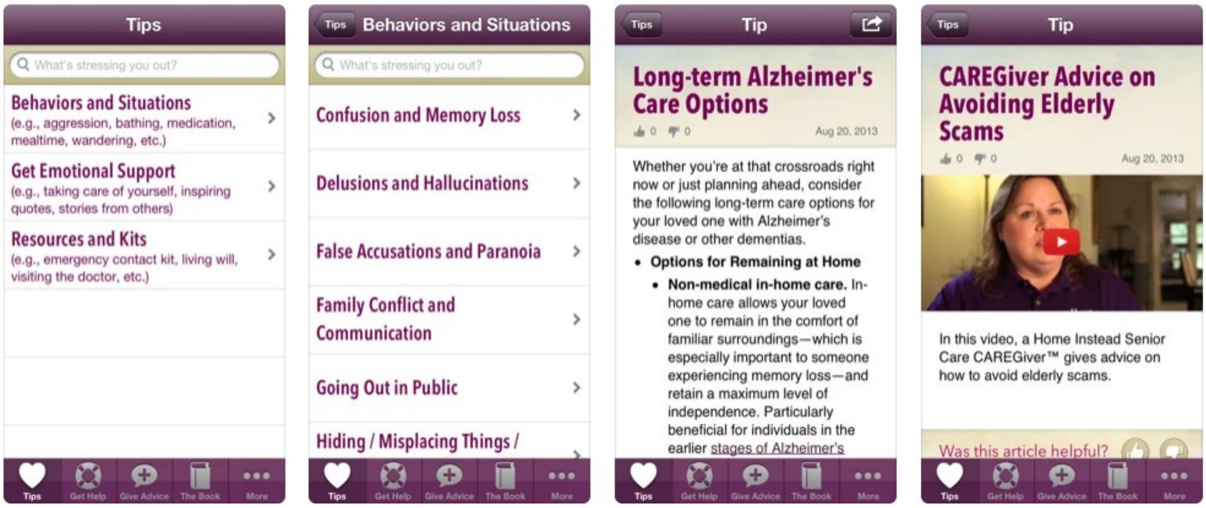

Figure 8-11 - Alzheimer's Daily Companion. Source: Home Instead Senior Care (2021)

Furthermore, health care professionals have a number of applications commercially available that provide tools to aid decision-making in a systematic and objective way, such as well-known evidence-based apps *palliMEDS* for palliative care medicine guidelines (**Figure 8-12**) (NPS MedicineWise and caring@home, 2021), *UpToDate* for general clinical decision support resources (**Figure 8-13**) (UpToDate Inc., 2021) or *MDCalc* for medical equation calculation and guidelines (**Figure 8-14**) (MDCalc, 2021). The latter, for instance, has relevant calculation capabilities in a user-friendly interface that allow quick and accurate estimations for a number of health indices.

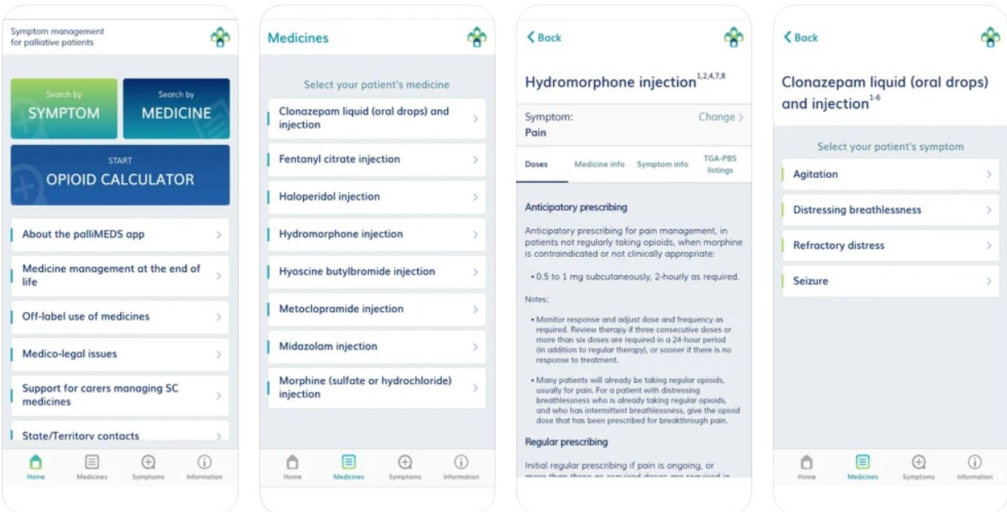

Figure 8-12 - palliMEDS app. Source: NPS MedicineWise and caring@home (2021).

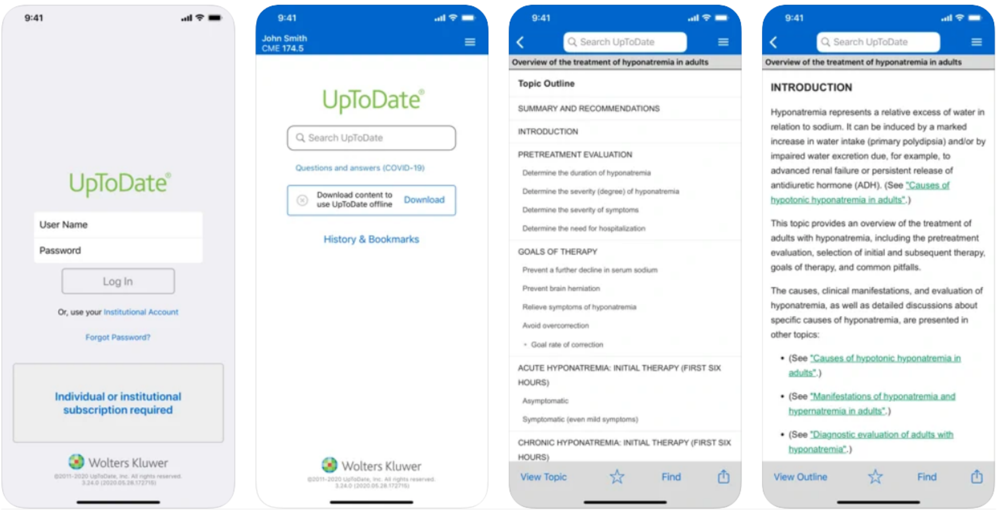

Figure 8-13 - UpToDate app. Source: UpToDate Inc. (2021).

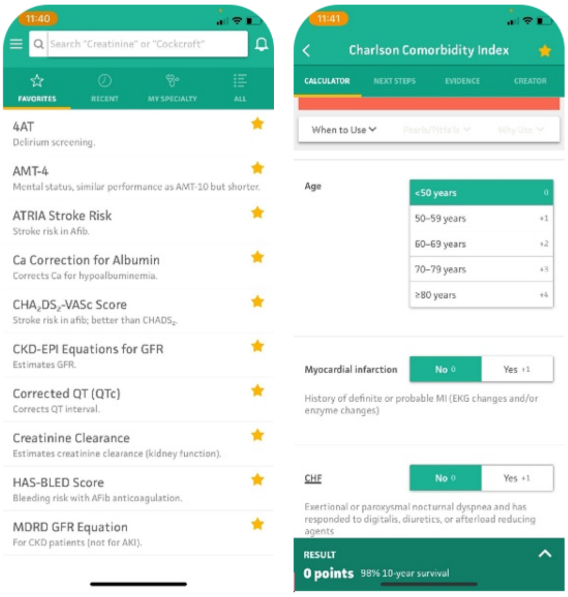

Figure 8-14 - MEDCalc app. Source: MDCalc (2021).

Other related health apps, aimed at the general public, deliver relevant functionalities and features, such as personal data recording, tracking and visualising. The *PainScale* app (**Figure 8-15**) (Boston Scientific Corporation, 2021), for instance, allows users to log and track chronic pain in order to identity triggers, minimize related daily disruptions, and get personalised reports and insights to better manage health conditions. It is commonly used for the management of Fibromyalgia syndrome among older people.

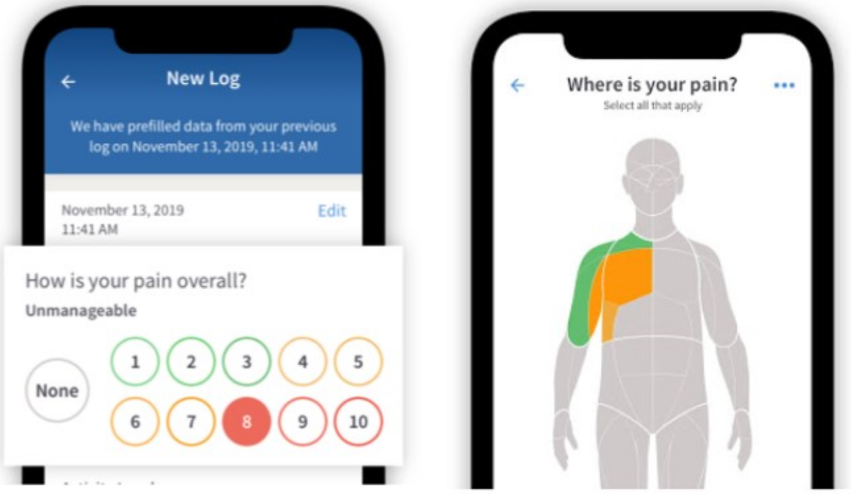

Figure 8-15 - PainScale app. Source: Boston Scientific Corporation (2021).

8.3.2. Personal Thermal Comfort App development

Considering the beforementioned references, the personal thermal comfort Apps were developed to cover a calculator feature, such as the ones present in the *CBE Thermal Comfort Tool*, the *Arup Advanced Comfort Tool* or the *MDCalc* app. In addition, the App was developed to deliver evidence-based information and strategies to help users act upon the predictions, similar to the guidelines present in the beforementioned apps for caregivers and health professionals. Additionally, a feature that allows users to save input data was added to provide the ability to track environmental conditions, which, in turn, can give insights into a building's performance, issues and possible causes.

To develop the calculator feature of the App, first the final state of each neural network model, which includes all final calculated weights and biases, were transferred from the *Jupyter Notebook* (Thomas Kluyver, 2016) (i.e., the computing environment used), developed in Python language, to a spreadsheet in *Microsoft Excel* (Microsoft Corporation, 2021), where the neural network was reconstructed using the functions described in **Chapter 6**. The spreadsheet was then imported to the online developing tool *Open As App* (Open As App GmbH, 2021), where a smart device interface was developed based on the personal models. The App, therefore, allows an easy and automatic way to calculate personal thermal comfort predictions without prior knowledge of Python or Excel.

The application allows users to input values to the six variables used in the models (i.e., dry bulb temperature, radiant temperature, relative humidity, air speed, metabolic rate and clothing level). The models' equations are then solved automatically according to these inputs, and the app provides the thermal preference prediction according to the calculated probabilities for each thermal preference category. The App displays that the older person in question prefers to be warmer when the probability of "preferring to be warmer" is equal to or higher than 50%; it displays that they want to be cooler when the probability of "preferring to be cooler" is equal to or higher than 50%; and it displays that they want no change when both probabilities of preferring to be warmer and cooler are lower than 50%. This is only possible because simultaneous non-null probabilities of "preferring to be cooler" and "preferring to warmer" are not possible in these specific models' predictions. This means that, when the probability of preferring to be warmer is higher than 50%, the probability of preferring to be cooler is always 0%, and vice-versa. The app also displays these three probabilities below the main prediction, to allow the users to assess the urgency or risks associated with different probability breakdowns.

The app was designed to be used by designers, caregivers or healthcare professionals. Each user type might profit from specific features of the app, as shown in **Figure 8-16**:

For designers

- Aids the decision-making process;
- Can be used in combination with measured data or building performance simulation tools.

For caregivers or health professionals

- Guides the control and adaptation of environments according to the older person's preferences, without disturbing them;
- Helps track and record data.

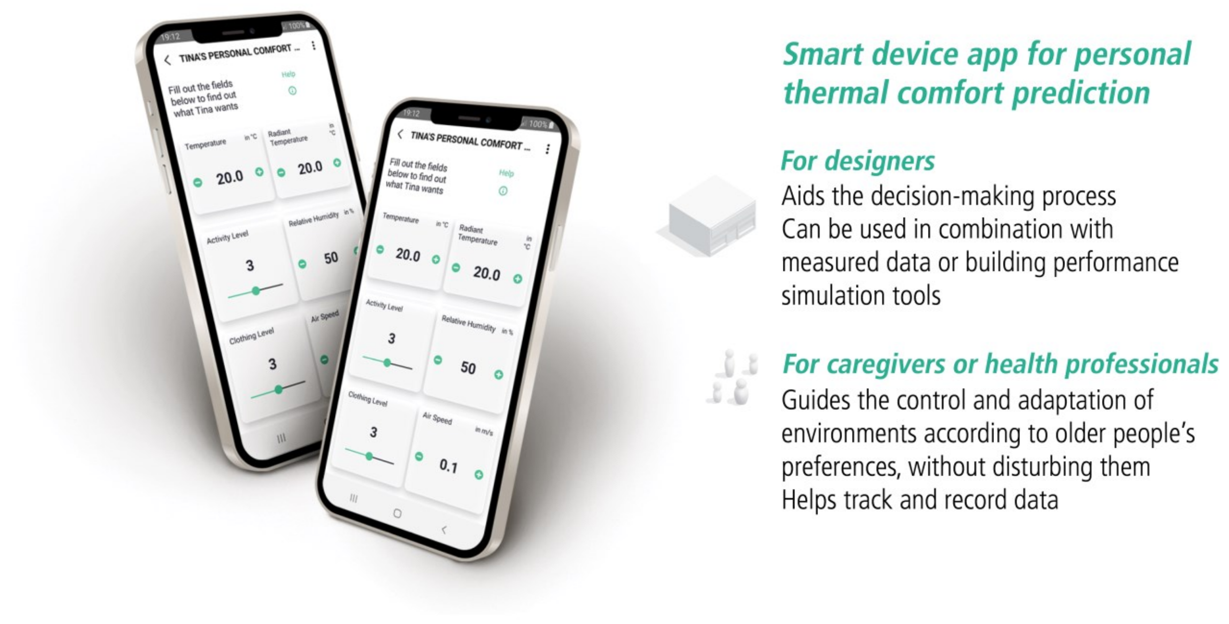

Figure 8-16 - Smart device app's user interface and user types

8.3.3. Results: app screen, features and functionalities

The Personal Thermal Comfort app has a single screen to allow easy access to the information provided. Users are first asked to fill out the input fields to calculate the older person's thermal preference at that moment. The temperature, radiant temperature, relative humidity and air speed inputs can be logged using the toggle buttons (i.e., "+" or "-") or by typing the values using an on-screen, automatically-activated number keyboard, as shown in **Figure 8-17**. The activity and clothing levels can be inserted by using sliders or the number keyboard. Note that the activity level is internally converted to the metabolic rate (as detailed in Chapter 6) to be used as an input in the thermal preference calculation.

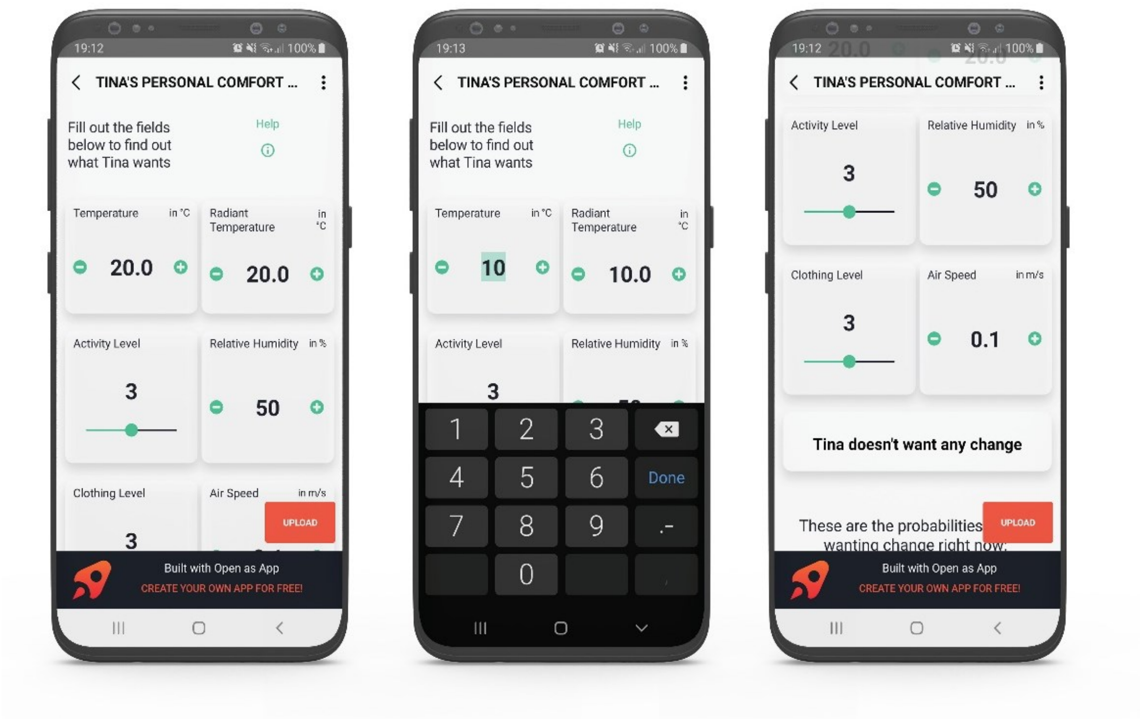

Figure 8-17 - Personal Thermal Comfort app calculator screen

Once the inputs are inserted, the thermal preference prediction is displayed automatically below the inputs. As previously mentioned, the app also displays the thermal preference categories' probabilities below the main prediction, as seen in **Figure 8-18**, to allow the users to assess the urgency or risks associated with different probability breakdowns. In case the predictions are "prefer to be warmer" or "prefer to be cooler", the app displays, below the probability predictions, a set of thematic strategies and guidelines to help increase comfort. By tapping on the themes, the app displays an overlay screen with more details on specific strategies. These evidence-based strategies were derived from "Thermal Comfort at Home: A guide for older South Australians" (Soebarto et al., 2021), which is one of the results of the ARC Discovery Project '*ARCDP180102019 - Improving the thermal environment of housing for older Australians*' from which this PhD thesis has stemmed. The strategies relate to personal and behavioural themes, as well as design and technology oriented guidelines. Tapping the "back" arrow on the top left-hand corner allows the user to return to the main screen. No strategies are shown when the prediction is "preferring no change".

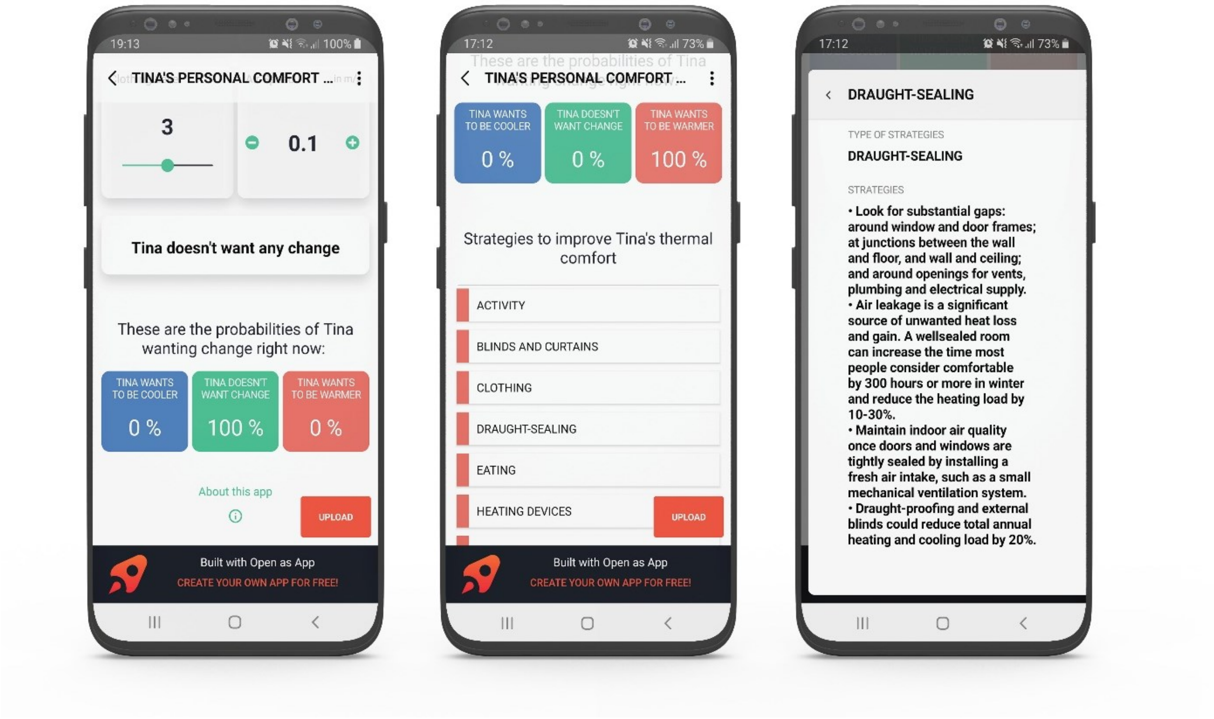

Figure 8-18 - Personal Thermal Comfort app prediction output and guidelines screen

The App also provides a “Help” button, which activates an overlay “Help” screen with the definition of each input and how to access or measure it. For each participant, the average of each indoor environmental input from the monitoring datasets, for each season, will be included in the “Help” screen to aid the calculation when right-here-right-now measurements are not available. To exit this screen, the user must press “OK” at the end of the screen. An “Upload” button is also included to save the inputs inserted by the user in a server, which can be accessed by developers for analysis and sent back to users by request. **Figure 8-19** presents these features.

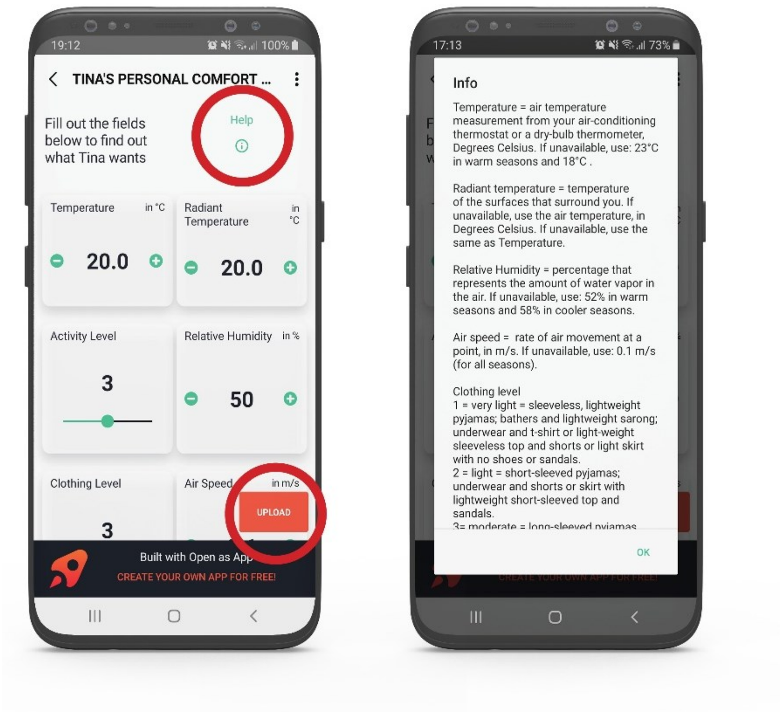

Figure 8-19 - Personal Thermal Comfort app “Help” and “Upload” buttons, and “Help” screen

An example of the app was developed for Participant ID32 (House 53). As mentioned previously, this personal model has optimal accuracy, thus being chosen as an example. The app can be accessed via a smart device, by first downloading and installing the *Open As App* application. After installing, ID32 app can be accessed by scanning the QR Code below (**Figure 8-20**). A web-browser version of the app can also be accessed through the link *https://oaa.app.link/launch-app-f65992fc-4e0a-4a01-ab93-fb32ac94266b.*

Figure 8-20 - QR Code to acess the app for Participant ID32

8.3.4. Discussion

Overall considerations

The conversion of the selected personal thermal comfort model into a web-based smart phone App proved to be successful in allowing the accessible and automatic calculation of thermal preferences for the selected participant. Although still not validated by the end users, the App showed potential to aid designers in the decision-making process, as well as to guide caregivers to anticipate needs and control thermal environments independently.

In terms of use of this web tool by designers, the tool could be integrated into building performance simulation workflows, such as the ones already highlighted in **Section 8.2.6**. The Energy Management System (EMS) component in EnergyPlus (Gunay et al., 2015) or co-simulation methods (Kontes et al., 2018; Peng and Hsieh, 2017) are recent research topics that could aid the integration of predictive models and related databases with simulation tools used for validating design and construction options in specific and individual scenarios. In addition, when measured data is used as inputs in the model (instead of assumptions or approximations), the web tool has enhanced reliability to be used by designers when testing an environment's possibilities. Consequently, improving building design, construction and operation could also result in a decrease in reliance on heating and cooling systems and related fuel consumption.

From the health care perspective, web tools such as the one presented in this study can be considered practical contributions to the worldwide trend and interest in high-performing person-centred approaches for health care delivery (Santana et al., 2018; Godfrey et al., 2018; Health Innovation Network South London, 2017). As accurately described by the Health Innovation Network South London (2017):

> "*Person-centred care is not just about giving people whatever they want or providing information. It is about considering people's desires, values, family situations, social circumstances and lifestyles; seeing the person as an individual, and working together to develop appropriate solutions*."

Australian health care organizations have also recognised person-centred care as the basis for achieving better health outcomes and experiences for patients, carers and families. The National Safety and Quality Health Service (NSQHS) Standards, for instance, identify seven main attributes that are important to achieve "person-centredness": (1) comprehensive care delivery; (2) clear purpose, strategy and strong leadership; (3) people, capability and a person-centred culture; (4) person-centred governance systems; (5) strong external partnerships; (6) person-centred technology and built environments; and (7) measurement for improvement. The work developed using personal thermal comfort models and web-tools could be considered a contribution for principle 6, providing technology that enhances patient experiences and outcomes and aiding person-centred design principles in the built environment, as prescribed by the Australian Comission on Safety and Quality in Health Care (2018) documentation on the topic.

Other terms used in the same realm as “person-centred care” are “precision health”, “precision medicine” and “precision public health” (Bilkey et al., 2019), which are all related to contemporary applications of strategies aimed at disease prediction, treatment and prevention, as well as health promotion, tailored for the individual. According to the U.S.A. Office of Genomics and Precision Public Health, precision health can be achieved through the use of a series of tools including personal smart devices, which can, for instance, monitor behaviours (e.g., diet or sleeping habits), help medication management, or even guide mindfulness practice (Office of Genomics and Precision Public Health, 2020). Once again, the work developed using personal thermal comfort models and web-tools could be inserted in the same context. “Precision Thermal Comfort” could become, therefore, a new concept to be explored in the future of health care.

Considerations on clothing levels

Apart from potential practical contributions to the field of thermal comfort, design and health care, the development of the personal models and their application on a smart device tool highlighted important insights into the use of clothing level as one of the input variables for the models, as well as the way this data should be interpreted in future field studies. As observed in the example of Participant ID32’s model, the higher the clothing level, the higher the probability of the participant preferring to be warmer because a higher clothing level indicates a cool or cold thermal sensation. This represents a rather counterintuitive correlation between these variables, since it is commonly expected that one would prefer to be warmer when they are less clothed.

This relationship between variables emphasizes three main insights. Firstly, it appears that the "clothing level" collected through survey answers from participants represents an adaptive behaviour taken by them to act upon their thermal preference at the moment, rather than representing their static clothing insulation status (i.e., the “clo” input in many traditional models). This means that, in this study, increasing clothing level is a result of feeling cold and preferring to be warmer, rather than the cause of a warm sensation and a preference to be cooler, which is what is normally expected in models such as the PMV. In other words, in the personal model, people wear more clothing layers because they feel cold; whereas in the PMV, people are predicted to vote 'cool' or 'cold' because they wear fewer clothing layers Therefore, not only is the dependent/independent relationship reversed (i.e., the cause-and-effect relationship), but the correlation is also negative in the personal models and positive in the PMV model. Consequently, for the smart device app to accurately predict the person's thermal preference at the moment, the clothing level has to be considered as an adaptive behaviour already taken by the person in question before the prediction is made. This relationship is also observed when analysing the data from the entire cohort, as presented in **Chapter 5**, **Section 5.3.2**, **Figure 5-17**.

This leads to a second consideration on the subject. This difference between how clothing levels interact in the current study's models and in the PMV model can partially explain the errors found in the PMV predictions when compared with participants' actual thermal sensation votes. In addition to the generalisation limitations of the PMV model, already discussed in this thesis, using the field work surveys' "clothing level" as a representation of *clo* in the PMV model equation is likely to result in the wrong PMV prediction. This highlights an important difference between field study and experimental (i.e., climate chamber) data collection procedures, which require especial considerations depending on the final application envisaged.

Thirdly, the explorations emphasised how the thermal preference for wanting to be warmer was more sensitive to clothing than other thermal preferences. Changing clothing levels appeared to be a more common adaptive behaviour when temperatures decreased and the probability of preference for warmer was higher, than when temperatures increased and the probability of preference for cooler was higher. This can be seen for the whole cohort dataset, as already discussed in **Chapter 5**, **Figure 5-17**, where lighter clothing levels are not as common in lower thermal sensations (e.g., cool, slightly cool) than higher clothing levels are in higher thermal sensations (e.g., warm, slightly warm). This is also observed for the example of ID32, as shown by the Clothing Level probability density distributions in **Figure 8-21**. The Clothing Level graph shows that higher clothing levels are more likely to be related to "preferring to be warmer" than lower clothing levels are to the other two thermal preference categories. Adaptive clothing behaviours and their relationship with environmental conditions and seasonal sensitivity, however, can vary among participants, and should be analysed at the individual level to aid the correct use of applications such as the app envisioned here.

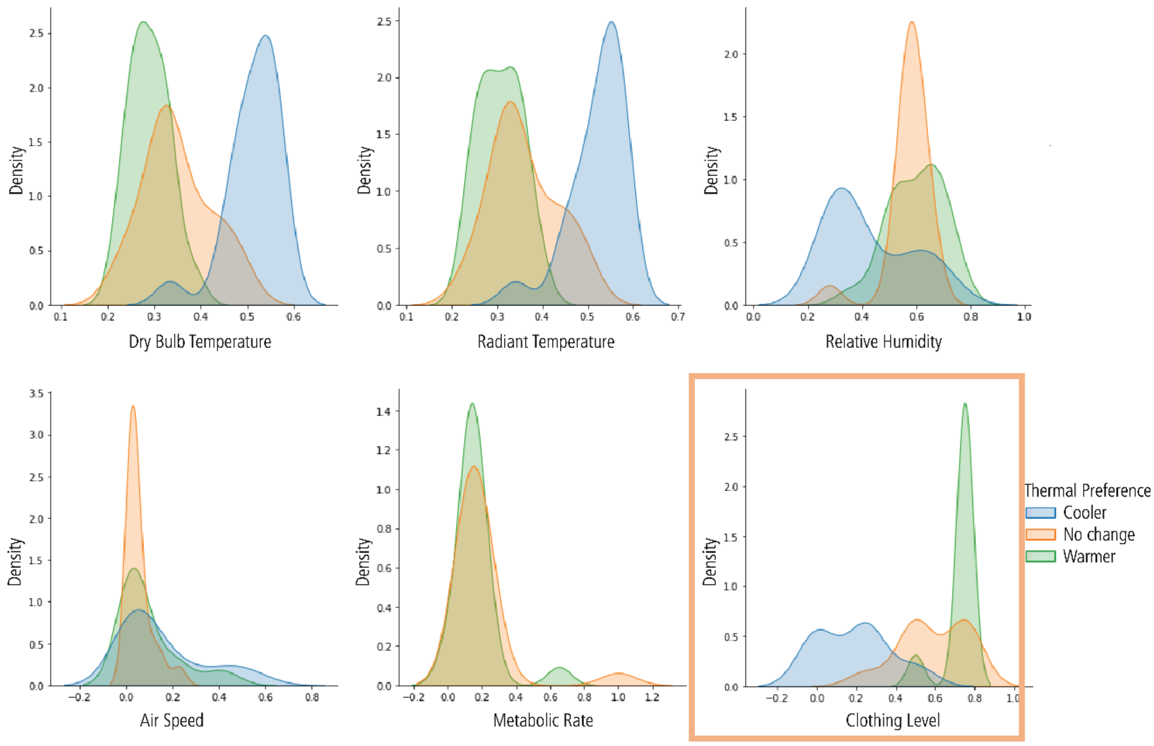

Figure 8-21 - Probability density distributions for the personal models' inputs, according to each thermal preference category, for ID32. Inputs are normalised from 0 to 1.

It is advised, therefore, that future studies on modelling and tool development consider clothing insulation and/or clothing level as a behavioural and adaptational thermal comfort variable, whose use differs from traditional applications in aggregate models such as the PMV.

8.3.5. Limitations and future research opportunities

Although basing this smart device application in the beforementioned references, the app presented here is an exploration of the models' application only, and still requires further testing in real scenarios, considering usability, readability, and accessibility (e.g., appropriate font and button size, colours and contrast) (Lidwell et al., 2010). It is also noteworthy that the development platform *Open As App*, despite numerous feature possibilities, still poses limitations in user-experience design.

In addition, although the strategies provided in the tool are evidence-based, derived from the "Thermal Comfort at Home: A guide for older South Australians" (Soebarto et al., 2021), resulting from the ARC Discovery Project '*ARCDP180102019 - Improving the thermal environment of housing for older Australians*', the language and level of detail might still require validation from designers and caregivers, since the document was originally developed with the input of older people only.

It is also important to highlight that each individual person is required to be monitored for data collection before the personal model is developed and then later converted into an individual App by a researcher/developer. This could result in limitations for deployment of the tool. Future research is, therefore, required for the development of a method that allows the end-user to upload their own data and train a model automatically. Similar conceptual system architecture and frameworks for data collection and automatic (or continuous) model training have been previously envisaged by Kim et al. (2018a).

8.4. Summary

This chapter presented two types of application for the personal thermal comfort models developed in this thesis. The first exploration assessed the opportunity to use the models to predict a set of new personal temperature thermostat set points for HVAC systems. Two case studies demonstrated how the personal set points can provide more accurate heating and cooling energy loads for older adults' environments than assumptions commonly used in the field of building performance simulation. The limitations of the analysis and further future investigation opportunities were highlighted. Among these opportunities, validation of the methodology for older adults in shared spaces is still required. In addition, a dynamic calculation of personal thermal preferences and instant HVAC control in building simulations could add even more realistic representations of occupant behaviours and reduce the models' inaccuracies.

The second investigation explored the use of the personal models in a web-based smart device tool, which allows automatic calculation of thermal preferences for older individuals. Although still not validated for usability and accessibility, the app has the potential to aid designers in the decision-making process and can be used in combination with building simulation results. Caregivers can also profit from the app, which can guide the control of environments without disturbing patients and helps track and record events for future consultation. Finally, users can profit from the app as a resource for information and guidelines on personal, technological and design strategies that can help increase comfort and decrease heating and cooling energy use.

Chapter 9. Main findings and conclusions

Through the lens of person-centred thermal comfort models, the research proposed in this thesis contributed to a better understanding of older people's diversity and unique characteristics as well as their complex effects on these individuals' thermal comfort, health and wellbeing. The outcomes of the research are summarised in this chapter, leading to the projects' main implications, contributions and recommendations.

Since the detailed discussions on each exploration developed in this thesis have been presented in each of **Chapters 5 to 8**, this chapter focusses only on the final outcomes and remarks, emphasising and aligning the knowledge building process driven throughout the thesis.

9.1. Main research findings

The main outcomes of this research are outlined below:

(a) The literature review presented in **Chapter 2** highlighted the importance of understanding people's intrinsic capacities (i.e., personal, genetic and health characteristics) to develop relevant plans and policies that foster healthy ageing. The chapter shows the strong links between environmental conditions, individual ageing trajectories and health, supported by several research studies developed throughout the past decades. In addition, the chapter presented an overview of the main thermal comfort modelling approaches to date, culminating in the current paradigm shift that, much like the one experienced by global health services today, thermal comfort studies are going through: moving from averaged population level analysis to a person-centred and individualising perspective.

(b) Drawing from the fundamental limitations of the current thermal comfort models presented in the previous chapter, **Chapter 3** introduced, through a systematic review of the literature published over the last two decades, the concept and modelling details of personal thermal comfort models. Developed with the aim to absorb individual differences in thermal comfort responses, the studies on personal comfort models have showed promising comfort and energy related results so far. Nevertheless, the review also highlighted issues such as the lack of a unified modelling framework and a lack of diversity in study settings, participants involved, and climates and buildings analysed. In addition, with most of the studies using machine learning techniques, the review has pointed to the challenges of "black box" models in the field. Finally, the review has indicated that personal input features using physiological sensing technologies could be further explored, especially considering the rapid advances seen today in wearable sensor technologies.

(c) Following the review of the literature (Chapters 2 and 3) and the summary of the quantitative methodologies chosen to address the research objectives (Chapter 4), **Chapter 5** responded to research questions (A) *What thermal conditions exist in the houses occupied by the older people participating in the study, and what are their thermal preferences and sensations?* and (B) *What variables are significant in explaining the thermal preferences and sensations of the older people participating in the study?*. Although the buildings analysed presented similarities as a group in terms of overall construction details, they also showed considerable differences in terms of age, size, design and operation, which could have contributed to diverse indoor thermal conditions profiles. In addition, participants' personal characteristics also differed within the group, indicating the need for a further individualised analysis. Furthermore, the study confirmed the use of environmental measures, such as indoor air temperature, relative humidity and air speeds, as important variables when explaining thermal sensations and preferences for the cohort studied. Varying clothing levels and metabolic rates were also found to be relevant in the analysis of the group's thermal responses, and were identified as potential adaptive behaviours taken by participants in general to adjust thermal sensations and preferences. Personal factors such as health/wellbeing perception were considered equally relevant for further analysis, although their relationship with the cohort's general thermal sensations and thermal preferences were not as statistically strong as hypothesised. Finally, skin temperatures were also found to be significant in explaining the thermal sensations and preferences of the older adults analysed.

(d) From the insights drawn from the initial analysis of the datasets and potential predictors presented in Chapter 5, **Chapter 6** responded to research questions (C) *How will the accuracy of personal thermal comfort models be affected by individual's input variables?* and (D) *How can the use of personal thermal comfort models lead to a more accurate prediction of older people's thermal preferences, in comparison with the prediction by a generalised model such as PMV?*. From the exploration of 28 personal thermal comfort models for older adults, the study found that the models developed using dry bulb temperature, radiant temperature, relative humidity, air speed (i.e., environmental variables), clothing level, metabolic rate and health/wellbeing perception (i.e., personal variables) as input variables presented, on average, an accuracy of 74%, a Cohen's Kappa Coefficient of 61% and an AUC of 0.83. This represented a significant improvement in predictive performance when compared with the generalised 'Converted' Predicted Mean Vote (PMVc) model, which presented an average accuracy of 50%, an average Cohen's Kappa Coefficient of 24%, and an average AUC of 0.62.

(e) Building on the findings of the personal comfort models presented in Chapter 6, **Chapter 7** provided further evidence to respond to research questions (C) and (D). The exploration of 4 personal thermal comfort models for older adults using skin temperature data combined with dry bulb temperature, radiant temperature, relative humidity, air speed, clothing level and metabolic rate as input variables resulted in an average accuracy of 67%, an average Cohen's Kappa Coefficient to 50% and an average AUC to 0.77. This represented a superior predictive performance of the individualised models when compared with the PMVc model, which predicted individual thermal preferences with an average accuracy of 51%, an average Cohen's Kappa Coefficient of 27%, and an average AUC of 0.63.

(f) Potential applications for the personal thermal comfort models developed in Chapters 6 and 7 were investigated in the following **Chapter 8**. This chapter was divided into two parts, with the first part responding to research question (E) *Can personal comfort models for older people be used to determine heating and cooling set points more accurately?*. Two case-studies were selected from the participants and corresponding buildings monitored in the project. The results for the first case-study showed a good agreement between the actual and simulated energy loads, for both heating and cooling energy loads. The heating load errors ranged from 4.8% to 26.5% of the actual energy load, while the cooling load errors ranged from -4.5% to 16.4%, depending on the weather data used. For the second case, however, the difference between the actual and simulated heating loads ranged from 12.3% to 19.1% of the actual energy load, while the cooling load errors ranged from -44.1% to -54.9%. Although the individual heating and cooling results were not optimal, the difference between the actual and simulated total loads were lower, between -8.0% and -10.2%. When comparing these error ratios with the ones resulting from simulations assuming a 21°C set point for heating and a 24°C for cooling, the study showed that personal set points significantly outperformed the traditional generalising assumptions.

(g) The second part of **Chapter 8** extends the use of the personal comfort models presented in Chapters 6 and 7 into a web-based smart phone App. The chapter responded to research question (F) *How can personal comfort models for older people be used to aid the control and adaptation of older people's environments to increase comfort, and health and wellbeing?*. The conversion of the selected personal model in a web-based smart phone's App proved to be successful and allowed the accessible and automatic calculation of thermal preferences for the selected participant. Although still not validated for usability and accessibility, the App showed potential to aid designers in the decision-making process, as well as guide caregivers to control thermal environments without disturbing patients or track and record events for future consultation.

From the summary of findings presented above, three potential implementation pathways are drawn for the personal thermal comfort models in the context of older adults, as seen in **Figure 9-1**. The first, called automation pathway, is based on the use of the predictions yielded from personal comfort models to control either HVAC systems, PCS or wearable comfort systems automatically. Although control automation can benefit all individuals, in different levels, it can be especially relevant as assistive tools for older adults with lower thermal sensitivity or with lower capacities to manually operate or adjust environments.

The second application pathway, called diagnostic pathway, relies on the use of the information gathered from personal datasets and the predictions yielded from personal thermal comfort models as tools to quantify individual preferences, and identify possible design improvements to meet these preferences, especially considering buildings without air-conditioning. This diagnostic information would aid not only designers but also older adults, as consumers, in the decision-making process to redesign their thermal environments to improve comfort, health and wellbeing. The combined use of personal comfort models with either building performance simulation tools or online smart device tools are inserted in this pathway.

The third pathway, identified as the public health pathway, is based on using the models in a broader sense to advise carers or health professionals on individual preferences. The app proposed in this thesis could be one of the possible tools to be implemented in this pathway. In addition, since extensive monitoring of new occupants may not be feasible for all settings, personal models from individuals with similar characteristics and preferences would be used to create a set of "clusters", "profiles" or "personas" according to trends among individuals, allowing a broader use with little or no monitoring period.

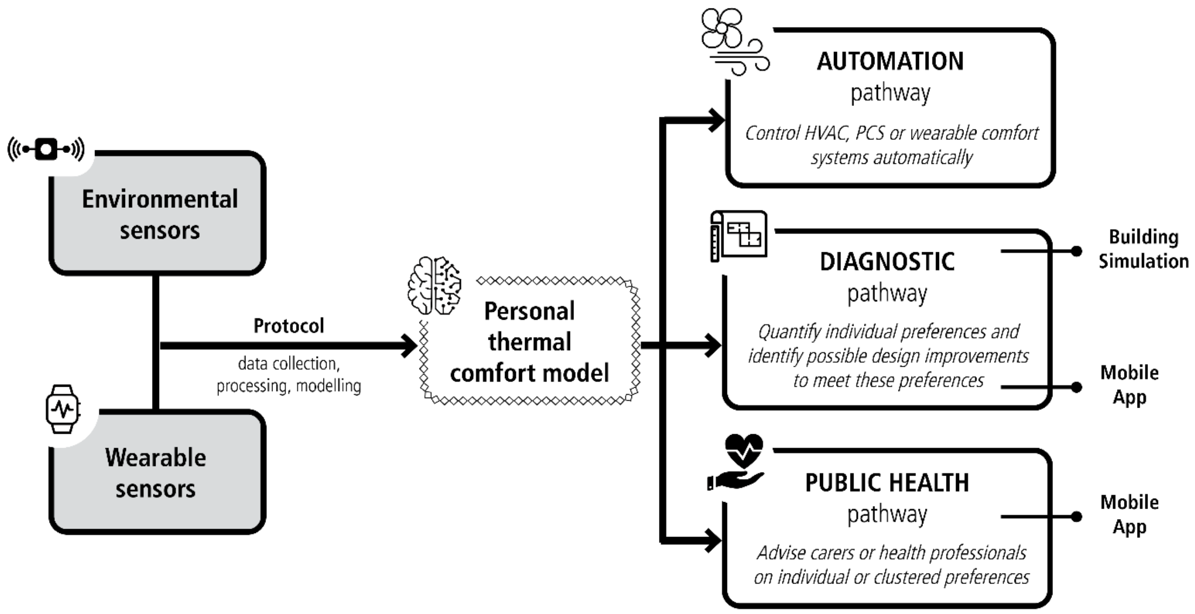

Figure 9-1 - Summary of the three potential application pathways drawn from the research

It is important to highlight, however, as already stated in **Chapter 6**, that a protocol will be required to prescribe the optimal data collection and processing techniques, as well as the modelling procedures, depending on different types of application. The modelling methodology, learning algorithms and input variables may differ depending on the complexity required for each sort of application envisioned. Using the models for HVAC control with live model-tuning (i.e., automation pathway) may require less computational-heavy models and higher accuracy to provide fast responses. On the other hand, models used in a more analytical sense (i.e., diagnostic pathway), may require more transparent and interpretable modelling techniques rather than optimum performance.

9.2. Implications of findings

The research indicates that, compared with aggregated models, personal models provide superior utility in predicting an individual's preferred thermal environment, which therefore offers potential for more accurate methods and tools to design, control and improve older people's living environments, so that comfort and wellbeing are optimised, healthy ageing is fostered and autonomy while ageing is prolonged. Consequently, improving building design, construction and operation could also result in a decrease in the reliance on heating and cooling systems and related fuel consumption.

9.3. Novelty and contributions

The novelty of this research lies in three areas. Firstly, while literature on personal comfort models has focussed solely on younger adults in office environments, this research has explored a methodology for predicting thermal comfort of older people in their dwellings. It therefore contributed to filling the current gap in the literature and to promoting the importance for future research and knowledge of the field of thermal comfort. Secondly, this research has novel methodological contributions. It introduced health/wellbeing perception as a predictor of thermal preference – a variable often overlooked in architectural sciences and building engineering. In addition, the research provided insights into a novel use of deep learning for future studies on thermal comfort. Finally, in addition to contributing to the existing literature, the findings of this research provided practical contributions to the worldwide novel trend and interest in precision public health and increasingly more person-centred approaches for healthcare delivery. The new concept "precision thermal comfort" could, therefore, be further explored as a new facet for future multidisciplinary research on architecture sciences, medicine and public health.

9.4. Limitations

This research presents limitations, which were explained in more detail in each of **Chapters 5 to 8**. The following list presents a summary of the main limitations of the study as a whole.

Firstly, the older adults involved in this research chose voluntarily to participate, introducing a self-selection bias to the analysis. In addition, despite the study including 3 different climate zones, it is still limited to a specific climatic context of South Australia. Likewise, although the older participants in this study represent a diverse cohort in terms of personal factors, other socio-cultural and economic factors that affect their thermal environments and perception still need to be addressed to build an holistic image of their diversity.

This study is limited to the analysis of 8 features that might affect thermal preference for older people. Other potentially relevant input variables might include: seasonal thermal expectations, other physiological data, more accurate representations of metabolic rates, and other socio-economic factors, which may influence people's thermal behaviours and preferences. Furthermore, given the nature of the study, only self-reported health/wellbeing perceptions were used, which might lack the accuracy of records from healthcare providers.

The second data collection involving skin temperature was conducted between the months of September and February. Further data collection periods in cool and cold seasons are required to allow a broader understanding of the effects of thermal exposure on skin temperatures of older adults.

Regarding the PMV scale conversion conducted in this research, it is acknowledged that thermal sensation and thermal preference scales cannot be considered interchangeable for all individuals. While neutral sensation and thermal preference for no change can be experienced simultaneously, it is still necessary to account for preferred sensations other than neutral. An alternative would be analysing different conversion rules for each individual participant depending on their thermal sensation and thermal preference answers.

Finally, the energy disaggregation method used in this study is based on the assumption that the heating and cooling use intensity of the building is solely climate dependent. The drivers of heating and cooling use intensity in buildings, however, can also be related to the number of occupants living in the households or their socio-demographic and contextual scenarios. In addition, other assumptions related to building model calibration, the HVAC systems' COP and EER, static occupancy and HVAC operation schedules, and static clothing and activity levels in the set point calculations should also be considered as potential causes of inaccuracies.

9.5. Recommendations and next steps

Through this research, several questions and topics have been raised which represent opportunities for future research and application. These have been detailed in each of the results chapters (5 to 8). The following list summarizes the main recommendations.

For researchers

(a) Future research is still required to advance the knowledge of other climatic scenarios and their related challenges, as well as of older people from other socio-cultural and economic backgrounds to build a more holistic image of their diversity.

(b) In order to insert the individualised modelling approach in standards and regulations, the consolidation of the technique needs to be further tested, and this depends on a unified modelling framework across the field. A protocol is recommended to prescribe the optimal data collection, processing, and management procedures and to guide the training, evaluation and reporting of models, depending on the application.

(c) It is recommended that the standards prescribe a set of initial models as common bases for each type of application, which can be used as a starting point for re-learning and updating for new and specific occupants and environments.

(d) The research also points to future research on combining physiological sensing, individualised predictive modelling and wearable personal comfort systems.

(e) Defining the thermal preference misclassification costs in the context of older people is also recommended in further studies on personal thermal comfort models.

(f) Regarding the application of personal comfort models for HVAC temperature set point calculations, daily set point calculation strategies can potentially generate better solutions for accurate energy use prediction. This could be achieved through incorporating personal comfort models in the building simulation workflow, using components such as the Energy Management System (EMS) object within EnergyPlus or co-simulation methods.

(g) Future investigations are necessary to validate personal HVAC temperature set points in shared spaces where occupants differ in thermal preferences and behaviours.

For designers, care givers and older adults

(a) The use of web-based tools is recommended for better control of building systems and consequently more accurate management of thermal environments in the context of older adults.

9.6. Closing remarks

In conclusion, the research has demonstrated that, as a concept, personal comfort models have the ability to absorb older people's diversity in the context of their living environmental conditions, and could, therefore, represent an important step towards providing knowledge aimed at enhancing health and wellbeing, promoting energy efficiency, and improving the overall resilience of the built environment.

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Appendices

A. Included journal publications

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A systematic review of personal thermal comfort models

Larissa Arakawa Martins *, Veronica Soebarto, Terence Williamson

School of Architecture and Built Environment, The University of Adelaide, Adelaide, South Australia, 5005 Australia

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Probabilistic models

ABSTRACT

Personal comfort models have shown to predict specific thermal comfort requirements more accurately than aggregate models, increasing occupant acceptability and associated energy benefits in both shared and single-occupant built environment. Although advances in the field of personal thermal comfort models are undeniable, there is still a lack of thorough and critical reviews of the current state of research in this field, especially considering the details of the predictive modeling process involved. This study has systematically reviewed 37 papers from over 100 academic publications on personal comfort models from the last two decades, and examined: (1) the data collection approach and dataset size, (2) number and type of participants involved, (3) climate, seasons and type of building involved, (4) model input and output variables, (5) modeling algorithm used, (6) performance indicator used, and (7) model final application. The review has identified a lack of diversity in building types, climates zones, seasons and participants involved in developing personal comfort models. It has also highlighted a lack of a unified and systematic framework for modeling development and evaluation, which currently hinders comparisons between studies. With most of the studies using machine learning techniques, the review has pointed to the challenges of "black box" models in the field. Finally, the review has indicated that personal input features using physiological sensing technologies can be further explored, especially considering the rapid advances seen today in wearable sensor technologies.

1. Introduction

International standards [1–3] adopt the PMV (Predicted Mean Vote) model [4] and the adaptive model [5,6] as the basis from which to establish the thermal requirements for human occupancy in the built environment. The PMV model, originally developed in the second half of the 1960s by Fanger, is an index that represents the mean value of the thermal sensation votes of a group of people occupying a specific environment, on a 7-point thermal sensation scale from −3 (cold) to 3 (hot). Based on data obtained through climate chamber studies and a selection of heathy adults, the model calculates thermal comfort sensations according to the heat dynamics occurring between the body and the environment. The model defines the thermal neutrality as the condition wherein a group of people does not feel either hot or cold in an environment. Furthermore, the PPD (Predicted Percentage of Dissatisfied) index, calculated as a function of the PMV index, quantifies the expected percentage of thermally dissatisfied people in an environment. The standards recommend that the optimal indoor temperature is defined when PPD is lower than 10%, which corresponds to a PMV index between −0.5 and 0.5. Hence, the application of this model results in the maintenance of a single optimal constant indoor temperature without any variations throughout an entire day or season.

Nevertheless, numerous studies on thermal comfort have considered it unreasonable to expect everyone to be satisfied within a centrally controlled environment. Non-neutral thermal preferences are common, questioning the thermal neutrality proposed as the only optimal thermal condition for people. In addition, very low and very high PMV values do not always represent a state of discomfort [7–9].

The adaptive comfort approach, developed by Humphreys et al. (2016) [6] and de Dear and Brager (1998) [5], analyzed field-study data from naturally-ventilated buildings. Through empirical models that correlate the comfortable indoor temperatures and the outdoor temperatures, they discovered that indoor temperatures considered to be most comfortable increased significantly in warmer climates and decreased in colder contexts. This indicates that people have an intrinsic ability to adapt to seasonal variations in environmental conditions, thus revealing that satisfaction with the thermal environment does not necessarily result in an environment restrained to an invariable indoor

* Corresponding author. School of Architecture and Built Environment, The University of Adelaide, Adelaide, South Australia, 5005 Australia.
E-mail addresses: larissa.arakawamartins@adelaide.edu.au (L. Arakawa Martins), veronica.soebarto@adelaide.edu.au (V. Soebarto), terence.williamson@adelaide.edu.au (T. Williamson).

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temperature [6,7,9,10].

Nonetheless, both PMV and the adaptive models are aggregate models, which means they are designed to predict the average thermal comfort of large populations. Other researchers have argued that predicting comfort at the population level presents limitations in real case scenarios. In fact, many studies have already pointed out to the high levels of thermal dissatisfaction among occupants in office buildings where the standard prescriptions are used for heating and air conditioning setpoint controls [11–14]. In addition, according to the pivotal work of authors Kim et al. (2018) [10], these aggregate models are also limited by (1) the difficult and costly attainment of input variables, (2) their inability to be calibrated, i.e., adapting to feedback and re-learning, and (3) their inability to incorporate new, relevant, input variables (such as age, health status, body mass index and contextual features) beyond their pre-defined factors.

"Personal comfort models" were created to overcome most of the restrictions that the PMV and adaptive models present. Instead of an average response calculated from the data of a group of people, a personalized model is based solely on thermal data from one single person. By analyzing individual datasets, this approach helps to unmask and quantify the differences between individuals in an environment, enabling a better understanding of specific comfort needs and requirements and collecting diagnostic information to identify problems [10]. This information, in turn, aids the decision-making process involved in designing and optimizing thermal environments to improve comfort satisfaction and energy efficiency. When HVAC (Heating, Ventilation and Air Conditioning) systems are used in shared spaces and an individual HVAC control is not possible, personal comfort models can be used as the basis for (1) consensus-based solutions [15–17], (2) personal comfort system's control automation [18,19] or (3) development of thermal comfort profiles (or personas) for general use (as conceptually indicated by Kim et al. (2018) [10]). In single-occupant spaces where individual control is possible, personal comfort models can be used to automate, with high precision, any type of conditioning systems. Although different levels of control automation can benefit all individuals [17,20,21], personal comfort models can be especially relevant as assistive tools for people with lower thermal sensitivity, such as older people, or for those with more limitations to thermal management and adaptation, such as people with disabilities [22]. Furthermore, these models can be calibrated and adapted according to new feedback and accommodate different types of variables depending on each person's specific comfort-driving characteristics. Addressing the issue of individual differences in an innovative way and empowered by the rapid developments in technology, this change of approach provides relevant comfort and energy related benefits [23] and allows more dynamic and flexible possibilities to absorb individual thermal comfort diversity and enhance model reliability [24].

The development of personal comfort models has been addressed using multiple frameworks, including different modeling architectures, diverse input variables and distinct data collection approaches. Nevertheless, although advances in the field are undeniable, a thorough and critical review to map the similarities and discrepancies between the predictive modeling details involved is still lacking. A structured review and compilation of the gaps and limitations will help facilitate and guide future investigations in the field.

This paper presents a systematic review on personal comfort models based on the literature published in the last two decades. It aims to provide a complete and unified overview of personal thermal comfort models, focusing specifically on the predictive modeling details. To the best of the authors' knowledge, there has not been a comprehensive, systematic and critical review specifically targeted at the predictive modeling specifics of personal thermal comfort models that rely solely on individuals as the unit of model analysis. A review by Čulić et al. (2021) [25], for instance, focused specifically on the smart technologies for data collection, drawing insights on sensing tools used and variables measured rather than modeling processes. Zhang and Tzempelikos (2021) [26], on the other hand, focused on the final stages of the process, namely the application or integration of personalized models into building control system. Xie et al. (2020) [27] brought forth a more comprehensive overview than the aforementioned studies but remained non-specific when addressing modeling details, disregarding the differences in models' dataset sizes, the experimental settings used (i.e., climate chambers or field studies) and the benefits of different modeling performance indicators. Similarly, Lee and Karava (2020) [28] provided a general overview of the topic without discussing details such as type of participants, climates, seasons and building settings involved, which can all affect modeling in different degrees. André et al. (2020) [29] targeted the details of personal comfort systems (PCS), i.e., the hardware effecting the comfort control, but not modeling details. Finally, although the pivotal work of Kim et al. (2018) [10] exposed 14 relevant papers on the subject, it does not constitute a systematic review.

This paper discusses research to date on personal comfort models and critically reviews: (1) the data collection approach and dataset size, (2) number and type of participants involved, (3) climate, seasons and type of building involved, (4) model input and output variables, including comfort scales used, (5) modeling algorithm used, (6) performance indicators used, and (7) model final application (when available).

The structure of this review is organized as follows. Section 2 discusses the research methodology. Section 3 presents the review results, highlighting the different aspects of the current efforts regarding personal comfort models' development. Section 4 discusses the gaps of knowledge and future research directions, and Section 5 concludes this review.

2. Research methodology

The selection process of academic publications in this study draws on the methodology adopted in manuals such as the *JBI Manual for Evidence Synthesis* [30]. The commonly adopted literature selection processes involve several steps: (1) scope delimiting, (2) identification of alternative terminology and creation of a logic grid, (3) defining the literature database, search rules and screening criteria, (4) database search, (5) final screening.

2.1. Scope delimiting

The main purpose of the review is to investigate the current state of research into personal thermal comfort prediction for the establishment of thermal requirements for human occupancy in buildings. Therefore, this review will focus on:

(a) buildings, excluding other built environments such as outdoor spaces or vehicles (e.g., cars or aircrafts);
(b) thermal comfort in buildings, excluding other forms of comfort, such as visual, acoustic or ergonomic comfort;
(c) predictive modeling of thermal comfort in buildings, excluding studies that only present descriptive statistical analysis, such as general distributions, dispersions, means, medians, variances, etc., of the data;
(d) and personal predictive modeling of thermal comfort in buildings, excluding aggregate or population-based prediction approaches.

Predictive modeling, in this paper, is termed as "the process of developing a mathematical tool or model that generates an accurate prediction", as defined by Kuhn and Johnson (2013) [31].

Fig. 1 illustrates the scope delimiting steps.

2.2. Identification of alternative terminology and creation of a logic grid

After delimiting the scope, a logic grid of key words was created. Table 1 presents the logic grid, highlighting the main key words,

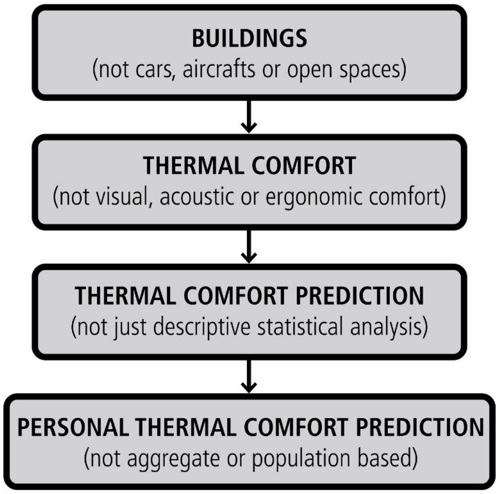

Fig. 1. Review's scope delimiting steps.

Table 1
Logic grid of keywords.

PERSONAL	THERMAL COMFORT	MODEL
personal* OR individual* OR occupant-cent* OR human-cent* OR customi* OR occupant-aware OR occupant-driven	"thermal comfort" OR "thermal discomfort" OR "thermal sensation" OR "thermal preference" OR "thermal behavior" OR "thermal behaviour" OR "thermal control" OR "thermal management" OR "thermal acceptability" OR "thermal satisfaction" OR "thermal complaint" OR "thermal dissatisfaction"	model* OR predict* OR data-driven OR smart OR "machine learning"

followed by the respective alternative terms. The logic grid was formatted considering basic search boolean operators (e.g., OR) and modifiers (e.g., asterisks for truncation, when different forms of the word are valid, and quotation marks, indicating when to keep phrases together).

2.3. Defining the literature databases, search rules and screening criteria

Scopus®, Web of Science® and Compendex® were the databases used in this study, as they cover architecture, engineering and computer science literature and allow a robust search of topics and fields. In terms of search rules, this study only reviewed literature published in peer-reviewed academic journals, as these were considered to be of higher quality than grey literature and conference papers. In addition, only publications written in English from 2000 to 2021 were included to filter the most recent studies on personal comfort models.

To select papers that strictly address personal comfort models, this systematic review only includes studies that:

(a) focus on individual occupants as a unit of model analysis;
(b) use real (non-synthetic) feedback from individuals;
(c) propose models that predict either thermal preference, sensation, acceptability, discomfort or dis/satisfaction; and
(d) present details on the development of the models.

2.4. Database search

The database search was conducted between January 2020 and September 2021. Using the keywords from the logic grid in titles, keyword lists and abstracts of publications, 1115 papers were initially identified in Scopus®, 1276 in Web of Science®, and 783 in Compendex®. These results, however, included duplicates, which were subsequently removed. Using the screening criteria mentioned in Section 2.3., all abstracts from the search results were read and selected for full-text screening if they met the criteria above. This process resulted in 109 papers chosen.

2.5. Final screening

Full-text screening involved a thorough analysis of the entire content of these 109 publications (i.e., not only title, keywords and abstract, but also the full content of the papers), filtering papers once again according to the screening criteria mentioned in Section 2.3. This process removed the papers that, although appearing to have the inclusion criteria in the titles, keywords and abstracts, upon a further analysis of the entire content, presented evidence for exclusion. This process also involved a second search through the selected publications' reference lists, to identify related papers that had not appeared in the first database search. This resulted in 7 papers being added to the list for full-text screening.

The final full-text screening resulted in 37 publications selected, which are described and analyzed in the next sections. Fig. 2 illustrates the research procedure of this study.

3. Results

Table 2 summarizes the 37 studies on personal comfort models reviewed for this paper.

3.1. Data collection approach and dataset size

From the papers that reported a total dataset size for all models developed (i.e., the sum of all individual models' dataset sizes), nearly half of them used up to 1000 data points. The smallest dataset reported was 321 data points presented in the study by Zhao et al. (2014) [66]. The other half of the studies had total datasets ranging from 1017 [59] to nearly 7000 points [43]. These total set sizes, however, were divided, in each study, into different numbers of individual datasets, according to the number of participants involved in each analysis. The smallest individual datasets ranged from 5 points per model [34,42] to slightly more than 400 points [45,58,59]. Such a wide range of dataset sizes is, however, expected as these studies used different modeling methods (explained in Section 3.5).

The data collection approach can highly influence the number of data points available for the individual personal comfort models. Studies that used either climate chambers or office rooms treated as structured experiments, and of which sessions lasted longer hours over multiple weeks, seemed to have higher survey response frequencies, and, consequently, higher individual datasets for each participant involved. Lu et al. (2019) [58], for instance, collected data through 14 2-h sessions, where participants answered a thermal comfort survey every 5-min. This resulted in relatively large datasets for the individual models (i.e., 362 to 413 points) although the study only involved two participants. Studies that used freely operated office rooms (i.e., not treated as structured experiments) reached similar individual dataset sizes by prompting thermal comfort votes from participants with frequent reminders. This was the case of Zhao et al. (2014) [65], who required participants to answer the thermal comfort surveys every hour, by sending online reminders to users' computers while they were working in the office environment. Similarly, Jayathissa, et al. (2020) [45] reached on average 416 data points per participant through the use of a smartwatch, which not only served as the main data collection tool and user interface, but also prompted the occupants with a small vibration requesting feedback from them at different timed points in the day.

Similar to the influence of the data collection approaches on the final

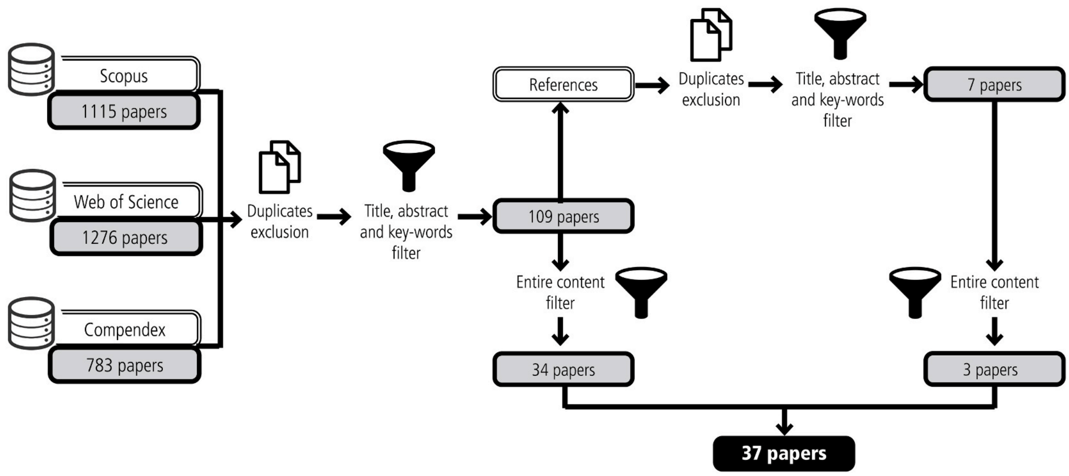

Fig. 2. Research procedure of this study.

dataset size, the impact of data pre-processing in the final data size is highlighted in some of the papers analyzed. Missing, anomalous or unlikely data points, as well as highly unbalanced datasets, need to either be discarded, decreasing the final data point count, or dealt with by oversampling in order to avoid low dataset sizes. K-Nearest Neighbors, for instance, was used by Liu et al. (2019) [56] to fill in missing data and avoid discarding relevant data points. Kim et al. (2018) [19] also used oversampling as a pre-processing tool to deal with unbalanced datasets (i.e., where one of the classification categories surpasses the other in number). Unlike undersampling, which discards data points until all classification categories match the minority category, oversampling avoids losing data points with the drawback of possible model overfitting.

Predicting thermal comfort without needing a large number of survey answers per user is, nevertheless, still possible. Natarajan and Laftchiev (2019) [59], for example, developed an Active Transfer Learning Framework to reach larger dataset sizes, at the same time avoiding disturbing participants with long monitoring periods. The framework uses knowledge from prior users to add to new users' datasets, reducing considerably the necessary size of individual labelled datasets.

3.2. Number and type of participants involved

The selected reviewed studies involved 2 to 576 participants to develop personal comfort models. It is noticeable that more than half of the studies had up to 10 participants, as seen in the histogram presented in Fig. 3. This can be partially explained by the common limitations of thermal comfort data collection processes, such as long monitoring periods or relatively intrusive data collection tools (e.g., repetitive survey and feedback required or continuous sensing), which might have affected subjects' willingness to participate.

The intrusiveness of thermal comfort prediction is, in fact, a recurrent topic throughout the studies analyzed, especially the ones involving human physiological parameters' sensing. Aryal and Becerik-Gerber (2019) [41], for instance, emphasized that not only can wearing devices discourage participant engagement because of the intrusiveness and privacy concerns, but it can also cost considerably more than using environmental sensors alone. Hence, in their study, they evaluated the accuracy trade-offs between using a wrist-worn wearable device, a thermal camera, and an environmental sensor to predict the individual thermal comfort of 20 participants. Likewise, Lee, et al. (2020) [53] recognized the impracticability of long-term collection of occupant feedback through participatory interfaces. In their study, both voluntary and requested feedback data were explicitly incorporated as types of behavior into the thermal preference learning models, to analyze differences in the model accuracy for 5 participants. Similarly, Li, et al. (2018) [54], Shan, et al. (2020) [61] and Lu et al. (2019) [58] tested different options for collecting skin temperature as inputs for personal comfort models using less intrusive and more accurate approaches. Their number of participants in each of those studies, however, was low (12, 3 and 2, respectively), and could have benefitted from further explorations, especially considering the diversity of subjects involved. Nevertheless, since the main objective of these studies was to analyze subjects at the individual level, having lower counts of participants is not necessarily negative.

From the 2 studies with more than 100 participants, Auffenberg, et al. (2018) [42] were able to reach the highest number of participants – 576 people – by using the ASHRAE RP-884 dataset [67], plus their own experimental period. The dataset was then divided into subsets for each participant who answered at least 5 thermal comfort votes.

Although not all studies reported further details about the participants, it is still clear from the analysis that such studies involved younger adults in their twenties considered to be healthy and maintained an overall balance of female and male participants (Table 3). This is in line with the traditional approach of thermal comfort studies to select younger healthy adults [4], possibly to avoid individual influences of age, health conditions, intellectual or physical impairment or medication use in thermal sensation and sensitivity [9,68]. Participants who were office workers and students were also common in the studies analyzed, as seen in Table 3. Weight, height and BMI (Body Mass Index) were reported by few of the studies selected and deemed more relevant when considering personal and physiological parameters, such as skin temperature or heart rate, as inputs for the personal comfort models [18, 56,61].

3.3. Climate, seasons and type of building involved

As presented in Table 2, nearly all reviewed studies used office environments to collect data for the personal comfort models developed. When climate chambers were used or office spaces were treated as an experimental setting, the activities simulated were mainly sedentary (e.g., sitting down, working on computer, reading), which means activities undertaken in residential settings (e.g., eating, cooking, walking) were not explored. This can be limiting when considering the diversity of thermal conditions in residential environments in comparison with more controlled office environments. Likewise, while in offices the activity and clothing levels are normally similar throughout the year, in home environments they often change, providing more diverse thermal conditions [43].

Nevertheless, considering the application aimed for in these studies, focusing on office environments is an expected trend. This is because

Table 2
Studies on personal comfort models and their characteristics.

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
Aguilera et al. (2019) [39]	Denmark	Denmark	465 (assumed from graph in study)	50 to 110	7	Office	3 weeks, March–April 2018	FC	not mentioned	0	Ti	Thermal preference	29% of occupants' thermal comfort improved with occupant-driven HVAC control
Aryal and Becerik-Gerber (2020) [40]	USA	USA	1276	85 (average)	15	Office[6]	July–August 2019	RF, KNN, SVM, DT	5-fold cross-validation	STemp (wrist, forehead, nose, left cheek, and right cheek) [7]	Ti, RH, ASp, mTr, Heater state, Fan state [5]	Thermal sensation and thermal satisfaction	Average accuracy across participants: Thermal sensation: 72–90%[8] Thermal satisfaction: 69–94%
Aryal and Becerik-Gerber (2019) [41]	USA	USA	543	27 (approx.)	20	Office[4]	June–August 2018	RF, SVM, KNN, Subspace KNN, Subspace LDA	5-fold cross-validation	STemp (wrist and 4 points in face) [9]	Ti [6]	Thermal comfort, thermal satisfaction and combination of both	Average accuracy across participants: Thermal sensation: 72–85%[8] Thermal satisfaction: 85%–94% Combination thermal sensation and satisfaction: 62–76%
Aryal et al. (2021) [21]	USA	USA	not mentioned	125.1 average (phase 1) and 224.8 average (phase 2)	14	Office	15 weeks, October–March 2020	RF, KNN	5-fold cross-validation	Clo	Ti, RH, Tr, To, Rho, ApT [10], Time, Heater state, Fan state	Thermal sensation and thermal satisfaction	Average accuracy across participants: Thermal sensation: 74–77%[8] Thermal satisfaction: 81–86%
Auffenberg et al. (2018) [42]	UK	Pakistan, Greece, USA, UK	not mentioned	5 to 150	576	Office and residential	from 5 to 60 days	BI	Cross-validation mentioned but not detailed, increasing training observations in steps of 1	Seasonal adaptation	To, OpT, RH	Optimal comfort temperature, Thermal preference (desired change), Thermal sensation, Thermal sensitivity	Average accuracy gains, across participants: Compared to PMV: 25.8% Compared to adaptive model: 13.2%

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Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
Daum et al. (2011) [43]	Switzerland	Switzerland	6851	not mentioned	28	Office	2006 to 2009	MLR	not mentioned	0	Ti	Thermal sensation	not mentioned
Fay et al. (2017) [34]	UK/Ireland	Ireland	477	5 to 227	78	Office	4–306 days per user	GPM	5 data points for testing, randomly repeated 50 times	0	Ti, RH, To	Thermal sensation	Average RMSE across participants: 0.71 Standard deviation of RMSE across participants: 0.28 Average PSE across participants: 34.1
Ghahramani et al. (2015) [44]	USA	USA	2393	19 to 202	33	Office	several months in 2012, 2013 and 2014, different seasons, 5–90 days per person	BI	not mentioned	0	Ti	Thermal sensation	Average accuracy across participants: 70.14% Average specificity across participants: 76.74%
Guenther and Sawodny (2019) [33]	Germany/ Singapore	Singapore	not mentioned	not mentioned	18	Office	10 months	GPM and Polynomial Basis Function	Cross-validation mentioned but not detailed	0	Ti, Supply T at the outlet of the fan coil units, Fan level, To, GSR, Time, Day of week, Variation of each parameter (except for day and time)	Thermal sensation	Average RMSE across participants: 0.68 Median RMSE across participants: 0.58 Right tendency across participants: 74%
Jayathissa et al. (2020) [45]	Singapore	Singapore	4378	416 average	30	Office	2 weeks	RF	60-40 split	NBTemp, HR, PrefH, Room	Time, Lighting, Noise, Ti, RH	Thermal, visual and aural comfort preference	Average F1-micro-score across participants, for thermal preference: 0.60–0.66[8]
Jazizadeh et al. (2014) [16]	USA	USA	328	61 to 114	4	Office[4]	3 weeks, autumn	FC	10-fold cross-validation for different numbers of fuzzy sets between 1 and 100, increasing training	0	Ti	Thermal sensation	Average[11] error between true and predicted temperatures associated with each thermal sensation, across

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Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
									observations in steps of 10				participants: 1.165 °C
Jazizadeh et al. (2014) [15]	USA	USA	not mentioned	not mentioned	6	Office	October–December 2012 and April and June 2013	FC	not mentioned	0	Ti	Thermal sensation	Average thermal comfort rating after using personalized HVAC control, across participants: 8.4 on 1–10 scale (10 being most comfortable)
Jiang and Yao (2016) [46]	UK	China	1199	38 to 63	20	Climate chamber	Summer 2008 to 2010	SVM	50-50 split 5-fold cross-validation	MET, Clo	Ti, MTr, aSp, RH	Thermal sensation	Average accuracy across participants: 89.82%
Jung and Jazizadeh (2019) [47]	USA	USA and Switzerland	not mentioned	not mentioned	6	Office	Varies, depending on the dataset	BI	not mentioned	0	Ti	Thermal sensation	not mentioned
Jung et al. (2019) [48]	USA	USA	not mentioned	not mentioned	18	Climate chamber	not mentioned	RF, SVM, LR	3 scenarios for train-test split[12]	Heat flux, STemp (wrist)	Ti	Thermal preference	Median accuracy across participants: Scenario 1: 42.6–61.2%[8] Scenario 2: 44.8–72.9% Scenario 3: 68.7–97%
Katić et al. (2020) [18]	The Netherlands/ Denmark	The Netherlands	476	238	2	Climate chamber	January–February and November–December 2017	SVM, DT Ensembles (Bagged trees, Boosted trees and RUSBoosted trees)	5-fold cross-validation	PCS Control Intensity, STemp (mean and hand)	Time, Ti, RH, MTr	Thermal sensation	Average accuracy across participants[11]: Approach 1[13]: 59.45–95.6%[8] Approach 2: 62.4–85.55% Average ROC AUC, across participants: Approach 1: 0.5–0.84[8] Approach 2: 0.645–0.8
Kim et al. (2018) [19]	USA	USA	4743	123 (average)	34	Office	April–October 2016	DT, GPM, GB, SVM, RF, Regularized LR	2-fold cross-validation, repeated 150 times	PCS Control Intensity, PCS Heating/ cooling Location, PCS Occupancy Status, PCS Occupancy Frequency,	Ti, OpT, RH, Ti slope, HVAC control settings, HVAC Thermostat reading (TI, aSp, Damper position, Heating output, Discharge T), To,	Thermal preference	Average ROC AUC across participants: 0.61–0.71[8]

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Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
										Ratio of PCS Control Duration over Occupancy Duration, PCS Control Frequency, Clo	Sky Cover, Weighted Mean Monthly T, Precip, Day of week, Hour of day		
Kim (2018) [49]	South Korea	Not mentioned for first data set and USA	2480	26 to 133	24	Office	March–August 2017 and July 2012–August 2013	ANN	not mentioned	0	Time, Ti, To	Thermal discomfort	Average[11] MSE across participants: 0.002975
Konis and Annavaram (2017) [50]	USA	USA	1490	8 to 80	45	Office	2 weeks	LR	not mentioned	0	Ti	Thermal satisfaction separated for heating and for cooling	Percentage of incorrect predictions <10%: met for 16 of 16 heating models and for 19 of 21 cooling models
Lee and Ham (2020) [51]	USA	USA	953	63 to 115	10	Office	4 weeks, August–September 2019	KNN, GB, LVQ, SVM, RF	10-fold cross-validation	STemp, SCond, HR, MET	Ti, RH	Thermal sensation	Average[11] accuracy across participants: 71–77%[8] Average Cohen's Kappa across participants: 0.216–0.441[8]
Lee et al. (2017) [38]	USA	North America	1712 - first phase, not mentioned - last phase	from 10	11	Office	not mentioned	BI	8 data points for training and remaining for testing	MET, Clo	Ti, MTr, ASp, RH	Thermal preference	Logistic loss of −28.5 when compared to −30 from another study (assumed from graph in study)
Lee et al. (2019) [52]	USA	not mentioned	432	48	9	Office[4]	8 days in October and November 2017	Variational BI	2 to 8-fold cross-validation, increasing training dataset in steps of 6	MET, Clo	Ti, mTr, RH, ASp	Thermal preference	ROC AUC of approx. 0.8 (assumed from graph in paper)
Lee et al. (2020) [53]	USA	USA	not mentioned	48 (assumed for requested phase), not mentioned (for participatory phase)	5	Office[4]	March–April 2019	Linear OP, BI	not mentioned	0	Ti	Thermal preference	Median Expected Squared Error, for each participant[14]: approx. 10–30[8]
Li et al. (2017) [14]	USA	USA	271 - first case study, 362 - second case study	31 to 57	3 and 7	Office and residential	June–July 2016 and 3 weeks in November–December 2016	RF	10-fold cross-validation	Act, Clo, HR, STemp	Ti, RH, Window State, To, RHo	Thermal preference	Average[11] accuracy across participants: First case study, mechanical ventilation:

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Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
													62.5–80.2%[8] First case study, natural ventilation: 53.3–78.4% Second case study: 54–81.8%
Li et al. (2018) [54]	USA	USA	720 (assumed according to vote frequency)	60 (assumed according to vote frequency)	12	Office[4]	December 2017–February 2018	RF	10-fold cross-validation	STemp max. measurement of face[15], STemp gradient (forehead, nose, cheeks, ears, mouth, and neck)	0	Thermal preference, for cooling, heating and both phases	Average accuracy across participants: Cooling phase: 91.6% Heating phase: 92.7% Both phases: 85.0%
Li et al. (2020) [55]	USA	USA	1800	180	10	Office[4]	December 2017–February 2018	LR	10-fold cross-validation	STemp (cheeks)	0	Thermal comfort	Average[11] accuracy across participants: 67.4%
Liu et al. (2019) [56]	USA	USA	3848	275 (average)	14	Anywhere, indoor and outdoor	2–4 weeks, March to May 2017 and November to December 2016	LDA, LR, ANN, SVM, KNN, NB, CART, J48, DT, RBC, C5.0, Bagged DT, RF, RF by Randomization, GB	80-20 split, 5-fold cross-validation, repeated 20 times	STemp (wrist and ankle), NBTemp, HR, Wrist Acc [16]	To, RH, ASp, SR	Thermal preference	Average[11] accuracy across participants: 64.7–72.9%[8] Cohen's Kappa across participants: 0.16–0.27[8] ROC AUC across participants: 0.6–0.76[8]
Liu et al. (2007) [57]	China	China	not mentioned	not mentioned	113	Office[4]	June to October 2004	ANN	20 datapoints for training and 4 for testing	0	Ti, RH, ASp, MTr	Thermal sensation	Veracity[17] of approx. 80% after replacing the first 20 datapoints (paper only shows 1 participant's results)
Lu et al. (2019) [58]	USA	China	775	362 to 413	2	Office[4]	6 days, March 2018	RF, SVM	80-20 split, 5-fold cross-validation	Clo SurfTemp, STemp (cheek), STemp difference between consecutive measurements	Ti, RH	Thermal sensation	Average[11] precision across participants: 37.9–98.75%[8] Average recall across participants: 42.75–97.5%[8] Average F1-score across participants: 38.5–98.05%[8]
	USA	USA	1017	97 to 400	5	Office[4]	Average 14 days per user				Ti, RH, ASp [10]	Thermal sensation	Average RMSE across

(*continued on next page*)

Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
Natarajan and Laftchiev (2019) [59]								LinR with Active and Transfer Learning	50-50 split, 5-fold cross-validation	HR, STemp, CBTemp, PrefTemp [18]			participants: 0.818
Pazhoohesh and Zhang (2018) [60]	UK/China	not mentioned	not mentioned	not mentioned	9	Office	November 2016–January 2017	FC	not mentioned	0	Ti	Thermal preference	Average margin of error across participants: 12.95% Percentage of occupants rating “Just Right” when model is used for HVAC control: 73%
Shan et al. (2020) [61]	China	China	450	150	3	Office[4]	June–August	ANN	10-fold cross-validation, repeated 10 times	STemp (wrist, neck, of the point 2 mm above the wrist)	0	Thermal sensation	Average accuracy across participants: 89.2% Average MAE across participants: 0.16 Average MSE across participants: 0.06
Shan et al. (2018) [62]	Singapore/Australia	Singapore	not mentioned	not mentioned	22	Office[4]	not mentioned	LDA	not mentioned	EEG [19]	0	(Thermal) Mental state	Average accuracy (classification rate) across participants: In Resting state: 98% In Task state: 99%
Sim et al. (2016) [63]	South Korea	South Korea	840	not mentioned	8	Climate chamber	not mentioned	Stepwise LinR	not mentioned	STemp (fingertip, radial artery, ulnar artery, upper wrist temperature) [20]	0	Thermal sensation	Average RMSE across participants: 0.95–1.24[8]
Xu et al. (2018) [64]	China	China	not mentioned	not mentioned	4	Office	not mentioned	MLR	not mentioned	0	Ti	Thermal sensation	Consumed power of the VAV system with proposed approach: 23% less than the traditional fixed set-point control strategy.
Zhao et al. (2014) [65]	China	China	2679	300 (average)	9	Office	November 2009–January 2010	LLS	67-33 split	0	Ti, RH, MTr	Thermal sensation	Average[11] across participants:

(*continued on next page*)

Table 2 (*continued*)

Authors, year and Ref.	First author affiliation location	Data collection location	Dataset size[1] (total in the study)	Dataset size[1] (in individual models)	No. of participants	Type of Building	Period of monitoring	Modeling Algorithm[2]	Train-test split and/or cross-validation	Inputs Personal[3]	Inputs Environmental[4]	Outputs	Model Predictive Performance[5]
Zhao et al. (2014) [66]	China	China	321	not mentioned	6 and 11	Climate chamber	June–August 2011 and same period in 2012	LLS	leave-one-out validation method	0	Ti, RH	Thermal complaint	Regression MSE: 0.4782 Prediction MSE: 0.53373 Regression Bias: 0.00188 Prediction Bias: 0.03382 Average[11] FNR across participants: For Hot complaint: 0.0783 For Cold complaint: 0.055 Average FPR across participants: For Hot complaint: 0.5245 For Cold complaint: 0.365

[1] "Dataset size" refers to the number of datapoints used in the studies, i.e., the total number of observations used for model training, validation and testing.
[2] FC = Fuzzy Classification, RF = Random Forest, KNN = K-Nearest Neighbors, SVM = Support Vector Machine, DT = Decision Tree, LDA = Linear Discriminant Analysis, BI = Bayesian Inference/Classification, MLR = Multinomial Logistic Regression, GPM = Gaussian Process Model, LR = Logistic Regression, ANN = Artificial Neural Network, GB = Gradient Boosting, LVQ = Learning vector quantization, OP = Ordered Probit, LinR = Linear Regression, NB = Naive Bayes, RBC = Rule-Based Classifier, CART = Classification and Regression Trees, LLS = Least-squares linear estimation, J48 = J48 Decision Tree.
[3] STemp = Skin Temperature, Clo = Clothing, NBTemp = Near Body Temperature, MET = Metabolic Rate, HR = Heart Rate, SCond = Skin conductance, Act = Activity level, SurfTemp = Surface Temperature, Acc = Accelerometry, CBTemp = Core Body Temperature, PrefTemp = Preferred Temperature, EEG = Electroencephalogram, PrefH = Preference History.
[4] Ti = Indoor Air Temperature, RH = Relative Humidity, aSp = Air Speed, mTr = Mean Radiant Temperature, Tr = Radiant Temperature, RHo = Outdoor Relative Humidity, To = Outdoor Air Temperature, OpT = Operative Temperature, ApT = Apparent Temperature, T = Temperature, GSR = Global Solar Radiation, SR = Solar Radiation, HVAC = Heating, Ventilation and Air Conditioning, PCS = Personal Comfort System, Precip = Precipitation.
[5] Definitions of Accuracy, Precision, Recall, Specificity, FNR, FPR, F1-score, ROC AUC can be found in Ref. [32]; Right tendency = average percentage of votes whose signs are predicted accurately, defined in Ref. [33]; PSE = percentage signed error, defined in Ref. [34]; RMSE = root mean squared error, MSE = mean squared error, MAE = mean absolute error, with further definitions found in Ref. [35]; Cohen's Kappa = inter-rater agreement, further defined in Refs. [36,37]; Logistic loss = loss function for logistic regression, defined in Ref. [38].
[6] Treated as an experiment.
[7] Instant measurement at the time of vote, min., max., average, std., overall change between first and last values in the time window, and average of the derivative of the measurements.
[8] Ranges indicate max. and min. across different input set combinations, phases and/or modeling techniques compared in the studies.
[9] Min., max., average, std. and median of measurements in the 5-min. window and of first derivative of the data stream; coef. obtained by fitting first degree and second degree polynomials to the measurements in the 5-min window; most recent measurement, average of last 10s, and average of first derivative for the last 10s.
[10] Average and changes in the last 1, 5, 10 and 30min. prior to a vote for all features.
[11] Average calculated by this review paper using available data from papers, to allow comparison between studies.
[12] Scenario1 = training on first half of the experiment and testing on second half of the experiment; scenario 2 = training on the second half of the experiment and testing on the first half of the experiment; scenario 3 = cross validation on all the data points combined.
[13] Approach 1 = thermal preference in scale heating demand, neutral, cooling demand; Approach 2 = thermal preference in scale heating demand, slightly heating demand and no change.
[14] Average cannot be calculated from graph supplied by the paper.
[15] Measurement and its gradient, max., min. and average.
[16] Average and gradient for 5min and 60min prior to a vote.
[17] Term "veracity" not defined in the study.
[18] Average, variance, median, min., max., simple moving average between 2 and 9 samples immediately prior to a vote.
[19] 42 frequency ranges (within 3–45 Hz range) for each of the 14 channels.
[20] Average, time differential, average power of a specific frequency band, temperature gradient between positions.

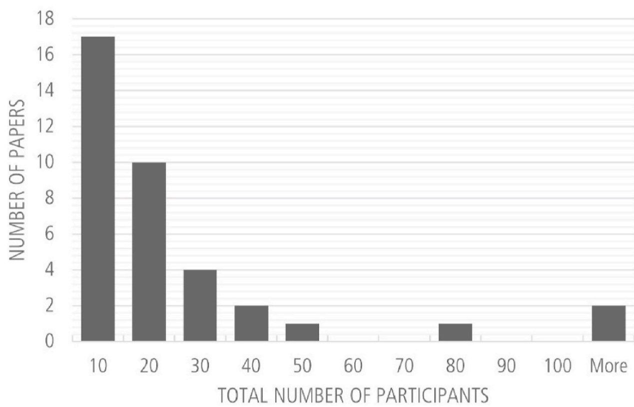

Fig. 3. Histogram of total number of participants in the studies selected.

these studies mainly aimed to evaluate the application of personalized thermal comfort models as optimization and automation strategies for HVAC systems in highly controlled environments, which are more commonly found in office buildings. These studies will be discussed further in Section 3.7.

The USA and China are the main locations reported by the selected studies, followed by Singapore and a small number of European countries, as seen in Fig. 4. The climate zones analyzed span from warm temperate (*Cfa*, *Cfb*, *Csb*) [15,16,18,19,21,34,39–41,43,44,46–51,56–59,61,64,69], to equatorial (*Af*) [33,45,62], to colder climates (*Dfb* and *Dwa*) [14,54,55,63,65,66], following the *Köppen-Geiger Climate Classification*.

In general terms, the studies screened have diverse monitoring periods, shown in Table 2. Summer and winter periods are understandably more common than autumn and spring throughout all studies, as capturing extremes in environmental conditions can help create a more diverse dataset upon which to develop thermal comfort models. There is a tendency, however, to analyze a single season in the individual studies (i.e., either summer or winter months), which can be limiting when attempting to capture the entire range of thermal sensations and preferences.

3.4. Model input and output variables

The range of the number of input variables to develop personal comfort models varied widely across the studies analyzed. While several studies used one to fifteen variables as features to predict thermal comfort, some studies used more than 100 features [41,59,62]. In the latter, apart from the raw measurements collected for each input variable, the researchers extracted other properties from the measurements, such as mean, variance, minimum, maximum or standard deviation, to create additional input variables that could represent intrinsic

Table 3
Participants details in each study analyzed.

Ref.	No. of participants	M (male)/F (female)	Age group	Health	Body Composition	Other characteristics
[39]	7	*	*	*	*	office workers
[40]	15	11 M and 4 F	20s	healthy	H 168.9 ± 10.1 cm, W 65.4 ± 7.3 kg	*
[41]	20	12 M and 8 F	20s–30s	healthy	H 171.8 ± 10.9 cm, W 73.8 ± 16.1 kg	*
[21]	14	4 M and 10 F	20' – 50s	*	*	office workers, researchers, students
[42]	576	*	*	*	*	office workers, students (partially)
[43]	28	*	*	*	*	office workers, researchers
[34]	78	*	20s–40s	*	*	office workers, researchers, students, diverse international background
[44]	33	*	*	*	*	office workers, researchers, students
[33]	18	*	*	*	*	*
[45]	30	15 M and 15 F	*	*	*	office workers
[16]	4	*	*	*	*	office workers
[15]	6	*	*	*	*	office workers
[46]	20	*	20s	healthy	*	*
[47]	6	*	*	*	*	office workers, researchers
[48]	18	12 M and 6 F	*	healthy	*	*
[18]	2	2 F	20s	healthy	W 57 and 62 kg, BMI 26.7 and 22.9 kg/m^2, Fat 34.9 and 27.8%, BMR 38.2 and 38.6 W/m^2	*
[19]	34	*	*	*	*	office workers
[49]	24	*	*	*	*	office workers
[50]	45	*	*	*	*	office workers, researchers
[51]	10	6 M and 4 F	20s–30s	*	H 163–195 cm, W 51–100 kg	office workers, white people and Asians
[38]	11	*	*	*	*	office workers
[52]	9	*	20s–40s	*	*	*
[53]	5	4 M and 1 F	20s–30s	*	*	students
[14]	3 and 7 **	*	*	*	*	office workers
[54]	12	7 M and 5 F	20s	healthy	*	students
[55]	10	*	20s	healthy	*	students
[56]	14	8 M and 6 F	20s–40s	healthy	H 163–185 cm, W 52–86 kg, BMI 17.4–28.7 kg/m^2	office workers, students
[57]	113	65 M and 48 F	20s (average)	healthy	H 165 cm (average), W 55 kg (average)	*
[58]	2	1 M and 1 F	20s	healthy	*	*
[59]	5	3 M and 2 F	20s–30s	*	*	*
[60]	9	*	*	*	*	researchers
[61]	3	3 M	20s	healthy	H 171–174 cm, W 62–78 kg, BMI 21–26.7 kg/m^2	*
[62]	22	14 M and 8 F	*	healthy	*	students
[63]	8	6 M and 2 F	20′	healthy	BMI 22.45 ± 2.63 kg/m^2	*
[64]	4	*	*	*	*	*
[65]	9	*	*	*	*	researchers, students
[66]	6 and 11 **	2 M and 4 F, 7 M and 4 F	20' – 30s	*	*	office workers, students

*Not reported; ** Study had 2 phases.

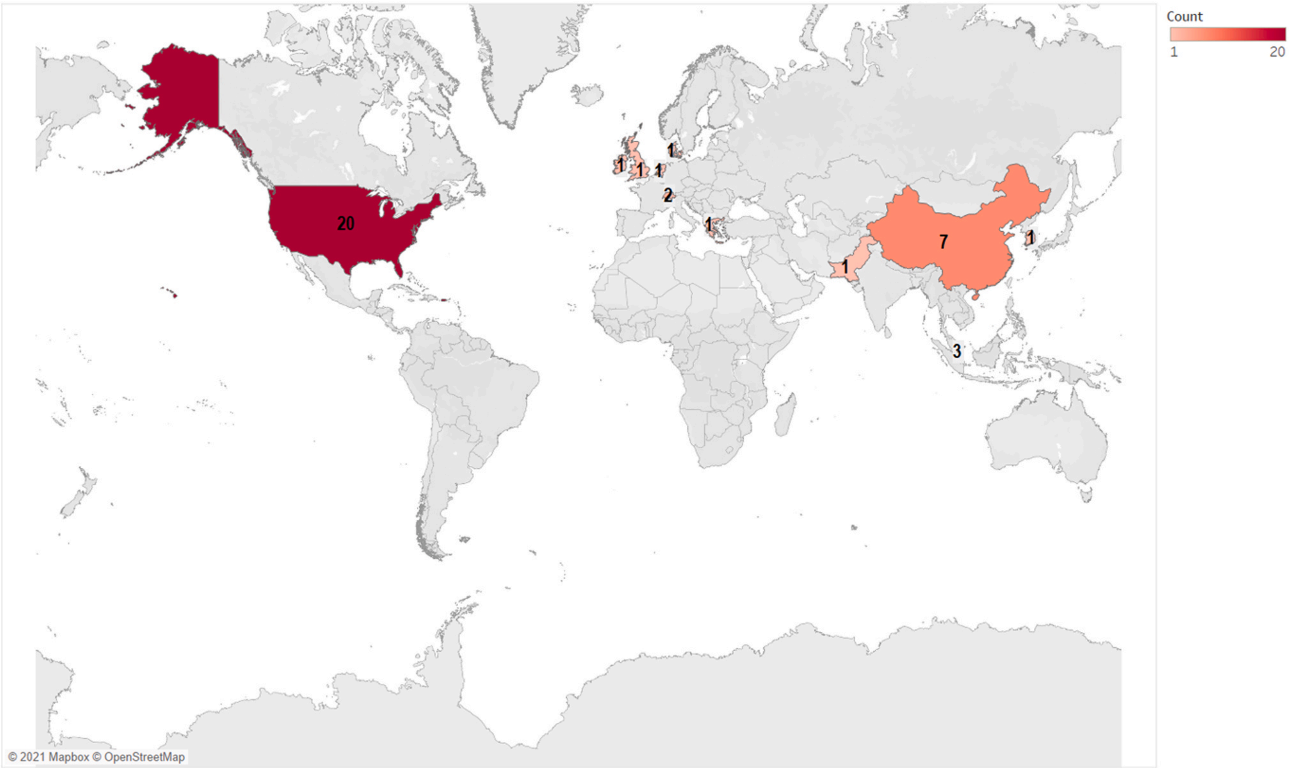

Fig. 4. Number of studies per data collection country.

properties of the data and increase the predictive performance of the models. This process is called feature engineering. Aryal and Becerik-Gerber (2019) [41], for instance, used not only direct values of indoor air temperature and skin temperature measured on the wrist and 4 points on the face, but also the minimum, maximum, average, standard deviation and median of the measurements in the 5-min window; the minimum, maximum, average, standard deviation and median of the first derivative of the data stream; coefficients obtained by fitting first degree and second degree polynomials to the measurements in the 5-min window; and the most recent measurement value, average value of the last 10 s, and average of the first derivative for the last 10 s. By extracting 108 features as input variables for the personal models, the researchers expected to capture overall values, trends, and patterns of changes in the data streams over time.

Likewise, Shan, et al. (2018) [62] used a high number of input features available. These, however, were extracted from electroencephalogram (EEG) measurements, where 42 frequency ranges for each of the 14 channels available from the measuring equipment resulted in the total number of 588 features available. It is important to highlight that, while the use of multiple input parameters can enhance the predictive power of models, it can also result in higher complexity and computational load when it comes to feature selection and model scalability [70]. In the case of EEG-based studies, it is also noteworthy that although this type of data can provide a wide range of input variables to explore, it is knowingly more susceptible to high levels of noise resulting from muscular activity [71,72], which can greatly impact model's reliability especially in field studies.

The input variables used can be divided into environmental and personal variables, as shown in Table 2. Environmental variables include traditionally used parameters such as indoor air temperature and relative humidity, mean radiant temperature, outdoor air temperature and relative humidity and air speed. As presented in the Euler

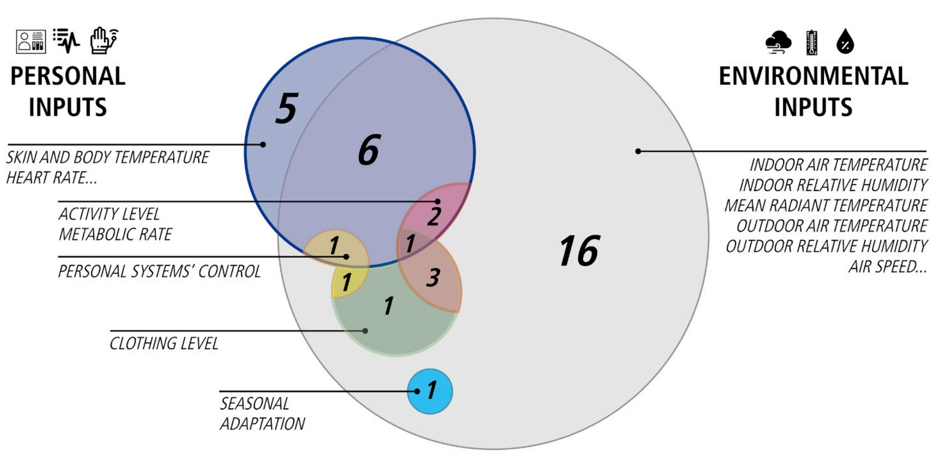

Fig. 5. Euler diagram of the number of studies that used personal and/or environmental inputs.

diagram in Fig. 5, 32 out of the 37 studies selected used at least one of these variables as inputs. Less frequently used environmental variables were solar radiation, time of day, day of the week, and window, fan, and the HVAC system operational states. The control setting of personal comfort systems (PCM), such as heated or cooled chairs, was also used in two studies as input parameters for individual thermal comfort models [18,19]. Both studies highlighted the importance of occupant behavioral attitudes and interactions with thermal control devices as a non-intrusive and practical method to understand individuals' thermal needs and collect continuous streams of data.

Personal variables, on the other hand, include people's intrinsic characteristics, such as skin and body temperature, heart rate, clothing level, activity level and metabolic rate, or previous temperature preferences or preference histories. From the studies selected, more than half used at least one personal feature, although most of the time this was combined with environmental inputs, as presented in Fig. 5. Among these features, skin temperature, captured by wearable sensors or thermal cameras, remained the main personal variable utilized [14,18,40,41,48,51,54–56,58,59,61,63].

The models' predictive performance appeared to increase when a combination of both environmental and physiological variables was used as inputs. Aryal and Becerik-Gerber (2019) [19], for instance, reported that using data from environmental sensors for predicting thermal comfort resulted in a higher accuracy compared to using just physiological data. However, combining data from both environmental and physiological sensors led to a slightly higher accuracy (3%–4%) than using environmental sensors only. A further study from the same authors [20] confirmed similar results. Jung et al. (2019) [21] indicated a much greater increase in performance when including physiological features as input parameters to personal thermal preference models. The study's best performing modeling algorithm presented a median accuracy of 71% when using air temperature as a sole feature, 93% with the addition of skin temperature and 97% with the addition of heat flux. Likewise, Li, et al. (2017) [23] reported that the combination of both environment and human data (i.e., activity level, clothing, heart rate, skin temperature) achieved approximately 80% accuracy, improving the classification accuracy by 24% and 39% when compared to using only environmental features and only physiological factors, respectively. Similarly, Katić, et al. (2020) [22] evaluated different combinations of occupants' PCS heating behaviors, their mean and hand skin temperatures, and environmental data, producing the lowest accuracy when using just environmental data.

Although the impact of the input variables on the predictive performance of the models is a significant criterion when selecting the best options among possible variables, the choice of model parameters can also be dictated by the cost of data collection [19]. As mentioned in Section 3.2, the cost and intrusiveness of the data collection process can affect not only the participants' willingness to participate, but also the type of data available, their quantity and quality.

In terms of the output variables, thermal sensation and preference were the main targets chosen for prediction in the studies selected. The sensation or preference scales used, however, differed greatly across studies, as seen in Table 4. They differed from binary to 100-point scales, from discrete to continuous scales and across different terms and categories of sensitivity used. In addition, many scales were converted to lower numbers of points, shown in Table 4, depending on the study's approach, modeling technique and possible application. It should be noted that, in order to avoid incorrect interpretations of the studies and scales used, the outputs in Table 4 are presented as they were in the studies (e.g., "thermal comfort", "thermal satisfaction", "thermal preference"), although some can be considered interchangeable.

Like the input variables, the choice of output variables and scales is subject to the cost of continuous survey feedback for both participants and researchers. According to studies by Katić et al. (2020) [18] and Kim et al. (2018) [19], a practical solution to collect this sort of data would be the use of PCS control behavior to act as potential replacements for

Table 4
Thermal scales used in the studies selected.

Ref.	Output	Scale
[62]	Mental state	Cool, Neutral, Warm
[42]	Thermal preference ("desired change")	I want it to be much colder, to be colder, be a bit colder, stay as it is, be a bit warmer, be warmer, be much warmer
	Thermal sensation	Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot
[66]	Thermal complaint	Complaint or comfortable
[55]	Thermal comfort	Uncomfortably cold, Comfortable, Uncomfortably hot
[41]	Thermal comfort	Cold, Comfortable, Hot
	Thermal satisfaction	Satisfied, Dissatisfied
	Combination of both	Cold and satisfied, Cold and dissatisfied, Comfortable and satisfied, Comfortable and dissatisfied, Hot and satisfied, Hot and dissatisfied
[49]	Thermal discomfort	Cold to hot on a −6 to 6 scale (Normalized from a −100 to 100 scale)
[53]	Thermal preference	I prefer Warmer, I am Satisfied, I prefer Cooler
[39]		Much Warmer, Warmer, Slightly Warmer, No Change, Slightly Colder, Colder, Much Colder, as a Thermal Profile (from a 18-point scale converted in a 7-point scale)
[48]		Uncomfortably cool, No change, Uncomfortably warm (11-point scale converted to 3-point scale)
[38]		Want warmer, No change, Want cooler
[14]		Warmer, Neutral, Cooler
[60]		Warmer, Neutral, Cooler (from a scale from −50 to 50, 10 in 10)
[19]		Warmer, No Change, Cooler
[54]		Warmer, No Change, Cooler
[56]		Warmer, No Change, Cooler
[52]		Warmer, No Change, Cooler, as Thermal Profile
[45]		Prefer warmer, Comfy, Prefer Cooler
[50]	Thermal satisfaction	Satisfied/Dissatisfied or Bothersome/Non-bothersome (from a 5-point scale converted to binary)
[61]	Thermal sensation	Cold, Cool, Neutral, Warm, Hot (from a 7-point scale converted to a 5-point scale)
[65]		Cold, Cool, Neutral, Warm, Hot (on a continuous scale from −3 to 3)
[46]		Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot
[34]		Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot (on a continuous scale)
[57]		Cool, Comfort, warm (from a 7-point scale converted to a 3-point-scale)
[51]		Cool, Neutral, Warm (from a 7-point scale converted to a 3-point scale)
[18]		Heating demand, neutral, cooling demand (from a 7-point thermal sensation scale)
[33]		Much too cool, Too Cool, Comfortably Cool, Comfortable, Comfortably Warm, Too Warm, Much too warm
[43]		Too Cold, Comfortable, Too Hot, as a Thermal Profile (from a 7-point scale converted in 3-point scale)
[64]		Uncomfortably Cold, Comfortable, Uncomfortably Hot (from a 7-point scale converted to a 3-point-scale)
[44]		Uncomfortably Cool, Comfortable, Uncomfortably Warm (from a 11-point scale converted in a 3-point scale)
[47]		Uncomfortably Cool, Comfortable, Uncomfortably Warm, as a Thermal Profile (from a 100-point scale converted in a 3-point scale)
[59]		Very Cold, Cold, Chilly, Comfortable, Warm, Hot, Very Hot
[58]		Very Cold, Cold, Cool, Neutral, Warm, Hot, Very Hot
[63]		Very Cold, Cold, Cool, Slightly Cool, Neutral, Slightly Warm, Warm, Hot, Very Hot
[15]		Very Cold, Cold, Neutral, Warm, Very Warm, as a Thermal Profile

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Table 4 (*continued*)

Ref.	Output	Scale
[16]		Very Cold, Cold, Neutral, Warm, Very Warm, as a Thermal Profile (from a 7-point scale converted into a 5-point scale)
[40]	Thermal sensation	Cold, Comfortable, Hot
	Thermal satisfaction	Satisfied, Dissatisfied
[21]		Cold, Comfortable, Hot
		Satisfied, Dissatisfied

participants' feedback, standing as the "ground truth" of personal comfort models. According to the aforementioned authors, PCS could learn occupants' thermal preferences based on their control behavior and automatically activate heating or cooling according to the patterns recognized. Hence, user behavior could serve as a proxy for thermal comfort feedback so that long monitoring periods or experiments would not be necessary, data could be collected continuously in a practical way, and nuances in scale interpretations could potentially be avoided.

3.5. *Modeling algorithm used*

Overall, there seems to be a predominance of probabilistic modeling techniques among the studies selected. Unlike deterministic models, which give a single exact outcome for a prediction, probabilistic models provide a solution as a probability distribution to account for randomness and quantify uncertainty in the events analyzed [73,74]. Probabilistic methods are especially relevant when analyzing systems that are inherently stochastic and/or highly uncertain due to insufficient data [75]. This, therefore, is in line with the nature of thermal comfort modeling in general, as thermal comfort perception and variables (e.g., people's behavior) are naturally uncertain, and data, especially when developing comfort models at the individual level, can be relatively scarce.

As seen in Table 5, it is possible to identify a frequent use of (1) Bayesian classification and inference [38,42,44,47,52], (2) Fuzzy Classification (using the Wang-Wendel model to create Thermal Profiles) [15,16,39,60], and (3) common Machine Learning techniques, including Classification Trees [18,19,40,56], Gaussian Process Classification [18,19,33,34], Gradient Boosting Method [19,51,56], Support Vector Machine [18,19,40,41,46,48,51,56,58], Random Forest [14,19,21,40,41,45,48,51,54,56,58], K-Nearest Neighbors [19,21,40,41,51] and Artificial Neural Networks [49,56,57,61]. In fact, many of the studies tested and compared combinations of these techniques. Liu et al. (2019) [56], for instance, applied 14 commonly used machine learning classification algorithms, divided into 4 groups: linear methods, non-linear methods, trees and rules, and ensembles of trees. According to the authors, the selections of these algorithms balanced the prediction biases and avoided the over or underestimations that could result from specific prediction systems. From the four algorithm categories used, the ensembles of Trees (e.g., Gradient Boosting, C5.0 and Random Forest) presented the best performance for the personal comfort models developed.

Table 5
Modeling technique of papers selected.

Ref.	FC	RF	KNN	SVM	DT	LDA	BI	MLR	GPM	LR	ANN	GB	LVQ	OP	LinR	NB	RBC	CART	LLS	J48	C5.0
[39]	X																				
[40]		X	X	X	X																
[41]		X	X	X		X															
[21]		X	X																		
[42]							X														
[43]								X													
[34]									X												
[44]							X														
[33]									X												
[45]		X																			
[16]	X																				
[15]	X																				
[46]				X																	
[47]							X														
[48]		X		X						X											
[18]				X	X				X												
[19]		X		X					X	X		X						X			
[49]											X										
[50]										X											
[51]		X	X	X								X	X								
[38]							X														
[52]							X														
[53]							X							X							
[14]		X																			
[54]		X																			
[55]										X											
[56]		X	X	X	X	X				X	X	X				X	X	X		X	X
[57]											X										
[58]		X		X																	
[59]															X						
[60]	X																				
[61]											X										
[62]						X															
[63]															X						
[64]								X													
[65]																			X		
[66]																			X		

* FC = Fuzzy Classification, RF = Random Forest, KNN = K-Nearest Neighbors, SVM = Support Vector Machine, DT = Decision Tree, LDA = Linear Discriminant Analysis, BI = Bayesian Inference/Classification, MLR = Multinomial Logistic Regression, GPM = Gaussian Process Model, LR = Logistic Regression, ANN = Artificial Neural Network, GB = Gradient Boosting, LVQ = Learning vector quantization, OP = Ordered Probit, LinR = Linear Regression, NB = Naive Bayes, RBC = Rule-Based Classifier, CART = Classification and Regression Trees, LLS = Least-squares linear estimation, J48 = J48 Decision Tree.

3.6. Performance indicators used

The performance of the personal comfort models analyzed is measured by a variety of indicators. When reported, the choice of metrics in these studies depended, for instance, on the model technique applied, the nature of the datasets used (e.g., unbalanced or balanced) or the need for easy comparison between or across studies or models. Table 2 presents the studies' performance indicators and respective predictive performances.

Accuracy was one of the main performance meters used [14,18,21,40,41,44,46,48,51,54–56,61,62]. It represents the number of correct predictions (i.e., when the computed result is equal to the ground-truth from participants' feedback) divided by the total number of predictions and is normally presented in percentage form. It was used in nearly half of the studies and sometimes accompanied by other less common metrics such as Cohen's Kappa Coefficient and/or RMSE (Root Mean Square Error). Accuracy, as described by Ben-David (2008) [37], is a simple and straightforward indicator; however, it does not take into account the proportion of the correct predictions that result from random chance. When considering datasets in which thermal comfort categories are not evenly distributed, accuracy can be extremely misleading. Cohen's Kappa Coefficient complements the measurement of accuracy as its scalar meter compensated for the agreements that can be attributed to chance. It is normally represented on a 0 to 1 scale, with 1 being perfect agreement. The selected studies by Lee and Ham (2020) [51] and Liu et al. (2019) [56] acknowledge this metric.

Measuring error – the difference between the computed and the correct value – was also common among the studies, using diverse approaches [16,33,34,42,49,50,53,59,61,63,65]. The Root Mean Square Error, or the standard deviation of the prediction errors, was reported in many of the studies selected. Although it contains certain limitations, it is a common error measurement in many fields and recommended when the model errors follow a normal distribution [76]. Nevertheless, as stated by Chai and Draxler (2014) [76], as with accuracy, caution is always required when interpreting error measurements, as "any single metric provides only one projection of the model errors, and therefore only emphasizes a certain aspect of the error characteristics".

Although less used among the studies analyzed, the Area Under the Receiver Operating Characteristic Curve, or the Area Under the Curve (AUC), is frequently used in machine learning studies [37] and can be an interesting performance indicator for the personal comfort models. It was used by Katić et al. (2020) [18], Kim, et al. (2018) [19], Lee, et al. (2019) [52] and Liu et al. (2019) [56]. The Receiver Operating Characteristic Curve provides a way of describing the predictive behavior of a binary classifier, by plotting the probability of true positive rate (i.e., "successes", also called sensitivity or recall) over false positive rate (i.e., "false alarms", also called fall-out) across all possible discrimination thresholds. By computing the area under this curve, it is possible to compare different models using a single performance indicator. The AUC can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement. The measure is, however, conceptually not intuitive, especially when analyzing non-binary classification problems [37].

Regardless of the indicator used, k-fold cross-validation was reported in most studies as the resampling technique used to estimate models' performance on unseen data, either during hyperparameter tuning (also known as model selection stage) or at the final model evaluation stage [77]. The most used values of k were 5 and 10, as seen in Table 2. Training, validation and testing dataset splits were normally chosen according to overall dataset size and modeling technique used.

3.7. Model final application

Automation and optimization of HVAC systems can be considered the main application for the personal comfort models in the papers selected. As already indicated by Jung and Jazizadeh (2019) [78], the research effort to explore the potential of personalization techniques in the control of HVAC systems has significantly increased, shifting the field towards Human-In-The-Loop (HITL) control strategies. By incorporating individual thermal comfort models in the system optimization, these studies investigate comfort-aware operation schedules and settings to enable higher energy efficiency in buildings.

Nevertheless, from the studies analyzed, most did not test the personal comfort models' application in HVAC systems, focusing more on the modeling aspect of the process. From the studies that evaluated the models' application, only a few evaluated tests in real environments – treated as experiments or during normal daily activities.

Zhao et al. (2014) [66] performed a validation experiment with 11 participants in two test-beds, where the model learning procedure was incorporated into the control of an air conditioning system. In their test, the system sequentially updated the user's complaint region after every feedback, using the method proposed, and updated the set-point of the control target. They applied a post-experiment questionnaire for each participant to capture their subjective evaluation of the thermal environment of the test-bed. After 8 days of continuous experiments, the participants' evaluation scores tended to achieve a higher and steadier level and their number of complaints per day decreased from 3 to less than 1, on average.

Aguilera et al. (2019) [39] incorporated the personalized models of seven participants into a user-driven HVAC control system and tested it in a real open-plan office scenario. Thermal preferences were used to create individual thermal discomfort profiles, which were later aggregated to calculate a single set point for the entire office. The results showed that only 29% of the occupants' thermal comfort improved. The performance of the control strategy was found to be influenced by insufficient and imbalanced data and the effect of thermal expectations on occupants' thermal responses across different times of day and after repeated thermal stimuli.

Li et al. (2017) [14] used two real-life scenarios to demonstrate their framework to improve thermal comfort in single and multi-occupancy spaces. Their HVAC control loop included two algorithms: the Mode Selection Algorithm that chose the optimum conditioning mode and the Collective Decision Algorithm that evaluated the highest group comfort score that can be achieved in the mechanical conditioning mode. Participants' thermal preferences were continuously predicted to determine the optimum HVAC set point temperatures, adjusted by a programmable Wi-Fi enabled thermostat. They then compared a scheduled scenario where the thermostat followed a predefined fixed schedule, and a dynamic scenario where their personalized algorithm was implemented to adjust the temperature set points dynamically. On average, the total number of uncomfortable reports were reduced by as much as 53.7% on average after implementing their framework.

Jazizadeh et al. (2014) [15] conducted a study in a real building setting using the comfort profiles of six participants. After the personalized comfort profiles were obtained, each new request from occupants triggered the calculation of the desired temperature using the customized scale of each user's comfort profile, which was then passed to the HVAC controller. Using interviews at different stages of the experiments, the researchers assessed the comfort consequences of the framework and found that the average of participants' comfort rating was 4.7 out of 10 before enabling the framework; 6 during training; and 8.4 after model training. Additionally, the study showed an overall 39% reduction in daily average airflow when the desired temperatures were applied by the HVAC system, compared to the legacy HVAC system operations with predefined temperature set points. As airflow can be considered proportional to HVAC systems' energy consumption, the study also indicated an improvement in the energy efficiency of the building analyzed.

4. Discussion and future research directions

This systematic literature review has shown a plurality of approaches and frameworks to develop and evaluate personal thermal comfort models. Although some aspects can be considered similar in all studies, there seems to be an overall lack of a unified modeling approach that takes into account not only the methodology used, but also the performance evaluation tool that enables easy comparison across studies.

4.1. Considerations on data collection

Disparities begin from the data collection stages of the studies. While controlled climate chamber experiments allowed many of the studies to reach a larger size of datasets and a greater variability of thermal sensations recorded from participants, studies that used data from real scenarios appear more transferable to real applications, as discussed in Section 3.7. The recommendation for data collection on real scenarios, thus, lies on increasing the dataset size by encouraging more occupants to engage and interact with the surveys and the systems' controls. Studies that used wearable sensors with accessible feedback platforms, or that used occupants' behavior through personal comfort systems' operation as a proxy for thermal preference, are possible options to obtain a continuous data stream to enlarge datasets in real-world contexts.

In that regard, although larger dataset sizes are normally expected when dealing with more complex classification tasks and higher number of features [79], the review also proves that individual dataset sizes can vary greatly. When machine learning models are used with insufficient training data, techniques such as transfer learning, where a pre-trained model is reused on a new problem, can be applied [80]. In addition, although not treated in depth by all studies reviewed, the way the data is pre-processed is another key aspect to avoid data loss before model training. Properly dealing with noisy or missing data points, highly heterogeneous datasets in terms of granularity of raw features, or highly imbalanced datasets that might misrepresent the observed data is essential to maintain sufficient data size and avoid losing relevant information for prediction. Future research on personal thermal comfort models should, therefore, address the specificities of thermal comfort datasets and the challenges of data preparation associated with them.

4.2. Considerations on participants involved

Despite the low number of participants in most of the studies reviewed being coherent with the aim of personalizing comfort models for each individual, the generalization of the results, that is, the potential that personal comfort models will be applicable to anyone, is still debatable. This is because not only do the studies deal with small numbers of building occupants, but they also select participants with relatively similar characteristics. Although males and females are present in almost all studies in a relatively balanced way, the presence of younger adults is more prevalent, leaving out other age groups (e.g., children or older people) who may also profit from individualized comfort predictions in their associated environments. In the same way, although the use of healthy adults is commonly preferred in traditional generalized thermal comfort studies to avoid the influence of illness or health conditions on the averaged thermal predictions, the observed trend to use only healthy participants in personal comfort model studies does not correspond to the goal of individualizing comfort models, which is to deal with people whose personal characteristics and thermal preferences fall outside the averages. In fact, continuous health status measurements or self-rated feedback could be added as personal inputs in the models, allowing an interesting investigation on the impacts of health on thermal comfort perception, sensitivity, or preference.

Likewise, collected data on diverse body compositions, sociodemographic characteristics and activity contexts are missing in the studies reviewed. Including more heterogeneous occupants would enable a broader analysis and consequently increase the generalization power of the studies.

4.3. Considerations on climates, seasons and type of buildings involved

Further explorations in more diverse climates are necessary to identify associated challenges of personal comfort models in different locations. Longitudinal studies that span through several consecutive seasons or years could, in the same way, allow a more comprehensive analysis than the ones conducted so far. In addition, residential settings are yet to be better represented in the studies. Not only do living environments provide more diverse thermal conditions, activity and clothing opportunities in comparison with office environments, they also allow more possibilities for user intervention than the HVAC-controlled work environments. This includes considering easier or unrestrained window or blinds operations as well as refurbishment or layout modifications. Although this issue may add another level of complexity to the personalized models, adding diversity to the studies' environments can help, once again, create more balanced thermal preference datasets when collecting data, and expand the application of the personalized models to other settings.

4.4. Considerations on model input and output variables

When it comes to model input features used in the reviewed studies, the explorations are again coherent with the aim of investigating possible individual differences affecting thermal comfort. Both environmental and personal characteristics are used, although personal features using physiological sensing could still be explored further, especially in light of the rapid advances seen today in wearable sensors technologies. Personal comfort systems, including heated chairs or personal fans, are promising tools not only to collect larger datasets but also to reduce the need for occupants' long-term feedback. Personal comfort systems could also help avoid the potential misinterpretations caused by the nuances in the thermal comfort, sensation or preference scales used, which vary greatly across studies and approaches.

4.5. Considerations on modeling algorithm and performance indicators

When analyzing the modeling methodology applied so far, it is evident that the field lacks a more unified and systematic framework. As already highlighted by Kim et al. (2018) [10] and confirmed by this literature review, instead of developing a structured and ultimately transferable approach to apply the models in real scenarios, the main studies on personal thermal comfort models are focused on the final predictive accuracy of specific modeling techniques. This is clear in the plurality of modeling techniques and performance evaluators used in the publications reviewed. Model evaluation, especially, needs uniformity to allow a clear comparison between studies and approaches, and consequently to enable a more straightforward decision-making process. Kim et al. (2018) [10] highlighted three main criteria that could help the model evaluation process: prediction accuracy, prediction consistency, and model convergence. Although the metrics used in each of these criteria may differ depending on the technique used (e.g., deterministic or probabilistic), they represent a more systematic way of assessing model performance.

4.6. Considerations on model interpretation, input parsimony and redundancy

With the majority of the studies using different forms of machine learning techniques, it becomes important to highlight the presence of "black box" models among them and acknowledge their challenges. The term black box refers to models that, although open to inspection of isolated components, are less interpretable, in the sense that their complexity and sometimes recursive mathematical nature are not easily comprehensible by humans [81]. Generally, the main objective of predictive modeling is to generate accurate predictions, leaving interpretation of the models and understanding of why they work as secondary objectives [31]. When prediction accuracy is the primary goal, increasing performance is normally derived from increasing models' complexity, and likely decreasing their parsimony (i.e., increasing number of parameters involved), which, in turn, renders models' interpretation more difficult. This trade-off between accuracy/performance and interpretability/parsimony is a common issue discussed in many fields using predictive modeling.

Less interpretable models can have negative implications, especially in situations where feature interactions matter more than the final outcomes. In the field of thermal comfort in general, being able to understand the underpinning laws between variables as well as distinguish between relevant, irrelevant, and redundant input parameters is undeniably beneficial to enhance the current knowledge on human thermal comfort. Nevertheless, the tradeoff between the cost of comfort and energy use associated with thermal comfort model's lower predictive accuracy and the reward of interpretability has not been addressed in the field, let alone in the studies reviewed here.

Nonetheless, although still frequently debated [81–84], explainable artificial intelligence is an emerging topic in many sectors [84] and aims to produce more interpretable models while maintaining high performance levels. Techniques such as the use of Input Feature Selection Algorithms are also alternatives to measure predictor importance in thermal comfort research, decreasing input redundancy, increasing performance and lowering computational efforts [85]. Lastly, some machine learning models are intrinsically resistant to redundant predictors, such as Tree- and rule-based models [31], comprising a middle ground between easily interpretable models (like linear regression) and opaque methods (such as neural networks).

5. Conclusion

This paper has presented a systematic review of personal thermal comfort models based on the literature published in the last two decades. Thirty-seven publications have been selected for screening and subsequently analyzed regarding: (1) their data collection approach and dataset size; (2) the number and type of participants involved; (3) the climate, seasons and building types in which the studies were undertaken; (4) the model inputs and outputs features utilized; (5) the modeling techniques used; (6) the performance indicators used; and, finally, (7) the application of the proposed model.

The review highlights a number of issues of personal comfort models:

- The field still lacks a more unified and systematic modeling framework. Model evaluation, especially, needs to allow for clear comparison between studies and approaches, thus enabling a more straightforward decision-making process.
- The generalization of the results is still debatable as many studies deal with small numbers of participants sharing relatively similar characteristics. Diversity needs to be introduced, considering different age groups, health status, body compositions, sociodemographic characteristics, and activity contexts.
- Diversity in climates, seasons and building types is not represented in many of the studies. Addressing these can help create more balanced datasets and expand the application of the personalized models into other types of environments.
- With the majority of the studies analyzed using different forms of machine learning techniques, it is important to understand "black box" models' challenges in the field of thermal comfort, investigating the tradeoffs between inherently interpretable models and less transparent techniques.
- Although both environmental and personal characteristics have been used in most studies, personal features gathered through physiological sensing technologies could be further explored, especially in light of the rapid advances in wearable sensor technologies. Personal comfort systems are promising tools to complement data collection, enlarge data sizes and reduce the need for occupants' long-term feedback periods.

Future research can, therefore, profit from the topics highlighted above and advance the knowledge on personal thermal comfort models from a uniform and holistic perspective.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Personal thermal comfort models: a deep learning approach for predicting older people's thermal preference

Larissa Arakawa Martins, Veronica Soebarto and Terence Williamson
School of Architecture and Built Environment, The University of Adelaide, Adelaide, Australia, and
Dino Pisaniello
School of Public Health, The University of Adelaide, Adelaide, Australia

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Abstract

Purpose – This paper presents the development of personal thermal comfort models for older adults and assesses the models' performance compared to aggregate approaches. This is necessary as individual thermal preferences can vary widely between older adults, and the use of aggregate thermal comfort models can result in thermal dissatisfaction for a significant number of older occupants. Personalised thermal comfort models hold the promise of a more targeted and accurate approach.

Design/methodology/approach – Twenty-eight personal comfort models have been developed, using deep learning and environmental and personal parameters. The data were collected through a nine-month monitoring study of people aged 65 and over in South Australia, who lived independently. Modelling comprised dataset balancing and normalisation, followed by model tuning to test and select the best hyperparameters' sets. Finally, models were evaluated with an unseen dataset. Accuracy, Cohen's Kappa Coefficient and Area Under the Receiver Operating Characteristic Curve (AUC) were used to measure models' performance.

Findings – On average, the individualised models present an accuracy of 74%, a Cohen's Kappa Coefficient of 0.61 and an AUC of 0.83, representing a significant improvement in predictive performance when compared to similar studies and the "Converted" Predicted Mean Vote (PMVc) model.

Originality/value – While current literature on personal comfort models have focussed solely on younger adults and offices, this study explored a methodology for older people and their dwellings. Additionally, it introduced health perception as a predictor of thermal preference – a variable often overseen by architectural sciences and building engineering. The study also provided insights on the use of deep learning for future studies.

Keywords Personal comfort models, Machine learning, Thermal comfort, Older people, Health, Personalised comfort

Paper type Research paper

1. Introduction

International standards, such as ANSI/ASHRAE Standard 55 (ANSI/ASHRAE, 2020), adopt the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) model (Fanger, 1970) and the adaptive model (de Dear and Brager, 1998; Humphreys *et al.*, 2016) as the bases to stablish the thermal requirements for human occupancy in the built environment.

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Both PMV/PPD and the adaptive models are aggregate models, which means they are designed to predict the average thermal comfort of groups of people. These models however have limitations when used to predict occupant's comfort in real case scenarios, as individual thermal sensations and preferences can vary significantly (Wang *et al.*, 2018; Schweiker *et al.*, 2018; Shipworth *et al.*, 2016). Furthermore, these models' inability to be calibrated with new feedback or to incorporate new input variables (e.g. age, health status, body mass index) other than their pre-defined factors (Kim *et al.*, 2018a) prevent them to be updated for different individuals. In addition, the models used in standards have been developed based on data from either climate chambers (Fanger, 1970) or field studies in office buildings (de Dear and Brager, 1998; Humphreys *et al.*, 2016). This can also be limiting when considering the diversity of thermal conditions and adaptive opportunities residential settings generally provide in comparison to controlled office environments (Karjalainen, 2009).

To address these limitations, recent studies have shown an increasing number of strategies to develop personal thermal comfort models as an alternative to the conventional approaches (Kim *et al.*, 2018a). Instead of an average response from a large population, personalised models are designed to predict individuals' thermal comfort responses, using a single person's direct feedback and/or personal characteristics as calibration inputs. This represents a relevant paradigm shift in the field today, replacing the centralised and fixed-set-points approach with occupant-centric thermal conditioning management in the built environment (Wang *et al.*, 2018). In addition, with the rapid development of Internet of Things (IoT) and smart sensors, predicting individual's needs directly from data collected in their everyday environment and acting upon these predictions has become substantially easier.

Significant advances have been made in the last decades in the personalised models' field, comprehending a plurality of approaches. A systematic literature review, conducted by the present authors, analysed 37 recent publications on personal thermal comfort models, emphasising current trends and future research directions in the field (Arakawa Martins *et al.*, 2022). The use of personal comfort systems (PCS), such as heated and cooled chairs or personal fans (Katić *et al.*, 2020; Kim *et al.*, 2018b; André *et al.*, 2020), for instance, has been highlighted as a promising option for individual data collection, leveraging integrated data acquisition techniques that can potentially replace occupant survey feedback as proxy for thermal comfort. In addition, there is an increasing body of research focusing on personal comfort models driven by physiological variables, such as skin temperature or heart rate (Jung *et al.*, 2019; Lee and Ham, 2020; Shan *et al.*, 2020; Natarajan and Laftchiev, 2019).

The review (Arakawa Martins *et al.*, 2022) pointed to a vast variety of modelling approaches explored in the field, such as Bayesian classification and inference (Jung and Jazizadeh, 2019; Auffenberg *et al.*, 2018; Lee *et al.*, 2019), Fuzzy Classification using the Wang-Wendel model (Pazhoohesh and Zhang, 2018; Aguilera *et al.*, 2019; Jazizadeh *et al.*, 2014b), and Machine Learning techniques. The latter includes more interpretable approaches such as Classification Trees (Aryal and Becerik-Gerber, 2020), or less transparent but relatively more accurate techniques such as Gaussian Process Classification (Guenther and Sawodny, 2019; Fay *et al.*, 2017), Gradient Boosting Method (Lee and Ham, 2020), Support Vector Machine (Aryal and Becerik-Gerber, 2019; Jung *et al.*, 2019; Jiang and Yao, 2016; Lu *et al.*, 2019), Random Forest (Jayathissa *et al.*, 2020; Aryal *et al.*, 2021; Lu *et al.*, 2019), K-Nearest Neighbours (Aryal and Becerik-Gerber, 2019; Aryal *et al.*, 2021) and Artificial Neural Networks (Kim, 2018; Shan *et al.*, 2020). Artificial Neural Networks (ANNs), specifically, have shown promising results. Kim (2018) reported an average MSE (Mean Squared Error) of 0.00298 across 24 personal models' predictions, using ANN trained with environmental variables from an office setting. Similarly, Shan *et al.* (2020), on a study involving three people in offices, reported an average accuracy of 89.2%, an average MAE (Mean Absolute Error) of 0.16 and an average MSE of 0.06 across participants' ANNs trained using skin temperature measurements.

Nevertheless, although representing an important paradigm shift, studies on personal comfort models maintained the traditional trend to focus on office environments and younger adults. Studies on personal comfort models for older adults and dwellings are still absent in current literature (Arakawa Martins *et al.*, 2022). In addition, people with acute or chronic diseases or people with disabilities are not included in recent studies. These gaps in knowledge are especially relevant because, despite intragroup diversity being present in both younger and older cohorts, this heterogeneity tends to be greater in older than in younger ages. Older adults have been submitted to a greater range of cumulative social, economic and environmental factors across their individual life courses, which affect their health, needs and perceptions in significantly different ways (World Health Organization, 2015). For this reason, understanding diversity in older age becomes crucial to target specific requirements more efficiently and support healthier and independent ageing.

In addition, previous studies have emphasised the importance of smart technologies to help older people live independently (Kimberly Miller, 2013; van Hoof *et al.*, 2017). In this context, personal thermal comfort models have the potential to be applied in automation systems for the control of windows, blinds, or air-conditioning, allowing older people to manage their environments with less reliance on others.

Hence, this paper explores the development of personal comfort models, using real feedback as well as environmental and personal characteristics as input variables, to accurately respond to older adults' thermal needs in their own homes. In addition, this study aims to evaluate the modelling methodology proposed using deep learning as the engine behind the prediction of individual people's thermal preferences.

Focusing on South Australia, one of the Australian states with the largest proportion of people aged 65 years and over (Australian Bureau of Statistics, 2021), data were first collected through environmental monitoring and thermal comfort surveys in dwellings of older people, excluding those who live in residential aged care facilities. Individual datasets were balanced and normalised and models were subsequently tuned by testing different hyperparameters combinations, which were subsequently selected according to their predictive performance. The models were then evaluated using an unseen testing dataset and compared with a "converted" PMV model on the same testing datasets. Finally, recommendations for the application of the models in HVAC (Heating, Ventilation and Air Conditioning) systems' control, as well as in diagnostic tools for design and retrofitting and in a broader public health context were discussed.

2. Data collection

The sample for this study derived from a research project that monitored 71 participants (23 males and 48 females) aged 65 years and over from 57 households located in South Australia, in three climate zones: hot dry (*BSk*), warm temperate (*Csa*) and cool temperate (*Csb*), according to the *Köppen–Geiger Climate Classification System* (Beck *et al.*, 2018). All older adults who participated in the first two stages of the research project (van Hoof *et al.*, 2019; Soebarto *et al.*, 2019) were invited to participate voluntarily in the house monitoring stage and further volunteer recruitment was done through press releases in various media formats (e.g. radio and newspaper calls for volunteers). The inclusion criteria were participants who: (1) were 65 years old or over; (2) lived independently in the State of South Australia; and (3) were able to communicate in English. Data were collected during a period of 9 months, from mid-January to mid-October in 2019.

Each dwelling was visited at least twice. During the first visit, a questionnaire about sociodemographic information, health and overall thermal preferences was applied and an open-ended interview was conducted about buildings' details. In addition, indoor environment data loggers were installed in each dwelling's main living room and main bedroom. The indoor environment data logger contained sensors that measured air temperature, globe temperature, air speed, and relative humidity. The data logger coordinated measurements from the sensors, undertaken at 30-min intervals and when a participant completed a comfort survey.

A thermal comfort survey tablet was also installed to be used by the participants to answer a survey about their thermal environment and their preferences and sensations at least once a week, throughout the 9-month period. The thermal comfort survey tablet allowed participants to complete surveys electronically about their clothing, activity levels, window and door state, heating, cooling, and fan state, as well as their thermal sensation (TSV) and thermal preference (TPV). Thermal sensation was assessed using the question "How do you feel right now?" with possible responses being "Cold", "Cool", "Slightly cool", "Neutral", "Slightly warm", "Warm" or "Hot". Thermal preference was assessed using the question "Would you prefer to be . . . " with possible responses being "Cooler", "No change" or "Warmer". The survey also included a question about their self-reported health and wellbeing perception at that point in time: "How would you describe your health and wellbeing at the moment?", with possible answers being "Very good", "Good", "Reasonable", "Poor" and "Very poor". Participants were asked to answer the survey whenever possible, but no less than 2 times a week.

Figure 1 shows the data loggers and user interface used. More details on the data acquisition tool, including its applicability for studies with older users, have been reported by Soebarto *et al.* (2020).

During the second visit to each dwelling, conducted at the end of the monitoring period, an additional questionnaire was used to collect further information about the participants, including their frailty status according to the Modified Reported Edmonton Scale (Rose *et al.*, 2018). Each participant's body composition was also assessed to measure height, weight and body mass index (BMI), using a Tanita Inner Scan RD-953 scale (Tanita Corporation, 2016).

Figure 1.
Indoor environmental data logger and thermal comfort survey tablet

3. Modelling methodology

3.1 Learning technique and task

This study applies artificial neural networks, also known as deep learning (Goodfellow *et al.*, 2016), to develop personalised comfort models for a subset of the participants of the monitoring study. Deep learning is a class of machine learning technology, based on the representation-learning method (LeCun *et al.*, 2015). It solves tasks such as classification, regression, and anomaly detection, by introducing multiple layers of representations, or features, expressed in terms of other simpler representations. By learning from previously seen data, this method avoids the need of a human engineer to formally specify these multiple layers of representations (Goodfellow *et al.*, 2016).

The models' task is to specify to which of the *k* categories an example (or data point) belongs. In general terms, the model is shown an example and follows a set of mathematical expressions to produce an output in the form of a score (or probability) for each category. A function then measures the error between the outputs and the desired patterns of scores and the model modifies its internal parameters (or weights) to reduce the error. The model is then shown a never-before-seen set of data points and produces a new and final set of probability outputs.

In this study, the models were developed to perform a multiclass classification task of occupants' thermal preference (TPV) on a 3-point-scale (preferring to be cooler, preferring no change or preferring to be warmer), and according to seven environmental and personal input features. The survey's thermal TPV was used as the ground truth to train the models and later verify the predicted values. Instead of the thermal sensation vote (TSV) scale – which is commonly used in thermal comfort studies – the TPV was used because it not only represents a measure of what ideal conditions would be for each person, but also suggests to which direction the change is desired, as already confirmed by Kim *et al.* (2018b). This is particularly relevant when considering the use of these models for the control of HVAC systems. In addition, using TPV rather than TSV avoids the assumption of associating comfort with neutral thermal sensation, which may not always be true (Humphreys and Hancock, 2007).

In this study, following common practices in computer sciences' studies (Kuhn and Johnson, 2013; Goodfellow *et al.*, 2016; LeCun *et al.*, 2015; Huang *et al.*, 2019), the input variables are called "features" and the thermal preferences classes corresponding to each of these combinations of input variables are called "labels". Anaconda version 2019.3 (Anaconda, 2019) was used as the platform to run all models using Python version 3.7 and PyTorch tensor library (Paszke *et al.*, 2017).

3.2 Input features selected

Both environmental and personal variables were used as input features for the personalised models. In total, seven input variables were used, 4 of which representing the environmental conditions of participant's rooms (i.e. dry bulb temperature, mean radiant temperature, relative humidity, and air speed) and 3 of which representing participant's personal characteristics (i.e. corrected metabolic rate, clothing level and health perception).

The corrected metabolic rate variable was calculated from participant's activity level answers in the survey. These were first converted to MET values according to the Compendium of Physical Activities (Ainsworth *et al.*, 2011), and then later corrected based on participants' sex, height, weight and age, according to Byrne *et al.* (2005) and Kozey *et al.* (2010) studies. Table 1 shows the activity level scale points and corresponding MET values.

These seven variables were selected to cover a wide range of variables and factors known in the architectural science, medicine, and public health fields of study to influence thermal comfort, sensation, and preference. Each input feature's data collection tool and unit or scale is shown in Table 1.

Type	Input features	Data collection tool	Unit or scale
Environmental	Dry bulb temperature	Thermometer in data logger	℃
Environmental	Mean radiant temperature	Calculated from the dry bulb temperature, globe temperature and air speed measurements according to ISO:7726:1998 (ISO, 1998)	℃
Environmental	Relative humidity	Hygrometer in data logger	%
Environmental	Air speed	Air speed sensor in data logger	m/s
Personal	Corrected metabolic rate	Survey in thermal comfort tablet – "describe your activity in the last 15 min in this space."	Very relaxed activity = 1 MET Relaxed activity = 1.3 MET Light activity = 1.5 MET Moderate activity = 2.5 MET Active activity = 3.3 MET
Personal	Clothing	Survey in thermal comfort tablet – "how are you currently dressed?"	Very light = 1 Light = 2 Moderate = 3 Heavy = 4 Very heavy = 5
Personal	Health perception	Survey in thermal comfort tablet – "how would you describe your health and wellbeing at the moment?"	Very good = 1 Good = 2 Reasonable = 3 Poor = 4 Very poor = 5

Table 1.
Input features and units or scales

A second round of models was also developed with the same datasets and variables, except for health perception, to check the relevance of health as a predictor of thermal comfort for each individual participant. Independent-measures *t*-test was used to evaluate if there is a significant difference between the results with and without health perception as an input variable.

It is important to note that personal characteristics such as height, weight, or health, although present in thermoregulation and physiology studies, are often overseen by architectural sciences and building systems engineering studies, hence the significance of their inclusion in the study.

3.3 Participant selection and characteristics

At the end the monitoring period, 10,787 survey votes were recorded from all 71 participants. Nonetheless, the classification task required that each participant voted at least 6 times in at least one of the three thermal preference classes, to allow a minimum of 5-fold cross-validation during model training, plus a minimum of 1 vote per category for testing. The cross-validation procedure is detailed in Section 3.5. Excluding the participants who did not meet this requirement resulted in 28 individual datasets selected for modelling.

It is important to highlight the level of diversity among participants selected, comprehending different older-age groups, weights, heights, health and frailty status, and climate zones of the dwelling locations, all of which can provide relevant insights on the influence of personal parameters in thermal response. Table 2 presents each of the selected participants' personal characteristics.

It should also be noted that the dwellings in this study represent a wide range of different construction typologies common in housing of older people in South Australia. These include double brick, brick veneer (also known as masonry veneer) or timber framed constructions (insulated and uninsulated); detached and semidetached layouts; 1 to more than 100 years old; and one or two stories high. Although building construction and design as well as natural ventilation and window orientation can have significant impacts on thermal preference, this correlation was out of the scope of this paper and will be the subject of future publications.

3.4 Dataset balancing and pre-processing

The individual datasets exhibited unequal distributions between thermal preferences classes, as seen in Figure 2. Therefore, the datasets were randomly resampled to obtain classes with the exact same number of data points. This procedure, called undersampling, consisted of sizing all majority classes according to the size of the minority class, by removing examples

ID[1]	Sex	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Frailty score[2]	Climate zone
1	F	71	157.0	78.9	31.9	Not frail	*Csa*
2	M	86	179.5	86.4	26.8	Not frail	*Csa*
3	F	79	156.5	64.6	26.4	Not frail	*Csa*
4	F	81	163.0	58.2	21.9	Apparently vulnerable	*Csa*
5	F	79	161.0	97.6	37.6	Not frail	*Csa*
6	M	76	175.5	88.5	28.7	Not frail	*Csb*
7	F	76	149.5	75.1	33.6	Not frail	*Csb*
8	M	82	174.0	89.9	29.7	Apparently vulnerable	*Csa*
10	F	86	151.0	110.4	48.4	Moderate frailty	*BSk*
13	M	90	173.0	94.5	31.6	Not frail	*Csb*
15	M	68	178.0	80.6	25.4	Not frail	*BSk*
16	F	72	151.5	63.0	27.5	Not frail	*Csb*
19	F	92	153.0	66.0	28.2	Not frail	*Csb*
21	F	78	158.5	78.0	31.1	Not frail	*Csb*
23	F	76	164.5	86.4	31.9	Apparently vulnerable	*Csb*
25	M	88	168.0	83.6	29.6	Not frail	*Csb*
27	F	75–79[3]	[4]	[4]	[4]	Apparently vulnerable	*Csa*
32	F	82	145.0	64.0	30.4	Apparently vulnerable	*BSk*
33	M	80	171.5	109.1	37.1	Not frail	*Csa*
35	M	73	160.0	119.0	46.5	Mild frailty	*Csa*
36	F	74	160.5	95.4	37.0	Apparently vulnerable	*Csa*
38	F	82	166.0	71.9	26.1	Not frail	*Csa*
40	M	86	175.0	85.9	28.0	Not frail	*Csb*
42	F	75	156.5	75.9	31.0	Apparently vulnerable	*Csa*
46	F	66	166.5	117.0	42.2	Not frail	*Csb*
50	F	81	162.0	60.0	22.8	Not frail	*Csb*
51	F	72	150.5	64.6	28.5	Apparently vulnerable	*Csb*
62	F	76	158.0	85.5	34.2	Apparently vulnerable	Csa

Note(s): 1 The IDs used in this paper are the original used for the monitoring of the 71 participants
2 Assessed according to the Modified Reported Edmonton Scale (MRES) (Rose *et al.*, 2018), on the scale "Not frail", "Apparently vulnerable", "Mild frailty", "Moderate frailty", "Severe frailty"
3 Participant answered only her age group
4 Not assessed

Table 2. Selected participants' personal characteristics, organised by ID number

from the dataset that belong to the majority class. Final individual dataset sizes can be seen in Table 3. Classes were also assigned a code from 0 to 2, where 0 corresponded to the "preferring to be cooler" class, 1 the "preferring no change" class and 2 the "preferring to be warmer" class.

Finally, the input variables were normalised to a single range from 0 to 1, using min-max normalisation Equation (1). The minimums and maximums used for normalisation are predefined and the same for all participants, to avoid information from the training sets to be leaked to the testing sets (i.e. data leakage). This created new values for the datapoints but maintained the general distribution and ratios in the original data, avoiding the negative influence of the different scales of each variable in the performance of the models.

$$x' = \frac{(x - \min)}{(\max - \min)} \tag{1}$$

where x' is the normalised variable; min is the predefined minimum for the variable in question; and max is its predefined maximum.

3.5 Hyperparameters, model tuning, model selection and model evaluation

Deep learning algorithms have hyperparameters, which are settings used to control the model's behaviour and capacity. These settings cannot be directly estimated from the data and are not learned by the training process, but rather appropriately chosen by the model's developer while tuning different model options to select the best performing one.

To choose the best set of hyperparameters for a model, the first step was to divide the available dataset into three separate subsets, namely training set, validation set and test set. The training set is the subset of examples used for learning (i.e. fitting the internal coefficients or weights of the classifier). The validation set is the set of examples used to guide the selection of the hyperparameters of a classifier, a process also called model tuning. Lastly, the test set is an independent subset of examples used only to assess the performance of a fully trained

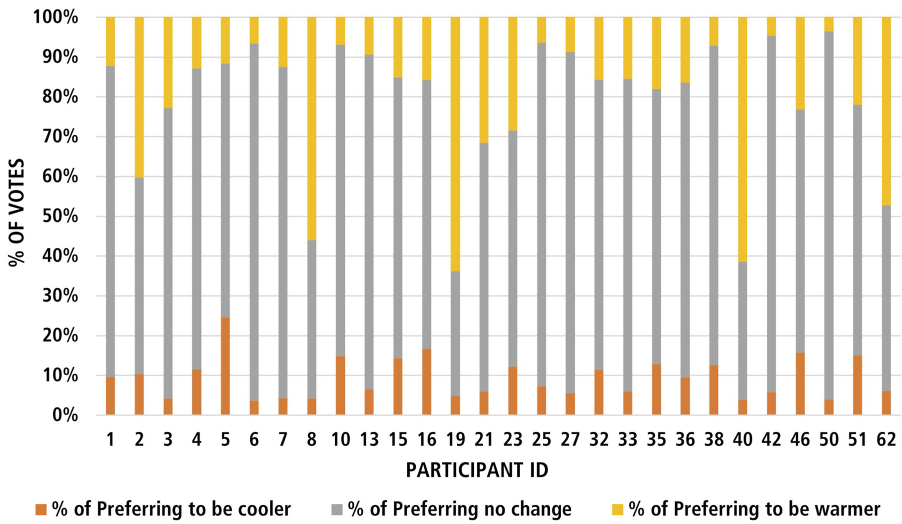

Figure 2.
Percentage of votes in each thermal preference class of each participant's original dataset

Table 3. Performance of personal comfort models (PCM) and Converted Predicted Mean Vote (PMV_C)

ID[1]	Dataset size		PMV_C			PCM without health perception			PCM with health perception		
	Original	Balanced	Accuracy	Cohen's Kappa	AUC	Accuracy	Cohen's Kappa	AUC	Accuracy	Cohen's Kappa	AUC
1	114	30	53.33	0.30	0.65	73.33	0.60	0.89	73.33	0.60	0.94
2	77	24	55.56	0.33	0.67	66.67	0.50	0.73	66.67	0.50	0.84
3	189	24	55.56	0.33	0.67	66.67	0.50	0.83	77.78	0.67	0.89
4	78	27	58.33	0.38	0.69	83.33	0.75	0.82	75.00	0.63	0.86
5	215	75	46.67	0.20	0.60	60.00	0.40	0.64	60.00	0.40	0.67
6	242	27	58.33	0.38	0.69	58.33	0.38	0.76	91.67	0.88	0.92
7	274	30	46.67	0.20	0.60	66.67	0.50	0.91	66.67	0.50	0.83
8	234	30	40.00	0.10	0.55	66.67	0.50	0.78	80.00	0.70	0.91
10	101	21	33.33	0.00	0.50	33.33	0.00	0.50	33.33	0.00	0.50
13	107	21	50.00	0.25	0.63	100.0	1.00	1.00	100.00	1.00	1.00
15	139	60	73.33	0.60	0.80	80.00	0.70	0.94	73.33	0.60	0.97
16	108	51	66.67	0.50	0.75	76.19	0.64	0.85	61.90	0.43	0.81
19	185	27	41.67	0.13	0.56	75.00	0.63	0.90	75.00	0.63	0.80
21	149	27	58.33	0.38	0.69	66.67	0.50	0.66	66.67	0.50	0.80
23	204	75	46.67	0.20	0.60	86.67	0.80	0.91	86.67	0.80	0.91
25	190	30	40.00	0.10	0.55	46.67	0.20	0.65	46.67	0.20	0.51
27	196	30	26.67	−0.10	0.45	46.67	0.20	0.70	46.67	0.20	0.58
32	218	75	46.67	0.20	0.60	100.00	1.00	1.00	100.00	1.00	1.00
33	181	30	46.67	0.20	0.60	73.33	0.60	0.84	73.33	0.60	0.88
35	117	45	46.67	0.20	0.60	86.67	0.80	0.90	86.67	0.80	0.93
36	73	21	50.00	0.25	0.63	100.00	1.00	1.00	100.00	1.00	1.00
38	182	39	66.67	0.50	0.75	66.67	0.50	0.73	66.67	0.50	0.76
40	153	18	66.67	0.50	0.75	100.00	1.00	1.00	100.00	1.00	1.00
42	172	24	11.11	−0.33	0.33	66.67	0.50	0.78	66.67	0.50	0.69
46	285	135	60.00	0.40	0.70	66.67	0.50	0.74	76.67	0.65	0.86
50	174	18	33.33	0.00	0.50	100.00	1.00	1.00	100.00	1.00	1.00
51	146	66	47.62	0.21	0.61	71.43	0.57	0.83	61.90	0.43	0.78
62	163	30	60.00	0.40	0.70	66.67	0.50	0.76	66.67	0.50	0.75
Average			*49.52*	*0.24*	*0.62*	*72.87*	*0.59*	*0.82*	*73.98*	*0.61*	*0.83*

Note(s): 1 The IDs used in this paper are the original used for the monitoring of the 71 participants classifier. The purpose of the test set is to simulate the model with data it has never seen before. This test performance is also called the generalisation performance (Ripley, 1996).

These three subsets of data were split as follows. First, each participants' total datasets were randomly divided in two groups with at least 5 votes in each thermal preference class for training and at least 1 vote for each class for testing. The training set was then divided once again into two subsets to allow 5-fold cross validation, with at least 4 votes per class being used for the training set and at least 1 vote per class for the validation set. 5-fold cross-validation was chosen such that each train/validation group of data samples were large enough to be a representative of the total dataset, while small enough to allow modelling for participants with low vote counts. Cross-validation was repeated 5 times to reduce the noise in the estimated model performance between different cross validations splits. The subsets' splits were done in a stratified way, to maintain the balance of each subset, with the same number of data points for each classification category within the subsets.

Although deep learning algorithms have multiple hyperparameters to be tuned, this study selected 3 known to have a higher effect on the model's behaviour: (1) the learning rate of the optimisation algorithm, (2) the number of hidden neurons in the neural network and (3) the batch size of each iteration. The learning rate was varied from 0.001 to 0.01 to 0.1. The number of hidden neurons in the hidden layer of the model was varied between 4, 5 and 6. Lastly, the batch size varied between 2 and 8 data points. The varying ranges of the hyperparameters tuned were chosen according to common practice in computer science studies (Kuhn and Johnson, 2013; Goodfellow *et al.*, 2016; Huang *et al.*, 2019).

Considering the low complexity of task undertaken by the neural network, the number of the hidden layers in the models was kept to minimal of 1. Therefore, a feedforward neural network was implemented including an input layer, a hidden layer, and an output layer. In order to go from one layer to the sequential one, the neurons compute a weighted sum of their inputs from the previous layer Equations (2) and (4) and pass the result through a non-linear function, called activation function (LeCun *et al.*, 2015). The models in this study used Rectified Linear Unit (ReLU) (Agarap, 2018) as the activation function between the input layer and the hidden layer Equation (3) and Softmax as the activation function between the hidden layer and the output layer Equation (5). The mathematical expressions of the models can be written in the following form:

$$z_j = \sum\nolimits_{i=1}^{7} w_{ij} \cdot x_i + b_j \tag{2}$$

$$y_j = f(z_j) = \max(0, z_j) \tag{3}$$

$$z_k = \sum\nolimits_{i=1}^{N_J} w_{jk} \cdot y_j + b_k \tag{4}$$

$$y_k = f(z_k) = \frac{e^{z_k}}{\sum_{k=1}^{3} e^{z_k}} \tag{5}$$

where x_i are the normalised data of the input variables, w_{ij} are the weights between the input and hidden neurons, b_j are the bias values of the hidden neurons, and y_j the output values of the activation functions (ReLU) in the hidden layer; while w_{jk} are the weights between the hidden and output neurons, b_k are the bias values of the output neurons, N_J is the number of hidden neurons, and y_k are the outputs of the activation functions (Softmax) in the output layer.

Cross Entropy function was used to measure the loss (L_{CE}) – or error – of the classification rounds Equation (6) and Stochastic Gradient Descent was used as the optimiser algorithm that aims to minimise the loss, with a learning momentum at 0.9. More details on the full optimiser algorithm can be found in Goodfellow *et al.* (2016).

$$L_{CE} = \sum_{k=1}^{3} t_k \log y_k \tag{6}$$

where t_k is the ground truth label, and y_k is the probability for the kth class.

Figure 3 represents a simplified diagram of the neural network described.

The following steps, based on the framework detailed by Raschka (2018) and represented in Figure 4, were used for the model tuning, selection and evaluation process of this study.

(1) Step 1: Each participant's total dataset was divided into three subsets, a training set for model fitting, a validation set for model selection, and a test set for model evaluation.

(2) Step 2: (model tuning): The learning algorithm was then used for different hyperparameter settings to fit models to the training dataset.

(3) Step 3: (model selection): These models' performances were evaluated using the validation set. The performance estimates were then compared, and the hyperparameters settings associated with the best model performance were chosen. Each participant's best performing model and hyperparameters can differ between each other, depending on individuals' data sizes, personal patterns, and data quality.

(4) Step 4: To increase the dataset and enhance the models' performance, training and validation sets were then merged into one dataset and the best hyperparameter settings from the previous step were used to fit a new model to this larger dataset.

(5) Step 5: (model evaluation): Finally, the independent test set was used to estimate the generalisation performance of the model resulted from step 4.

(6) Step 6: The final model could then be trained with the use of all the dataset. This final step was not performed in this study because the main objective was to test the model selection and evaluation rather than preparing for model deployment.

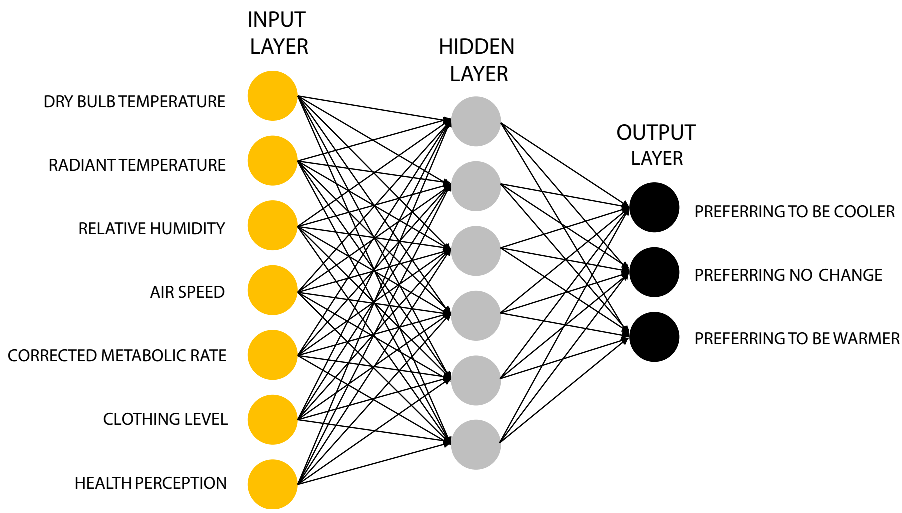

Figure 3. Simplified diagram of the neural network used

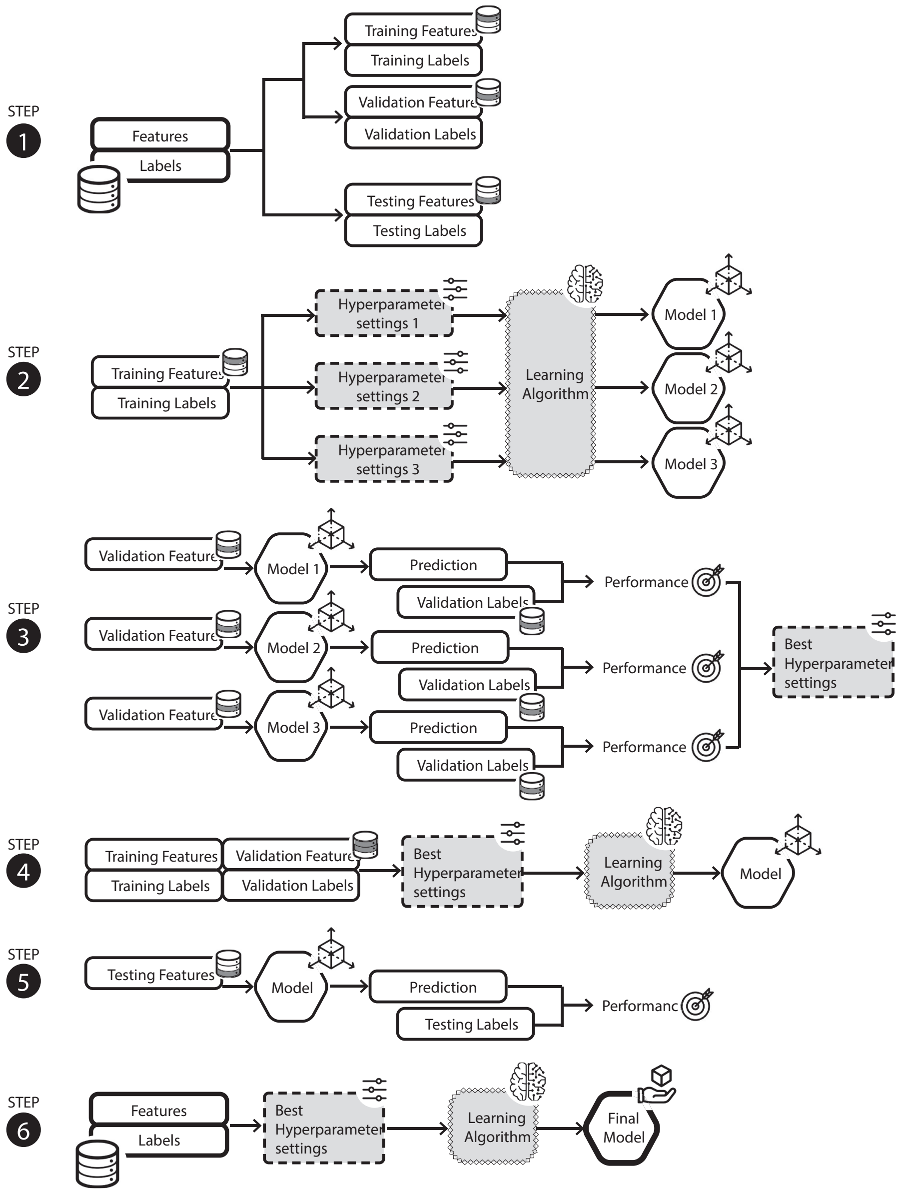

Figure 4.
Model tuning, selection, and evaluation process

3.6 Performance indicators

The performance indicators used in steps 3 and 5 of the modelling methodologies were the Accuracy, the Cohen's Kappa Coefficient, and the Area Under the Receiver Operating Characteristic Curve (AUC).

Accuracy was calculated as the percentage of correct predictions in relation to the total number of predictions. The Cohen's Kappa Coefficient (K) (Cohen, 1960) is a measure of reliability for two classifiers that are rating the same thing, corrected to exclude the frequency in which the classifiers may agree by random chance. It is defined by Equation (7):

$$\boldsymbol{K} = \frac{(p_o - p_e)}{(1 - p_e)} \tag{7}$$

where p_o is the relative agreement among classifiers, which is the same as the accuracy measure, and p_e is the hypothetical probability of a chance agreement.

The Cohen's Kappa Coefficient ranges from negative values to 1, where 1 means perfect agreement, 0 means no agreement among the classifiers other than what would be expected by chance, and negative values mean the agreement is worse than random. According to Cohen (1960), a Cohen's Kappa of 0.41–0.60 can be considered a moderate agreement between prediction and ground truth, 0.61–0.80 as substantial, and 0.81–1.00 as a perfect agreement.

The AUC is a measure frequently used in machine learning studies (Ben-David, 2008). First, the Receiver Operating Characteristic Curve (ROC) was built by plotting the probability of true positive rate (i.e. "successes", also called sensitivity or recall) versus the probability of false positive rate (i.e. "false alarms", also called fall-out) for all possible discrimination thresholds, for each of the three thermal preference classes using the "one versus the rest" method. Equations (8) and (9) define true positive rate (*TPR*) and false positive rate (*FPR*):

$$TPR = \frac{TP}{TP + FN} \tag{8}$$

$$FPR = \frac{FP}{FP + TN} \tag{9}$$

where *TP* (true positive) is the number of positive class correctly predicted in a binary classification model; *FP* (false positive) is the number of positive class incorrectly predicted; *TN* (true negative) is the number of negative class correctly predicted; and *FN* (false negative) is the number of negative class incorrectly predicted.

Finally, the area under the ROC was computed for each of the classes and averaged to obtain a single numeric performance indicator of the thermal preference model. AUC can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement.

3.7 PMV scale conversion for comparison

PMV was calculated according to ANSI/ASHRAE (2020), using the environmental parameters measured during the field study and the corresponding clothing and metabolic rate according to participants survey answers. As the PMV uses a 7-point scale to predict thermal sensation, the results were converted into three thermal preference categories to enable a comparison, in the same scale, with the personal comfort models developed in this study. Therefore, when the PMV model predicted values between 0.5 and −0.5 (i.e. normally considered a "neutral" sensation), the votes were labelled as "no change"; when PMV >0.5 (i.e. "slightly warm", "warm" and "hot"), the votes were labelled as "preferring to be cooler"; and when PMV < −0.5 (i.e. "slightly cool", "cool", "cold"), the votes were labelled as "preferring to be warmer". These cut-offs were chosen to represent the recommended limits for a 10% Predicted Percentage of Dissatisfied (PPD). This conversion of the PMV model is referred in this paper as "Converted PMV" or PMV_C. The AUC of the PMV_C was calculated using a single pair of probability of true positive rate versus probability of false positive rate, since the model is not a probabilistic classifier and does not allow plotting different discrimination thresholds.

4. Results and discussion

Table 3 presents a summary of the performance of each selected participant's models in predicting thermal preference with and without the use of health perception as an input variable. The Accuracy, Cohen's Kappa Coefficient and AUC shown in the table correspond to the model evaluation step (i.e. step 5 in Figure 4) and represent the generalisation performance of the personalised models when using the merged training and validation sets for learning, and the "never-before-seen" test set for assessment.

The generalisation accuracy of the personal comfort models (with health perception) ranges from 33.33 to 100%, with a mean of 73.98%; the Cohen's Kappa indicator ranges from 0.0 to 1.0, with a mean of 0.61; and the AUC ranges from 0.5 to 1.0, with a mean of 0.83. Although not optimal when considering individual performances of models such as ID 10 (33.33% accuracy, 0.0 Cohen's Kappa, 0.5 AUC), the personal comfort models developed still show an overall improvement in performance when compared to other similar studies in the field. Liu *et al.* (2019), for instance, reported an average Cohen's Kappa of 0.24 when analysing personal comfort models of 14 younger adults using different algorithms and input feature sets, in both indoor and outdoor environments. Likewise, Kim *et al.* (2018b) reported a median AUC of 0.73, when considering the best performing algorithm from each of the 34 individual models developed for younger adults.

Table 3 also provides the prediction results of the PMV_C model for each of the selected participants. On average, PMV_C predicted individual preferences with an accuracy of 49.52%, a Cohen's Kappa indicator of 0.24, and an AUC of 0.62 (i.e. slightly better than random guessing). In comparison, on average, the personal comfort models' accuracy is 49% higher, the Cohen's Kappa Coefficient is 151% higher and the AUC is 34% than the respective PMV_C model's indicators. This shows a significant improvement in the predictive performance of the personalised models when compared to PMV_C model.

Additionally, the results suggest that the models' generalisation performance may vary among participants, even after individual hyperparameter tuning. ID 32, for instance, reached the highest predictive performance with an accuracy of 100%, and a Cohen's Kappa and an AUC of 1.0. ID 5, on the other hand, only reached an accuracy of 60%, a Cohen's Kappa of 0.4 and an AUC of 0.67, even after multiple rounds hyperparameter tuning. Likewise, ID 10 represents a personal comfort model with considerably low performance and that was not able to provide any improvement when compared to the PMV_C model. The poor performance of models such as these might have been a result of a low sample size for training, the presence of anomalous data points, or the absence of input features that might also be influencing this person's thermal preference. Furthermore, when considering diverse individuals such as older people, it is expected that these other intrinsic characteristics play different roles for each person in different intensities and frequencies. In addition, as pointed out by Liu *et al.* (2019) and Katić *et al.* (2020), it is reasonable to expect that some individuals might be harder to predict than others.

Figure 5 presents a visual representation of the confusion matrices of the personal comfort models (using health perception) for each of the participants selected. Each row of the matrices represents the true thermal preference votes in each class (i.e. participants' survey answers), while each column represents the corresponding predictions. Not only do the matrices allow the visualisation of the overall performance of the models, but they also indicate the models' performance in predicting each individual class. They are the basis for the calculation of the Cohen's Kappa Coefficient and the AUC. Models such as ID 13, 32, 36, 40 and 50, for instance, clearly show a perfect agreement between the ground truth and the predictions, with classes predicted equally correct, and consequently identified as darker colours in the main diagonal of the confusion matrices. ID 21's confusion matrix, in contrast, shows that this model was better at predicting classes 0 (i.e. preferring to be cooler) and 2 (i.e. preferring to be warmer) than class 1 (i.e. preferring no change). On the other hand, ID 42's

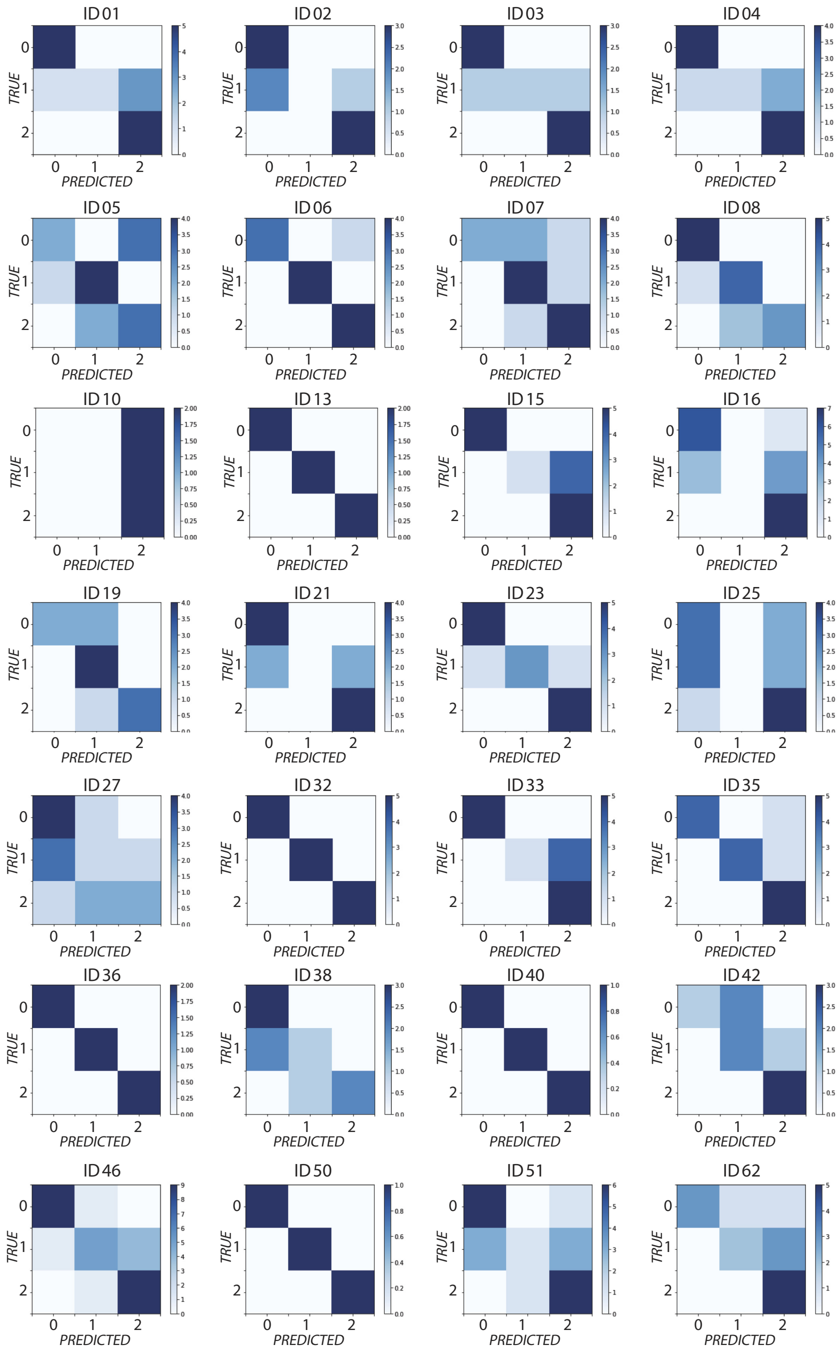

Figure 5.
Confusion matrix for PCMs with health perception, where 0 = preferring to be cooler, 1 = preferring no change, and 2 = preferring to be warmer

model, although having the same accuracy as ID 21's model, predicts class 2 (i.e. preferring to be warmer) better than classes 0 (i.e. preferring to be cooler) and 1 (i.e. preferring no change).

The Receiver Operating Curves (ROCs) and respective Areas Under the Curve (AUC) can also help the visualisation of models' performance in predicting each individual class. Figure 6 shows the ROC curve of each class, plotted using the "one versus the other" method, for ID 46's model (using health perception). As seen in the curves, and confirmed by the confusion matrix, this model is slightly better at predicting "preferring to be cooler" and "preferring to be warmer" categories than "preferring no change".

The confusion matrixes are equally relevant to visualise and analyse the cost of misclassification. In the case of thermal preference models, where the classes represent ordinal intensities, classifying a "preferring to be warmer" as a "preferring to be cooler" (and vice-versa) is more problematic than classifying a "preferring no change" as "preferring to be cooler" or "preferring to be warmer" (and vice-versa). ID 5 and 42 are examples of models that have similar performance indicators but have different misclassification patterns that might incur different costs when deploying the model. While ID 42 incorrectly classifies "preferring to be cooler" as "preferring no change", ID 5 misclassifies it as "preferring to be warmer". If both models were deployed in real scenarios for automatic heating and cooling control, for instance, ID 5 would have her system activated in the opposite direction of the change expected, incurring higher energy use and lower comfort levels than ID 42's system, which would similarly not meet its demand, but would not cause higher energy use than it should either. Although not addressed in depth this study, the misclassification cost of personal thermal comfort categories is a relevant topic in the field and an interesting area for future research.

The lower performance of the models can also be explained by examining the model training and testing procedures. Overfitting, for instance, can be identified in some of the individual models. Observing the training learning curves of these models, which represent the training and testing loss by epoch (i.e. the number of passes of the entire dataset through the model), the gap between the training loss and the testing loss was significantly large in some cases. This means that the model has learned the training dataset too well, including errors in the data and possible statistical noise. As a result, the fit obtained was not able to produce accurate estimates on new observations that were not part of the original training dataset (James *et al.*, 2013). Figure 7 exemplifies this hypothesis. When observing the learning curve from ID 5 – who yielded a 60% accuracy, 0.4 Cohen's Kappa and an AUC of 0.67 –, the gap between the training and testing loss is vastly larger compared to ID 35's model – who reached an 86.67% accuracy, 0.8 Cohen's Kappa and a 0.93 AUC. Possible reasons for overfitting could be related to the small data size, the input features used, or the cross-validation procedure applied. Moreover, overfitting might be a result of using a test set that does not represent well the entire dataset. Although strategies for preventing overfitting were used in this study, such as early stopping, these models would still benefit from further explorations.

Furthermore, Table 3 presents the performance of the models developed without health perception as one of the input variables. On average, the performance of models without the use of health perception as a predictor was slightly lower than the performance of the ones using this predictor. The difference between the two groups of results, however, was not statistically significant (i.e. $p > 0.05$) according to the independent-measures t-test.

Nevertheless, when examining individual models' results, it is still worth analysing the examples of models that performed better without the health perception indicator, such as ID 7, 16, 19, 25, 27, 42 and 51 are, as presented in Figure 8. In most of these cases, this could be a result of the low variability of the health perception input, which remained between "good" and "reasonable" regardless of the thermal preference or the other input variables. In other cases, where variability in health perception was indeed present, such as for ID 19, a possible

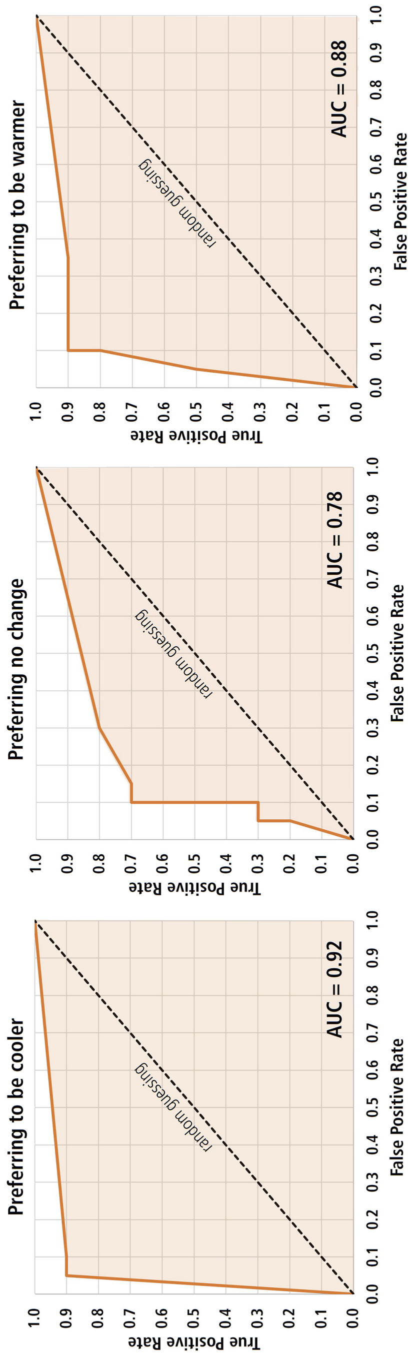

Figure 6.
Area under the receiver operating characteristic curves of model for ID 46 (with health perception), for each thermal preference class, plotted using "one versus the rest" method

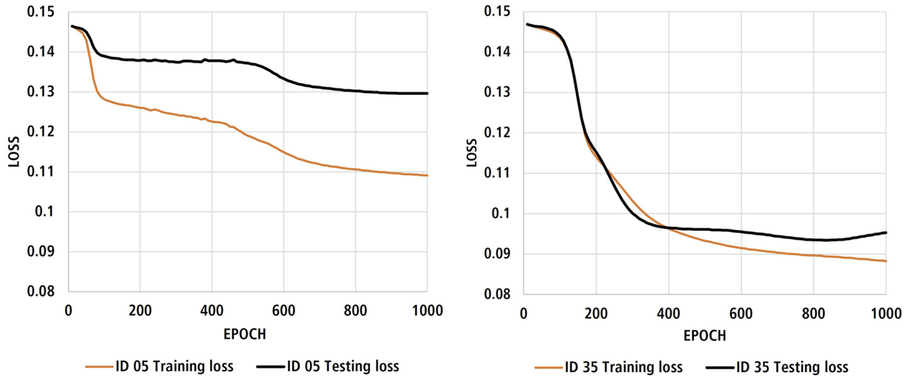

Figure 7.
Training learning curves for ID 5 and for ID 35

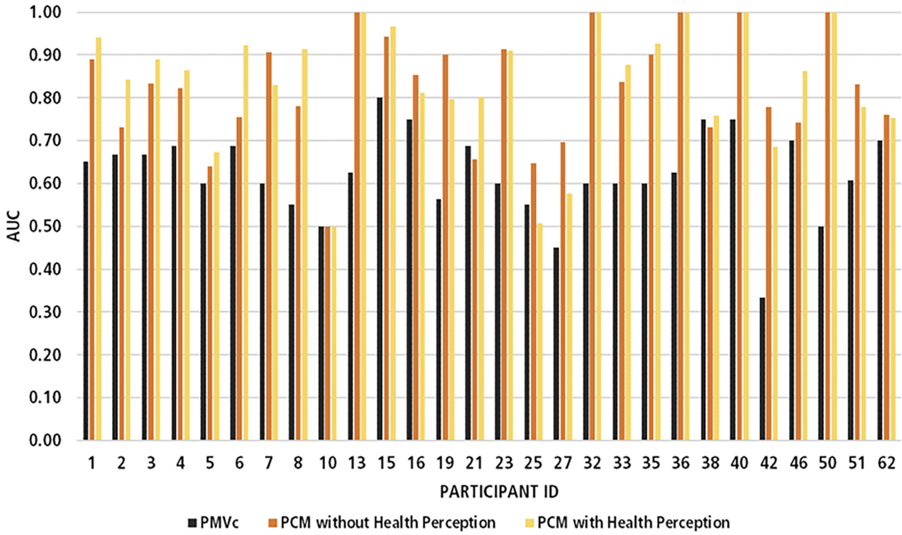

Figure 8.
AUC of PMV_C and PCM with and without health perception as one of the input variables

cause for a lower performance might be the absence of clear correlation between health perception and thermal preference, as indicated by ID 19's box plots in Figure 9.

Similarly, Figure 10 can indicate possible reasons why adding health perception as one of the input variables for ID 19 did not allow higher predictive performance to the personalised model. The figure shows the probability density of the distributions of the thermal preference classes depending on the seven input variables used, built using Kernel Density Estimation (KDE) (Zielinski *et al.*, 2018). The overlapping areas of the three thermal preference classes could indicate that ID 19 is likely to prefer different thermal conditions while having the same health perception. This is also more evident for air speed and metabolic rate for ID 19. It is possible to imply, therefore, that adding these variables as predictors of thermal preference might not be ideal for this person and could potentially compromise models' predictive performance.

Although the minimum dataset size required for personal models to reach maximum predictive performance can vary for each participant, larger sample sizes might allow a better statistical representation of the data. The data collected in this study, however, were not sufficient to allow the testing of larger datasets. Nonetheless, other similar studies on personal thermal comfort models have calculated the predictive performances of individual models increasing training datasets incrementally. Most of them reported minimum datasets of 30–90 datapoints for maximum predictive performance (Daum *et al.*, 2011; Jazizadeh *et al.*, 2014a; Kim *et al.*, 2018b; Lee *et al.*, 2019; Li *et al.*, 2017), which is in line with the average dataset sizes used in this study, as seen in Table 3.

5. Recommended applications

Three main implementation pathways are recommended through this study. The first, called automation pathway, uses the predictions yielded from personal comfort models for live control strategies of the HVAC temperature set points. Jung and Jazizadeh (2019), for instance, proposed an HVAC agent that decided the optimal temperature setpoint according to different personalised thermal profiles, using three different strategies, namely thermal vote-based predictions, thermal preference-based and the thermal preference and sensitivity-based. Likewise, Auffenberg *et al.* (2018) developed an HVAC control algorithm using personalised models to retain user comfort while also minimising energy consumption. These models can also be integrated into personal comfort systems (PCS), allowing the conditioning of individuals in a more cost-effective scenario. Although control automation can benefit all individuals, personal models can be especially important as assistive tools for older adults with lower thermal sensitivity or with disabilities.

The second implementation pathway, called diagnostic pathway, relies on the use of the information gathered from personal datasets as a tool to quantify individual preferences, and identify possible design improvements to meet these preferences, especially considering buildings without air-conditioning. If, for instance, an individual model reveals that comfort preferences are more sensitive to air movement than indoor temperatures for a specific occupant, then investing on strategies related to ventilation would be more effective than investing in adding insulation materials only. This diagnostic information would aid not only designers but also older adults in the decision-making process to redesign their thermal environments to improve comfort satisfaction.

The third pathway, called public health pathway, is based on inserting individual models in regulations and standards to be used in a broader sense, without, however, disregarding personal preferences. Since extensive monitoring of new occupants may not be feasible for all settings, personal models from individuals with similar characteristics and preferences would be used to create a set of "profiles" or "personas" according to trends between their

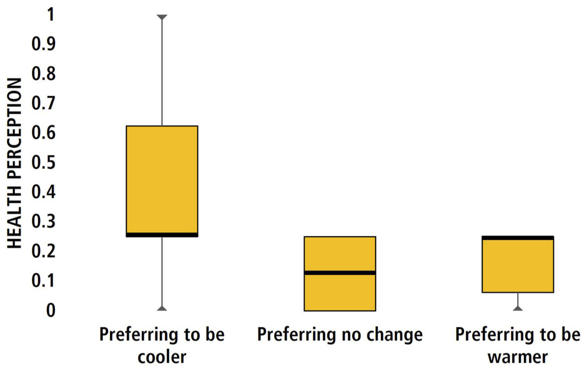

Figure 9.
Box plot of the health perception variable (normalised from 0 to 1, where 0 = "very good" and 1 = "very poor") according to the thermal preference classes, for ID 19

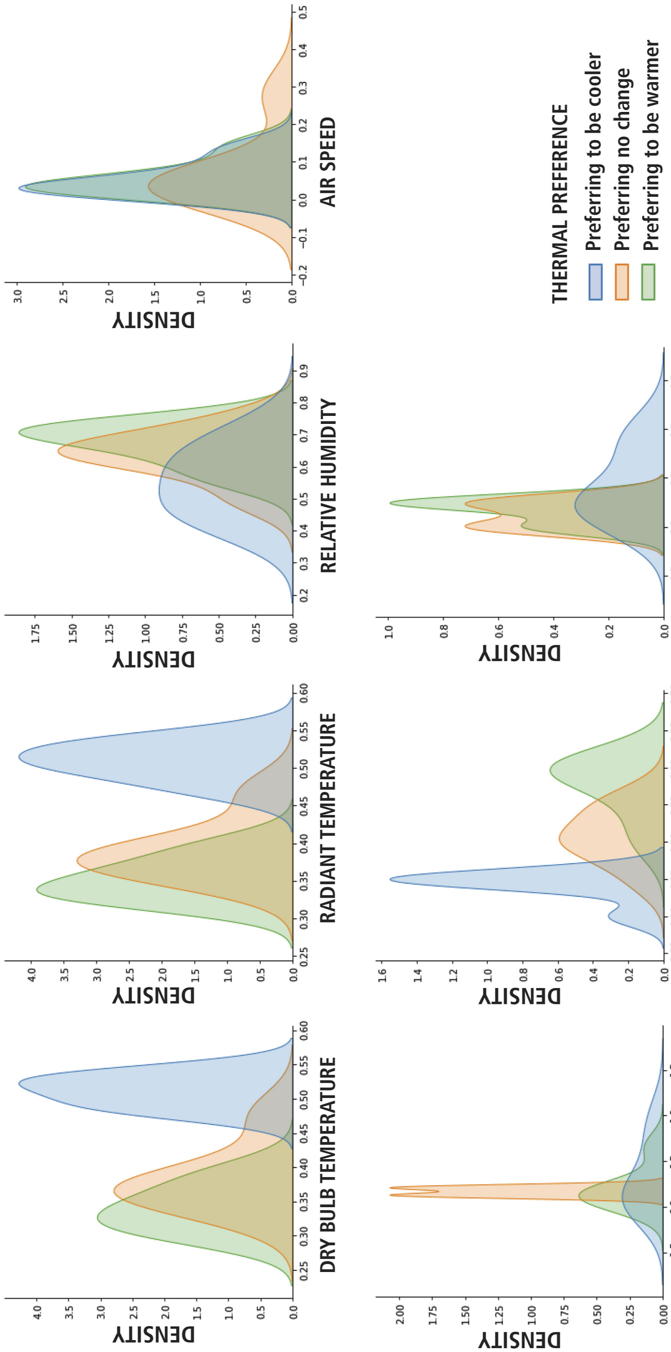

Figure 10.
Density plot of distributions of thermal preference votes against the seven input variables (normalised from 0 to 1) for ID 19

statistically significant variables, allowing them to be applied to other individuals, thus requiring a smaller set of relevant information and reduced or no monitoring period. Nevertheless, since this roadmap involves a broader application scenario, the consolidation of the individualised approach as a reliable and reproduceable technique needs to be further tested, and this depends on a collective research effort on the subject. A protocol will be required to prescribe the optimal data collection, processing, and management procedures and to guide the training, evaluation and reporting of models depending on the application. Finally, the standards should prescribe a set of initial models as common bases for each type of application, which can be used as a starting point for re-learning and updating for new and specific occupants and environments.

It is important to highlight that the modelling methodology, learning algorithms and input variables may differ depending on the complexity required for each sort of application envisioned. Using the models for HVAC control with live model-tuning when new data is available (i.e. automation pathway), for instance, may require less computational heavy models, lower training time and higher accuracy to provide immediate user satisfaction. On the other hand, models used in a more analytical sense, or when the relationship between features is more relevant than comfort predictions (i.e. diagnostic pathway), may require more transparent and interpretable modelling techniques rather than optimum performance.

6. Limitations

The current study presents the following limitations. Firstly, the use of undersampling as a strategy for balancing individual datasets has resulted in a reduction of the data size that can influence the model's predictive performance. In addition, undersampling can cause the loss of potentially useful data points. Possible alternatives are oversampling or SMOTE (Synthetic Minority Oversampling Technique) or increasing sample sizes with longer monitoring periods that allow more diverse thermal preference responses. Both strategies, however, have drawbacks. Oversampling can, on one hand, lead to model overfitting and an increase in learning time. Longer monitoring periods, on the other hand, can be intrusive for the participants, increase study cost and time, and add bias to participants' answers after repetitive tasks. The use of personal comfort systems is equally interesting to allow bigger sample sizes, since the system's control patterns can be collected continuously and later used as proxy for thermal comfort.

Secondly, the use of field studies instead of climate chamber experiments also poses challenges to dataset size and distribution. When monitoring real thermal environments, where conditions vary without the influence of researchers, extremes in thermal perception are naturally less often captured, making final imbalanced datasets almost unavoidable. Nevertheless, field studies provide an accurate representation of reality and its underlying conditions that controlled climate chamber experiments are rarely able to capture.

Thirdly, despite the study including three different climate zones, it is still limited to a specific climatic context of older people in South Australia. Future research is required to advance the knowledge on other scenarios and their related challenges. Likewise, although the older participants in this study represent a diverse cohort in terms of body composition, age, sex, health, frailty and living environment, other socio-cultural and economic factors that affect their thermal environments, as well as their thermal sensitivity and behaviour, still need to be addressed to build a more holistic image of their diversity.

Furthermore, this study is limited to the analysis of seven features that might affect thermal preference for older people. Other potentially relevant input variables might include time of day and seasonal thermal expectation, physiological data, such as skin temperature or heart rate, and more accurate representations of metabolic rate, such as accelerometry measured with wearable sensors or activity captured using image recognition.

Finally, it is important to point out that the PMV conversion used in this study poses limitations in the comparisons. This is because thermal sensation and thermal preference scales cannot be considered interchangeable for all individuals. While several people might experience neutral sensation and thermal preference for no change at the same time, it is still necessary to account for preferred sensations other than neutral. Although not applicable to all participants in this study because of insufficient and highly unbalanced sample sizes, an alternative to this conversion would be analysing different conversion rules and cut-offs for each individual participant depending on their thermal sensation and thermal preference answers, instead of a single scale conversion method for all.

7. Conclusion

Responding accurately to older people's thermal preferences in their dwellings is essential to enable comfort and support healthy ageing. In this paper, personal comfort models have been developed for 28 older people as an alternative to the traditional aggregate comfort modelling approaches used in the field that often disregard diversity in thermal preferences, living environments and health statuses.

Using deep learning as the modelling technique and both environmental and personal characteristics as model inputs, the study has demonstrated that:

(1) On average, the individualised models present an accuracy of 74%, a Cohen's Kappa Coefficient of 0.61 and an Area Under the Receiver Operating Characteristic Curve of 0.83, representing an overall improvement in performance when compared to other similar studies in the field and the PMV_C model.

(2) On average, the performance of models without the use of health perception as an input variable was slightly lower than the performance of the ones using this predictor, although the difference between the results was not statistically significant.

(3) The models' generalisation performance may vary among participants. Poor performance can be related to low sample sizes for training, the presence of anomalous data points, or the absence of input features that might also be influencing this person's thermal preference. Overfitting was also identified as a possible cause of low performance when testing the models.

(4) Personal comfort models for older adults are recommended as HVAC control automation strategies, as diagnostic tools for design decision-making, and as the basis for the development of thermal comfort profiles in the broader public health scenario.

The next step for this study includes expanding the models to take into account other physiological parameters such as skin temperatures, and testing the models' capabilities and feasibility by deploying them in real life scenarios.

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Corresponding author
Larissa Arakawa Martins can be contacted at: larissa.arakawamartins@adelaide.edu.au

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Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables

Larissa Arakawa Martins [a,*], Veronica Soebarto [a], Terence Williamson [a]

[a] *School of Architecture and Built Environment, The University of Adelaide, SA, 5005, Australia*

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ABSTRACT

Personal thermal comfort models hold the promise of a more accurate way to predict thermal comfort and therefore a more reliable approach for managing indoor thermal environments. They can be especially relevant as an assistive tool for people with lower thermal sensitivity or with limitations to thermal management and adaptation, such as older people. Nonetheless, although in constant development, studies on personal comfort models continue to focus on office environments and younger adults. This paper explores the development of personal comfort models to predict older people's thermal needs in their homes and evaluates the models' predictive performances in comparison with conventional generalised approaches. Machine learning and environmental, behavioural, health and skin temperature measurements were used to develop individual models for a set of older adults in South Australia. The results show that, on average, the personal thermal comfort models using all studied inputs, except for health perception, presented an optimal accuracy of 66.72%, a Cohen's Kappa of 50.08% and AUC of 0.77, a superior performance when compared with generalised approaches. Results have also highlighted the need for further research on combining physiological sensing, individualised predictive modelling and wearable comfort systems, as well as on defining thermal preference misclassification costs in the context of older people.

1. Introduction

Over the last two decades, the field of thermal comfort modelling has been going through an important paradigm shift. Studies on thermal comfort that focus on aggregated responses from a group of people, such as the PMV (Predictive Mean Vote) [1] and adaptive models [2,3], are being called into question by individualised and occupant-centric modelling alternatives [4–8]. To predict specific comfort requirements more accurately, instead of an average condition calculated from the responses of a group of people, the new personalised approach relies solely on thermal assessments from a single person. By absorbing individual diversity into thermal comfort management, this new modelling approach offers the potential to increase both occupant acceptability and related energy benefits in the built environment. As discussed in works by Kim et al. (2018) [4] and Arakawa Martins et al. (2022) [8], by using the individual as the unit of analysis, personal comfort models help unmask and quantify the differences between individuals in an environment, enabling a better understanding of specific comfort needs and requirements, such as acceptable temperature limits for a

* Corresponding author.
E-mail addresses: larissa.arakawamartins@adelaide.au.edu (L. Arakawa Martins), veronica.soebarto@adelaide.edu.au (V. Soebarto), terence.williamson@adelaide.edu.au (T. Williamson).

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given space, and collecting diagnostic information to identify problems. This information, in turn, aids the decision-making process involved in optimizing thermal environments to improve both comfort and energy efficiency. If, for instance, the acceptable temperature limits diagnosed are greater than the default HVAC (Heating, Ventilation and Air Conditioning) temperature setpoint ranges, energy savings can be expected by widening the setpoint temperatures. If HVAC systems are used in shared spaces and individual control is not possible, personal comfort models can still be used as the basis for consensus-based solutions [9], or the development of thermal comfort profiles for general use [4,10]. In single-occupant spaces where individual control is possible, personal comfort models can help automate any type of conditioning systems with higher precision. Although automatic control might not be a priority for some individuals, the automation provided by personal comfort models can be especially relevant as assistive tools for people with lower thermal sensitivity, such as older people, for those with more limitations to thermal management and adaptation, such as people with disabilities, or for those with less means to afford the cost of HVAC fuel consumption. Examples of energy savings resulting from the use of individualised thermal comfort models were experimentally demonstrated by Jazizadeh et al. (2014) [9] and Ghahramani et al. (2014) [11].

Personalised models have been the subject of multiple recent research studies. They have been developed through a plurality of frameworks, varying data collection approaches, model inputs and output variables and the modelling algorithms used [8]. When analysing the models' input variables specifically, environmental factors, such as indoor air temperature [12–17], relative humidity [18], air speed [19], mean radiant temperature [20] and outdoor air temperature [21,22], are most frequently used as single or combined predictors in these studies. There is, however, an increasing body of research focusing on personal comfort models driven by physiological variables, such as skin temperature or heart rate [23–32]. Powered by the recent development of wearable devices and the Internet of Things (IoT), this area of research is advancing towards novel ways to monitor and predict individual thermal responses in increasingly more accurate and less intrusive ways.

Nonetheless, although in constant development, studies on personal comfort models continue to focus on office environments and younger adults. While the literature contains multiple studies on thermal comfort for older adults [33–37] and age-related differences in thermal sensation and preferences [38–40], the studies focus on generalised conclusions in specific contexts. Studies on the development of personal comfort models that focus on older people, their specific physiological responses, and their living environments are still absent in the current literature [8]. This is despite the fact that the proportion of older people (i.e., those aged 65 years old and over) worldwide is increasing rapidly, projected to grow from 9% in 2019 to 16% by 2050, due to historically low birth rates combined with increased life expectancy [41]. Furthermore, this research gap is especially relevant because heterogeneity in personal capabilities and needs tends to be greater in older than younger people, as older adults have likely experienced a greater range of cumulative social and environmental factors during their individual lifetime [42]. Using a generalised thermal comfort model for older adults could result in a great proportion of them being exposed to unacceptable indoor thermal environments. Such thermal exposures can, in turn, interact with multiple comorbidities, leading to adverse health outcomes [43–45] and possibly premature institutional care. Personal comfort models thus hold the promise of a much more accurate approach to thermal environment management, which could potentially prevent both heat and cold related illnesses across a more diverse and vulnerable population. Furthermore, the human-in-the-loop (HITL) [46] automation enabled by the integration of these models with heating and cooling control systems may be especially relevant as an assistive tool for people with lower thermal sensitivity or for those with more limitations to thermal management and adaptation, such as people with disabilities.

Therefore, this paper explores the development of personal comfort models, using different combinations of environmental, behavioural, health and physiological (i.e., hand skin temperature) input variables, to predict older South Australians' thermal needs in their homes, and evaluates the models' predictive performances in comparison with conventional generalised approaches. Considering that approximately 80% of households in Australia have heating devices and 74% have cooling devices [47], the opportunities for the use of personal thermal comfort models for possible HVAC or personal comfort systems automation in the Australian context become especially relevant.

The structure of the paper is organized as follows. The following subsection 1.1 presents related works on personal thermal comfort models using both environmental and physiological features. Section 2 details the field study process and tools used for data collection, as well as the two modelling methodologies applied, a conventional generalised approach and a new personalised alternative. Section 3 explores the performance results of the two models while Section 4 discusses the main topics highlighted by the study's outcomes. Section 5 presents the study's limitations as well as future study opportunities, and Section 6 concludes this article.

1.1. Related literature on personal comfort models using environmental and physiological input variables

The recent literature on personal comfort models employing environmental and physiological variables as predictors for thermal comfort indicates that the models' predictive performance increases when a combination of both types of inputs are used. Aryal and Becerik-Gerber (2019) [23], for instance, monitored 20 participants, in their late teens to mid-thirties, through experimental sessions in an office building, and compared the accuracy of individual models using both environmental measurements and wrist and face skin temperatures. According to these researchers, using data from the environmental sensors for predicting thermal comfort resulted in a higher accuracy compared with using physiological data alone. However, combining data from both environmental and physiological sensors led to a slightly increased accuracy (3%–4%) over using environmental sensors alone. A further study from the same authors [24], involving 15 participants in their late teens to mid-twenties, also in experimental sessions in an office environment, confirmed similar results.

Jung et al. (2019) [25] indicated a much greater increase in prediction performance when including physiological features as input parameters for personal thermal preference models. In a climate chamber study involving 18 participants, the research used skin heat exchange via a heat flux gauge, skin temperature, indoor temperatures and humidity to infer personal thermal preferences. According to their results, the use of the heat exchange rate from the skin resulted in higher performance indicators than using skin temperature and indoor temperature as factors. The study's best performing modelling algorithm presented a median accuracy of 71% when using air temperature as a sole feature, 93% with the addition of skin temperature and 97% with the addition of heat flux, highlighting that the best performance was observed when skin temperature and heat flux were used along with ambient temperature.

Likewise, Lu et al. (2019) [31] conducted experimental sessions in an open-plan office with 2 healthy participants in their mid-twenties. The personal models predicted thermal sensations using three different feature sets, involving both environmental and physiological parameters. The models were trained using linear kernel Support Vector Machine, and the recall score (i.e., the proportion of all actual positive cases that were correctly predicted as positive), the precision score (i.e., the ratio between true positives and all predicted positives) and the F1 score (i.e., the harmonic mean of recall and precision) were used as the performance indicators [31]. The combination of indoor air temperature, relative humidity, skin temperature and clothing surface temperature achieved a 100% recall, precision and F1 score for the female subject and a 96.1%, 97.5% and 95% recall, precision and F1 score, respectively, for the male subject.

Li et al. (2017) [27] also reported that the combination of both environmental and human data (i.e., activity level, clothing, heart rate, skin temperature) can significantly improve the performance of personalised comfort prediction models. Through two field studies, involving 3 and 7 participants in both office and residential environments, their research showed that the combined feature set achieved approximately 80% accuracy, improving the classification accuracy by 24% and 39% when compared with the use of environmental features only and physiological factors only, respectively. A subsequent study by the same authors [28] explored personal comfort modelling using skin temperatures collected from different facial regions using thermal cameras. Through a series of experiments in an office environment with 12 participants in their early to mid-twenties, the researchers not only indicated that ears, nose, and cheeks skin temperatures are most indicative of thermal comfort, but also that their proposed framework can achieve an average accuracy of 85%. Building on these previous works, Li et al. (2020) [29] proposed the Human Embodied Autonomous Thermostat (HEAT) tool, where facial skin temperature and room air temperature were used to directly communicate with and control HVAC operations in multi-occupancy spaces.

Similarly, Liu et al. (2019) [30] collected physiological responses including skin temperature and heart rate, as well as environmental parameters such as air temperature and relative humidity, of 14 participants, through a series of wearable sensors, in both indoors and outdoors environments. Through the use of 14 different machine learning algorithms, the personal thermal comfort models presented a median Cohen's Kappa indicator of 24%, accuracy of 78% and Area Under the Receiver Operating Characteristic Curve of 0.79 (details on these performance indicators are presented in Section 2.7 of this paper). These results showed a significant improvement of predictive performance when compared with the PMV and adaptive models. A follow-up study by the same research group [48] used deep learning to develop personal thermal preference models for 7 of the original 14 participants, successfully testing transfer learning techniques in order to decrease data collection periods and test the generalisation of the models to other building occupants.

A recent study by Jung et al. (2022) [49] also explored the use of deep learning algorithms to optimize both thermal comfort and energy consumption of 4 young individuals in climate chamber experiments. Both environmental and physiological data were used as inputs. The results showed that the proposed optimization system could reduce by 10.9% the thermal discomfort of the occupants while maintaining their respective energy consumptions.

The literature review, however, confirms a lack of studies where older adults are involved, as well as a limited amount of research in residential settings. Furthermore, as pointed out by Arakawa Martins et al. (2022) [8], although a general idea of trends in outcomes can be extracted from previous studies, a direct comparison of different physiological sensing and modelling approaches among these studies is difficult. As seen above, multiple performance indicators (e.g., accuracy, recall, Cohen's Kappa and Area Under the Receiver Operating Characteristic Curve) and different experimental settings (e.g., climate chambers or field experiments, different body parts being monitored, and multiple types of sensing equipment) are used, making immediate conclusions on predictive performance difficult to draw. This study, therefore, aims to investigate an individualised modelling approach for older adults and their living environments, as well as a reproduceable modelling and evaluation methodology.

2. Study design and methodology

2.1. Data collection periods

The dataset used in this study is derived from two separate data collection periods, involving 11 participants (6 males and 5 females) who lived in 8 households located in 3 climate zones (hot dry (BSk), warm temperate (Csa) and cool temperate (Csb), according to the Köppen–Geiger Climate Classification System) in South Australia. The participants were volunteers who met the following criteria: (1) be 65 years old or over; (2) live independently, and (3) be able to communicate in English. These participants were part of a larger research project that investigated the thermal qualities of older adults' living environments [50]. While this research project involved 71 participants in 57 households, only 11 participants agreed to be involved in the further data collection, which involved measuring their skin temperature, as explained below. The study received approval from The University of Adelaide Human Research Ethics Committee (approval number H-2018-042).

In the first data collection period, indoor environment data were collected simultaneously in all houses, across a period of 9 months, from mid-January to mid-October in 2019. The sensors and data loggers were placed in each house's main living room and main bedroom and a portable electronic tablet was left for participants to answer a point-in-time survey about their thermal environment and their preferences and sensations at least twice a week. The indoor environment loggers recorded data from measurements of dry bulb temperature, globe temperature, air speed, and relative humidity, at 30-min intervals and when a participant completed a survey.

Mean radiant temperature was later calculated from the measured dry bulb temperature, globe temperature and air speed measurements applying the method from ISO 7726:1998 [51]. Participants were able to choose whether to answer the surveys in the living room or the bedroom, since the tablet was portable and could be carried between the rooms. The survey's first question asked participants to indicate in which room the survey was being conducted and the loggers' measurements were later sorted to match the corresponding rooms.

While the indoor environmental parameters were being recorded, each participant was asked to periodically respond to a thermal comfort survey through an electronic tablet. The survey comprised of questions about participants' clothing level, activity level, health/wellbeing perception (for which the answer scales are further detailed in Table 2), thermal sensation (TSV) and thermal preference (TPV). TSV was assessed using the question 'How do you feel right now?' with possible responses being 'Cold', 'Cool', 'Slightly cool', 'Neutral', 'Slightly warm', 'Warm' or 'Hot'. TPV was assessed using the question 'Would you prefer to be … ' with possible responses being 'Cooler', 'No change' or 'Warmer'. Details of the loggers and thermal comfort survey tablet have been reported by Soebarto et al. (2020) [52].

A questionnaire about sociodemographic information and an open-ended interview about house details were administered at the start of the monitoring period. Furthermore, frailty status (using the Modified Reported Edmonton Scale (MRES) [53]) and participants' height, weight and body mass index (BMI) (using a Tanita Inner Scan RD-953 scale [54]) were assessed at the end of the monitoring period.

After the conclusion of the first data collection period, a preliminary analysis of the data and further literature investigations highlighted a lack of physiological factors being investigated in the first stage of the study. Therefore, a second data collection was conducted with the same participants. Each house was monitored across 2 consecutive weeks, one house after the other, between the months of September 2020 and February 2021.

In this second data collection, the survey tablet, as detailed below, was modified to include a non-contact infra-red temperature sensor to measure the skin temperature of the back of participants' non-dominant hand after they completed each point-in-time survey. The other environmental measurements and the comfort survey questions remained the same as for the first collection period. Frailty and body composition assessments were redone and, after analysis, variations between the two data collection periods were considered minimal (i.e., maximum 1 unit change in the frailty score and a weight change under 5 kg). In addition, through new photographic documentation and interviews with participants, researchers ensured that the environments had not undergone major changes that could compromise the merging of the two collected datasets.

2.2. Hand skin temperature measurement tool

Human hands are known to contain a high number of arteriovenous anastomoses (AVAs), valves that regulate vasoconstriction and vasodilatation, and therefore influence heat loss by changing the peripheral blood flow [55]. This makes the skin temperatures of hands a possible indicator of a person's thermal state [56]. The skin temperature of the back of the hand (i.e., dorsal side of the hand) was chosen for this study in line with previous research that correlated thermal sensation to this specific body part [26,37,38,56] and according to ISO:9886:2004 [57]. The measurement of the back of hand also reduced the intrusiveness of the method since this skin surface is more frequently exposed to the environment than other body parts. In addition, the use of the dorsal side of the hand, in combination with the space and position available for the new sensors in the original tablet enclosure, allowed the most comfortable position for older participants to take the measurements whilst seated. The non-dominant hand was chosen to minimize the effect of frequent hand movements in the skin temperature measurements.

To include skin temperature measurements in the study, the original tablet and logger were modified to record and store data from a non-contact infra-red temperature sensor (model MLX90614-DCC). The sensor has a ±0.5 °C precision of temperature measurement and a field of view (FOV) of 35°. To measure a spot with a radius of approximately 1 cm on the back of participants' non-dominant hand, participants positioned their hands at a maximum distance of 1.5 cm from the sensor.

An Arduino line trace sensor (model LB-LR0005) was also included in the modified version of the equipment, serving as a proximity

Fig. 1. Thermal comfort survey tablet with infra-red skin temperature sensor and indoor environment data logger (left), and back of hand skin temperature measurement being taken (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

sensor to allow measurements only when the participants' hand was close enough to the infra-red sensor. In addition, a dark coloured upright partition was attached in front of the sensors to avoid accidental measurements triggered by surrounding reflective surfaces, and to guide participants' hand positioning. A buzzer was also included as an audible indication that a measurement had been taken by the skin temperature sensor and recorded by the tablet. Recorded measurements, however, could contain irregularities that were later analysed individually, as described in the next sections of this paper. The modified equipment and skin temperature measurement procedure was tested with 3 people (in their late fifties to mid-seventies) before deployment to ensure suitability for the cohort involved in the study. The accuracy of the setup was compared with a medical grade infra-red temperature device, presenting a ±0.5 °C error range.

Fig. 1 shows the indoor environmental data logger and thermal comfort survey tablet with infra-red skin temperature sensor used in the second data collection period and demonstrates how the skin temperature measurements were taken.

2.3. Participants and datasets

Table 1 presents the characteristics of the 11 participants. The exploration presented in this paper is divided in two parts, the first comprising of a conventional generalised modelling method (detailed in section 2.4) and the second contemplating a new individualised modelling approach using machine learning (detailed in section 2.5). The first exploration was developed from the full dataset from the second data collection period of the 11 participants. The second exploration is based on the individual datasets of 4 of the 11 participants involved. Only 4 participants were evaluated individually because the modelling methodology required that each participant voted at least 6 times in at least one of the three thermal preference (TPV) classes, to allow a minimum of 5-fold cross-validation during model training, plus a minimum of 1 vote per category for testing. Seven participants did not meet these criteria and therefore were excluded from the second exploration. The cross-validation procedure is based on common practice in the field of machine learning [58] and on similar thermal comfort studies [24,26,30,59].It is further detailed in Section 2.5.2. Since dealing with individual datasets reduced the dataset sizes for modelling, records from the first and second collection periods were merged to increase the number of data points for each of the 4 participants. In this case, k-Nearest-Neighbours technique was used to impute the missing values of skin temperature in the first data collection set. These 4 participants are highlighted in bold in Table 1.

It is important to note that, in the case of personal thermal comfort modelling, the number of data points for each participant (i.e., the number of thermal preference votes in each individual dataset) is more relevant for each model's robustness than the total number of participants involved in the overall study, as already pointed out by Li et al. (2020) [29]. In addition, the range and number of votes in each of the thermal preference categories are of great importance for model's predictive performance and reliability, especially when dealing with highly unbalanced datasets such as the ones commonly produced by field studies.

2.4. First exploration method: weighted least squares regression model

One of the most common methods to calculate thermal comfort predictions is through weighted regression models [60]. Therefore, the first exploration in this study is based on the following steps.

From 565 survey answers and environmental and skin temperature measurements derived from all 11 participants, 500 contained valid data for skin temperature (i.e., no measurement error or missing values). This valid dataset was first analysed for outlier detection in the skin temperature measurements, which may have been the result of issues such as accidental triggering of the sensor or moisture on the back of the hand. Outliers were considered as any data value that lay outside the range between the 3rd quartile plus 1.5 times the interquartile range and the 1st quartile minus 1.5 times the interquartile range. The outliers were then excluded from the dataset, resulting in a final dataset of 470 datapoints.

Next, the skin temperature measurements (i.e., the independent variable) were binned in 0.5 °C increments. The mean of the skin temperatures and corresponding thermal preference votes (i.e., the dependent variable) were then calculated for each bin. With binning, the ordinal thermal preference vote (TPV), assuming equal intervals, may be considered an interval variable and therefore amenable to inferential statistical analysis. A linear regression model was then fitted to the binned data points, weighted by the number of votes in each bin, using the weighted least squares regression method, which is widely used in thermal comfort field studies [60–63].

Further relationships between skin temperature and the other environmental (i.e., dry bulb temperature, radiant temperature, air speed, and relative humidity) and behavioural/physiological measurements (i.e., clothing level, health perception and metabolic rate)

Table 1
Participants' characteristics. Participants whose personal thermal comfort models were developed are highlighted in bold.

ID	Climate Zone	Sex (Female or Male)	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Frailty Score (MRES scale)
1	**Csa**	**Female**	**80**	**161.0**	**103.4**	**39.9**	**Not Frail**
2	Csa	Male	74	160.0	120.6	47.1	Mild Frailty
3	Csa	Male	81	171.5	111.1	37.8	Not Frail
4	**Csb**	**Female**	**67**	**166.5**	**115.6**	**41.7**	**Not Frail**
5	Csb	Male	66	183.0	68.3	20.4	Not Frail
6	Csa	Male	83	174.0	92.35	30.5	Apparently vulnerable
7	Csa	Female	83	166.0	72.85	26.4	Not Frail
8	Csa	Male	85	173.0	98.95	33.1	Not Frail
9	**Csb**	**Female**	**73**	**150.5**	**62.95**	**27.8**	**Apparently vulnerable**
10	Csb	Male	77	180.0	69.15	21.3	Not Frail
11	**Csa**	**Female**	**82**	**163.0**	**61.5**	**23.2**	**Apparently vulnerable**

were also analysed, using a similar method, with skin temperature as the dependent variable and the other factors as independent variables. In this case, dry bulb and radiant temperatures were binned in 0.5 °C increments, air speed in 0.1 m/s increments, relative humidity in 5% increments, metabolic rates in 0.1 MET increments and clothing level and health perception in their original 1 increment categories. This analysis was developed using IBM SPSS Version 27.0.0 [64].

2.5. Second exploration method: personal thermal comfort model

The second exploration conducted in this study investigates thermal preference predictions at an individualised level, using personal thermal comfort models. In this case, instead of the single dataset containing the thermal preference votes for all participants involved, individual datasets were used to develop personal models targeted for each participant.

Artificial neural networks (ANN), also known as deep learning [65], were used to develop these personalised comfort models. Although other high-performance machine learning techniques could have been used (e.g., Random Forests or Support Vector Machine) for thermal preference prediction, an extensive review of personal thermal comfort models highlighted a lack of exploration of artificial neural networks [8]. Furthermore, ANNs have the advantage of not imposing prior assumptions about data distribution before learning, unlike other conventional techniques, which significantly leverages the use of ANNs in different applications [66].

The models were developed to perform a multiclass classification task of occupants' TPV on a 3-category-scale (i.e., 'prefer to be cooler', 'prefer no change' or 'prefer to be warmer'). The survey's TPV were used as the ground truth to train the models and were later compared to the predicted values. It is important to highlight that, TPV was deemed more appropriate than TSV – which is commonly used in thermal comfort studies – because, as pointed out by Kim et al. (2018) [67], the thermal preference scale not only represents the ideal condition desired by each person, but also suggests in which direction a change may be desired.

In total, 8 input variables were used, 4 of which represented the environmental conditions of the participant's room (i.e., dry bulb temperature, radiant temperature, relative humidity, and air speed) and 4 of which represented the participant's personal, physiological, or behavioural characteristics (i.e., corrected metabolic rate, clothing level, self-reported health perception and hand skin temperature). These 8 variables were selected to cover factors known in the architectural science, medicine, and public health fields to influence thermal responses [68,69]. Table 2 shows each input's data collection tool and unit or scale.

Participants' activity answers in the survey were converted to MET values according to the Compendium of Physical Activities [70], and later corrected based on participants' sex, height, weight and age, according to Byrne et al. (2005) [71] and Kozey et al. (2010) [72]. Table 2 shows the activity scale points and corresponding MET values.

To compare the impact of different types of input on models' predictive performance, three different combinations of input variables were tested:

(1) Skin temperature;

Table 2
Input variables used.

Type	Input variable	Data collection tool	Unit or scale	Min and max used in normalization
Environmental	Dry Bulb Temperature	Thermometer in Data logger	°C	Min 5 °C Max 45 °C
Environmental	Mean Radiant Temperature	Calculated from globe thermometer, thermometer, and air speed sensor measurements in Data logger	°C	Min 5 °C Max 45 °C
Environmental	Relative Humidity	Hygrometer in Data logger	%	Min 0% Max 100%
Environmental	Air Speed	Air speed sensor in Data logger	m/s	Min 0 m/s Max 4 m/s
Personal	Skin Temperature	Infra-red temperature sensor in Thermal Comfort Tablet	°C	Min 20 °C Max 40 °C
Personal	Metabolic Rate	Survey in Thermal Comfort Tablet – 'Describe your activity in the last 15 min in this space.'	Very relaxed activity = 1 MET Relaxed activity = 1.3 MET Light activity = 1.5 MET Moderate activity = 2.5 MET Active activity = 3.3 MET	Min 1 Max 3.3
Personal	Clothing Level	Survey in Thermal Comfort Tablet – 'How are you currently dressed?'	Very light = 1 Light = 2 Moderate = 3 Heavy = 4 Very heavy = 5	Min 1 Max 5
Personal	Health Perception	Survey in Thermal Comfort Tablet – 'How would you describe your health and wellbeing at the moment?'	Very good = 1 Good = 2 Reasonable = 3 Poor = 4 Very poor = 5	Min 1 Max 5

(2) Skin temperature plus the "6PMV" variables, namely dry bulb temperature, radiant temperature, relative humidity, air speed, clothing and metabolic rate;
(3) Skin temperature plus the "6PMV" variables plus the participant's perception about their health.

The modelling process involved the following stages: (1) dataset pre-processing and balancing and (2) model tuning, selection, and evaluation. Anaconda version 2019.3 [73] was used as the package manager to script and run all models using Python version 3.7 and PyTorch tensor library [74].

2.5.1. Dataset pre-processing and balancing

In the 4 individual datasets, the middle category (i.e., 'prefer no change') was more frequently voted for than the extreme categories, resulting in highly imbalanced thermal preference distributions, as seen in Fig. 2. Therefore, undersampling was conducted, by randomly removing votes from the majority classes until reaching the size of the minority class. Final individual dataset sizes can be seen in Table 3. The use of undersampling as a balancing strategy has resulted in a reduction of the datasets' sizes. Although other balancing strategies such as oversampling or SMOTE (Synthetic Minority Oversampling Technique) [75] could have avoided the decrease in sample size, they are more likely to lead to model overfitting [76], and were, therefore, not chosen in the current study.

Nevertheless, although larger sample sizes might allow a better statistical representation of the data, other similar studies on personal thermal comfort models using machine learning techniques have reported minimum datasets of 30–90 datapoints for maximum predictive performance [15,27,67,77,78], which is in line with the average dataset sizes used in this study, as seen in Table 3. Considering personal models using ANNs specifically, Shan, et al. (2018) [12] reported an average accuracy of 89.2%, and an average MSE (Mean Standard Error) of 0.06 using 150 datapoints per model, while Kim (2018) [21] reported an average MSE of 0.0029 using 26 to 133 datapoints per model, supporting the data sizes of the current study. Furthermore, k-fold cross validation, detailed in the next section, was used to avoid the drawbacks due to limited sample sizes.

The categories were also coded from 0 to 2, where 0 corresponded to the 'prefer to be cooler' class, 1 the 'prefer no change' class and 2 the 'prefer to be warmer' class. Finally, the input variables were normalized to a single range from 0 to 1, using minimum and maximum values according to Table 2.

2.5.2. Model tuning, selection, and evaluation

Hyperparameters are settings used to control the model's behaviour and capacity [65]. To choose the optimal set of hyperparameters, model tuning was conducted. The first step of model tuning consisted of dividing the datasets into three separate subsets. The training set is the subset of data points used for learning (i.e., fitting the internal coefficients of the classifier). The validation set is the dataset used to guide the selection of the hyperparameters. The testing set is an independent subset of examples used to assess the performance of a fully trained model, evaluating the model with data it has never seen before [79].

First, each participant's total datasets were randomly split into training and testing sets, with at least 5 votes in each thermal preference class for training and at least 1 vote for each class for testing. The training set was then divided into two subsets to allow 5-fold cross validation, with at least 4 votes per class for the training set and at least 1 vote per class for the validation set. Five-fold cross-validation was chosen such that each training/validation group of data samples were large enough to be a representative of the total dataset, while small enough to allow modelling for participants with low vote counts. Stratified cross-validation was repeated 5 times to reduce the noise in the model performance between different cross validation splits.

After the validation-train-test split, the next step involved the imputation of missing values for skin temperature. This involved inputting values to substitute outliers and measurement errors from the second data collection period as well as missing values from the first data collection period. The K-Nearest-Neighbours technique was used due to its low complexity, robustness and frequent use in machine learning related approaches [80,81]. An optimal value of $k = 5$ was used for the imputation.

The next step of model tuning involved training the models, varying three main hyperparameters according to common practice in machine learning studies [80]. The learning rate was varied from 0.001 to 0.01 to 0.1. The number of hidden neurons in the hidden

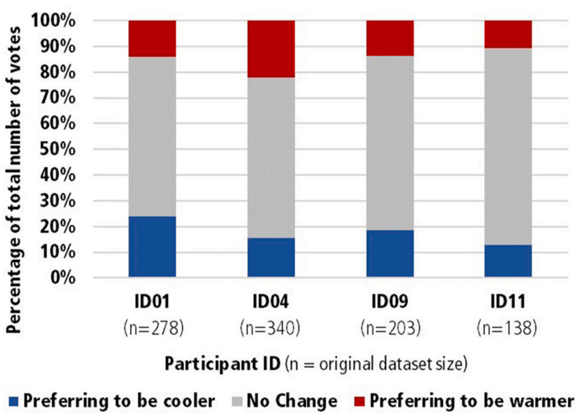


Fig. 2. Percentage of total number of votes of each thermal preference category, for each participant's original dataset.

Table 3
Predictive performance of Weighted Least Squares Regression (WLS), Converted Predicted Mean Vote (PMV_C) and Personal Comfort Models (PCM) with different input variables. The best AUCs (Area Under the Receiver Operating Characteristic Curve) for each participant across model types are highlighted in bold.

	Dataset size (balanced)			WLS[a]			PMV_C[a]			PCM[a]								
				Input variables: Skin Temp.			Input variables: 6PMV[a]			Input variables: Skin Temp.			Input variables: 6PMV[a] + Skin Temp.			Input variables: 6PMV[a] + Health + Skin Temp.		
ID	Training	Testing	Total	Acc[a] (%)	Cohen's Kappa (%)	AUC[a]	Acc[a] (%)	Cohen's Kappa (%)	AUC[a]	Acc[a] (%)	Cohen's Kappa (%)	AUC[a]	Acc[a] (%)	Cohen's Kappa (%)	AUC[a]	Acc[a] (%)	Cohen's Kappa (%)	AUC[a]
1	90	27	117	33.33	00.00	0.50	48.15	22.22	0.61	55.56	33.33	**0.71**	59.26	38.89	0.69	48.15	22.22	0.69
4	120	39	159	43.59	15.38	0.58	53.85	30.77	0.65	43.59	15.38	0.50	71.79	57.69	**0.87**	74.36	61.54	0.84
9	60	24	84	33.33	00.00	0.50	50.00	25.00	0.63	33.33	00.00	0.50	62.50	43.75	**0.72**	54.17	31.25	0.71
11	30	15	45	46.67	20.00	0.60	53.33	30.00	0.65	66.67	50.00	0.75	73.33	60.00	**0.79**	73.33	60.00	0.77
	Mean			39.23	8.85	0.54	51.33	27.00	0.63	49.79	24.68	0.62	66.72	50.08	0.77	62.50	43.75	0.75

[a] WLS = Weighted Least Squares Regression; PMV_C = Converted Predicted Mean Vote; PCM = Personal Comfort Model; 6PMV = dry bulb temperature, radiant temperature, relative humidity, air speed, metabolic rate, and clothing level; Acc = accuracy; AUC = Area Under the Receiver Operating Characteristic Curve.

layer of the model was varied between 4, 5 and 6. Lastly, the batch size was varied between 2 and 8 data points.

The models were trained using an input layer, a single hidden layer, and an output layer. In order to go from one layer to the next, the neurons compute a weighted sum of their inputs from the previous layer (Equations 1 and 3) and pass the result through a non-linear function, called the activation function [82]. The models in this study used Rectified Linear Unit (ReLU) [83] as the activation function between the input layer and the hidden layer (Equation (2)) and Softmax as the activation function between the hidden layer and the output layer (Equation (4)). The mathematical expressions of the models can be written in the following form:

$$z_j = \sum_{i=1}^{8} w_{ij} \cdot x_i + b_j \tag{1}$$

$$y_j = f(z_j) = \max(0, z_j) \tag{2}$$

$$z_k = \sum_{j=1}^{N_J} w_{jk} \cdot y_j + b_k \tag{3}$$

$$f(\vec{z})_k = \frac{e^{z_k}}{\sum_{o=1}^{3} e^{z_o}} \tag{4}$$

where x_i are the normalized data of the input variables, w_{ij} are the weights between the input and hidden neurons, b_j are the bias values of the hidden neurons, and y_j the output values of the activation functions (ReLU) in the hidden layer; while w_{jk} are the weights between the hidden and output neurons, b_k are the bias values of the output neurons, N_J is the number of hidden neurons, and $f(\vec{z})_k$ are the outputs of the activation functions (Softmax) in the output layer (as probability distributions from 0 to 1 for each class).

The Cross Entropy function was used to measure the error (L_{CE}) of each classification rounds (Equation (5)):

$$L_{CE} = -\sum_{k=1}^{3} t_k \log f(\vec{z})_k \tag{5}$$

where t_k is the target probability for each class, and $f(\vec{z})_k$ is the predicted probability for each class.

Stochastic Gradient Descent was used as the optimizer algorithm to minimize L_{CE}, with a momentum at 0.9 [65].

After each training round, the models' performances were evaluated using the validation set. The performance indicators (detailed in section 2.7.) were then compared, and the hyperparameters associated with the best model performance were chosen (model selection). Next, training and validation sets were merged into one dataset and the best hyperparameter settings from the previous step were used to fit a new model to this larger dataset. Finally, the test set was used to estimate the generalization performance of the model resulted from the previous step (model evaluation) [58]. More details of the modelling methodology used have been previously published [84].

2.6. Conversion of the PMV model for comparison

To allow a further comparison between generalised and individualised models, the PMV index was calculated according to ASHRAE Standard 55–2020 [85] using each participants' testing set. The PMV predictions on a thermal sensation 7-point-scale were transformed to a 3-point thermal preference scale to enable a direct comparison with the personal thermal preference models. When PMV <-0.5 (i.e., less than 'slightly cool' to 'cold'), the votes were labelled as 'preferring to be warmer'; when $-0.5 <$ PMV <0.5 (i.e., 'neutral'), the votes were labelled as 'no change'; and when PMV >0.5 (i.e., more than 'slightly warm' to 'hot'), the votes were labelled as 'preferring to be cooler'. The ± 0.5 cut-offs represent the recommended limits for a 10% Predicted Percentage of Dissatisfied (PPD), as prescribed by ASHRAE Standard 55–2020 [85]. The transformed PMV index is referred to in this paper as PMV_C.

2.7. Performance indicators

The performance indicators used during the personal comfort models' tuning and evaluation, as well as when comparing them with the weighted linear regression model and the PMV_C model, were the Accuracy, the Cohen's Kappa Coefficient, and the Area Under the Receiver Operating Characteristic Curve (AUC).

Accuracy was calculated by dividing the number of correct predictions by the total number of predictions. The Cohen's Kappa Coefficient (K) [86] was calculated using Equation (6) and compensates the measurement of accuracy, by taking into account the agreements that can be attributed to random chance. It ranges from negative values to 1, where 1 means perfect agreement, 0 means no agreement other than what would be expected by chance, and negative values mean the agreement is worse than random. In this paper, the accuracy and the Cohen's Kappa Coefficients are presented in percentages.

$$\mathrm{K} = \frac{(\mathrm{p}_o - \mathrm{p}_e)}{(1 - \mathrm{p}_e)} \tag{6}$$

where p_o is the accuracy measure, and p_e is the hypothetical probability of a chance agreement.

To calculate the AUC, first, the Receiver Operating Characteristic Curve (ROC) was built by plotting the probability of a true positive versus the probability of a false positive rate for all possible discrimination thresholds, for each of the three thermal preference classes using the 'one versus the rest' method. Equations 7 and 8 define the true positive rate (*TPR*) and the false positive rate (*FPR*):

$$TPR = \frac{TP}{TP + FN} \tag{7}$$

$$FPR = \frac{FP}{FP + TN} \tag{8}$$

where *TP* (true positive) is the number of positive class correctly predicted in a binary classification model; *FP* (false positive) is the number of positive class incorrectly predicted; *TN* (true negative) is the number of negative class correctly predicted; and *FN* (false negative) is the number of negative class incorrectly predicted.

Then, the area under the ROC was computed for each of the classes and averaged to obtain a single performance indicator. AUC is a measure frequently used in machine learning studies [87] and can vary between 0 and 1, where 0.5 denotes random guessing and 1 indicates perfect agreement. It is important to highlight, however, that the AUC for the weighted linear regression model and for the PMV_C model was calculated using a single pair of probability of true positive rate versus probability of false positive rate, since these models are not probabilistic classifiers and do not allow plotting of more than one discrimination threshold.

The differences between the models' performance, for each model type, were tested for statistical significance using Independent Samples t-tests. The level of statistical significance was set at $p < 0.05$.

3. Results

3.1. Weighted least squares regression analysis

Fig. 3 presents the histogram of hand skin temperature measurements collected during the second monitoring period of the 11 participants. Data outliers were found to be lower than or equal to 22.10 °C, and the mean hand skin temperature after the outliers were removed was 30.58 °C.

According to the regression analysis, among the independent variables tested against skin temperature as the dependent variable, significant relationships were identified between skin temperature and dry bulb temperature, radiant temperature, clothing level and health perception. This was indicated by higher R-squared values (i.e., the coefficient of determination, indicating the percentage of the skin temperature variance that the independent variable explains), statistically significant independent variable coefficients (i.e., $p < 0.05$) and a general visual indication in the raw data scatter plots. The R-squared values, p-values, and raw data scatters, as well as the binned means and corresponding weighted linear regression lines and equations for each analysis are shown in Fig. 4. The variance (R-squared values) of the binned data have increased (because they are now based on the bin-mean values) but still serve as an indicator of comparison between models for exploratory analysis.

When fitting a weighted least squares linear regression model for thermal preference prediction using skin temperature as the predictor, the independent variable coefficient remained statistically significant ($p = 0.001$), validating the model for further analysis. Fig. 5 presents the model fit. The performance of this model in predicting individuals' thermal preferences using the selected participants' testing datasets is presented in Section 3.2.

The box plot of skin temperatures for each of the thermal preference categories, presented in Fig. 6, illustrates the same relationship between skin temperature and thermal preference for the general sample of 11 participants. Nevertheless, when analysing participants' individual box plots, presented in Fig. 7, not only does this relationship differ among individuals, but it is also less evident than the case of the general sample, suggesting that an individualised analysis is required. Among the participants selected for the personal comfort models' analysis, highlighted in grey in Fig. 7, ID11 presents the most evident correlation between skin temperature and thermal preference. This is indicated by skin temperature medians and means for each thermal preference category at distinctively different levels and in a linear descending order from 'prefer to be cooler' through to 'prefer to be warmer'. The plots also show considerable range variations in skin temperatures across participants, emphasizing once again a need for a more individualised level of analysis.

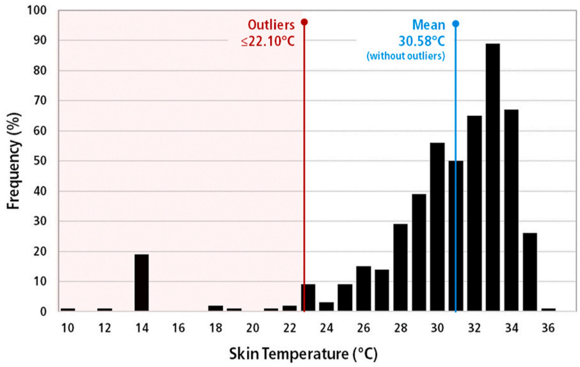


Fig. 3. Histogram of skin temperature measurements with indication of outliers identified.

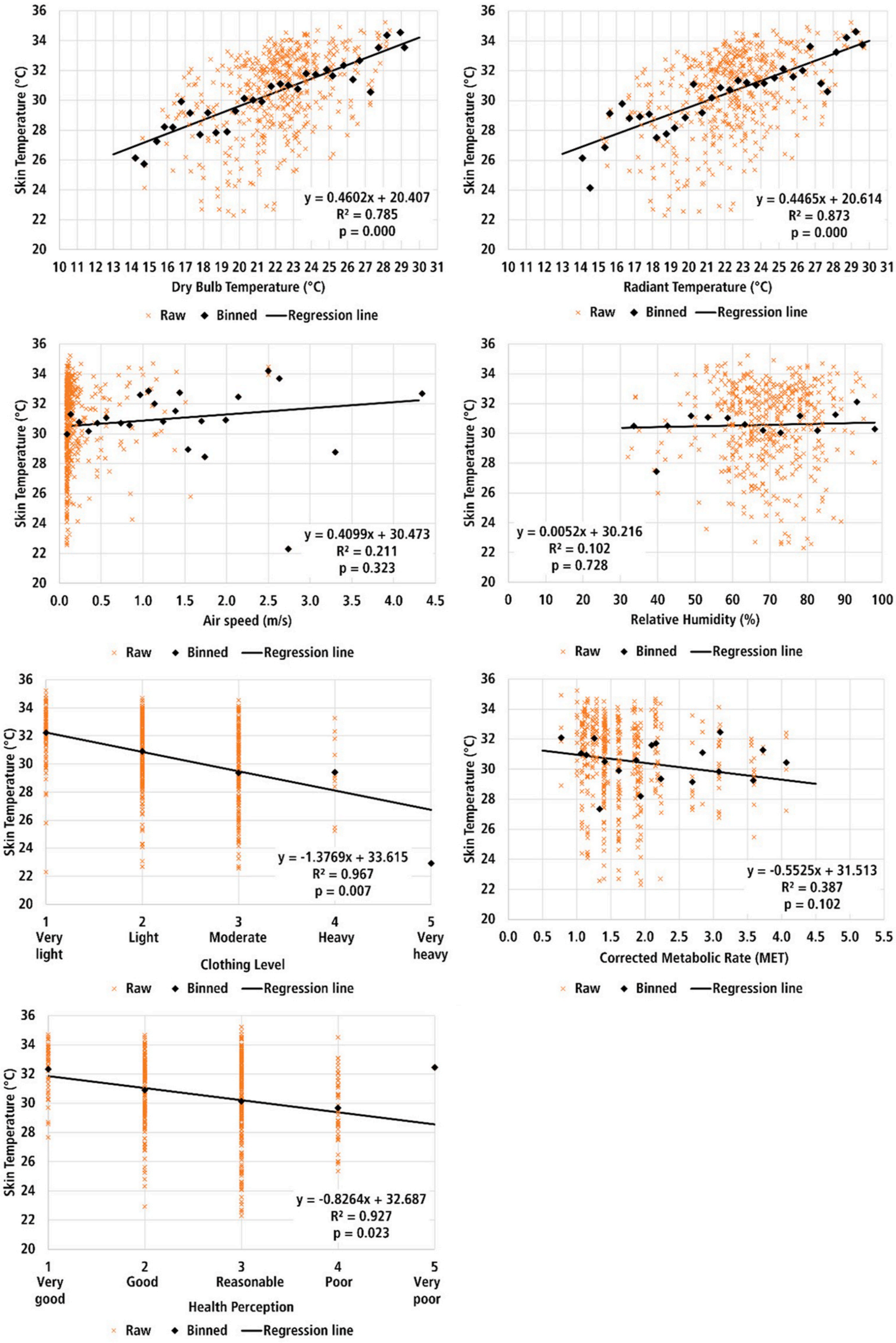


Fig. 4. Regression analysis between skin temperature and dry bulb temperature, radiant temperature, air speed, relative humidity, clothing level, corrected metabolic rate and health perception.

3.2. Personal thermal comfort models and comparison between approaches

Table 3 presents a summary of the predictive performance of the weighted least squares regression model (WLS), the converted predicted mean vote model (PMV_C) and the personal comfort models (PCM) using the 3 different input combinations. The predictive performance is presented as the Accuracy, Cohen's Kappa Coefficient and AUC for the testing dataset (i.e., the 'never-before-seen'

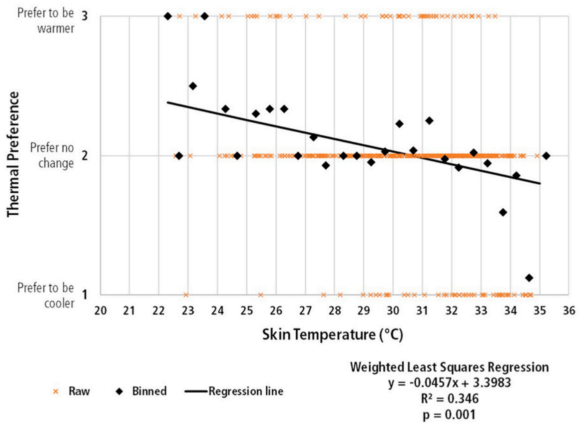


Fig. 5. Weighted Least Squares Regression model for thermal preference prediction using skin temperature.

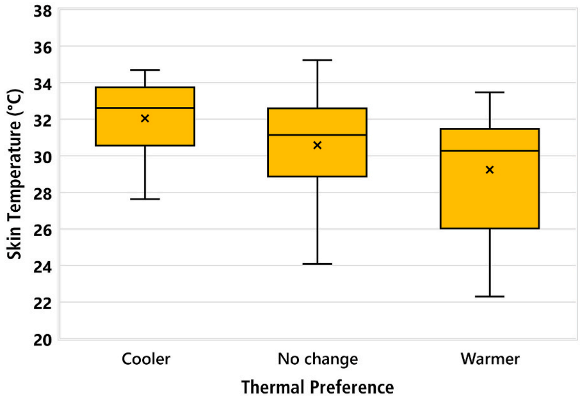


Fig. 6. Box plot of skin temperature for each thermal preference category, for all participants (n = 470).

dataset) of each participant.

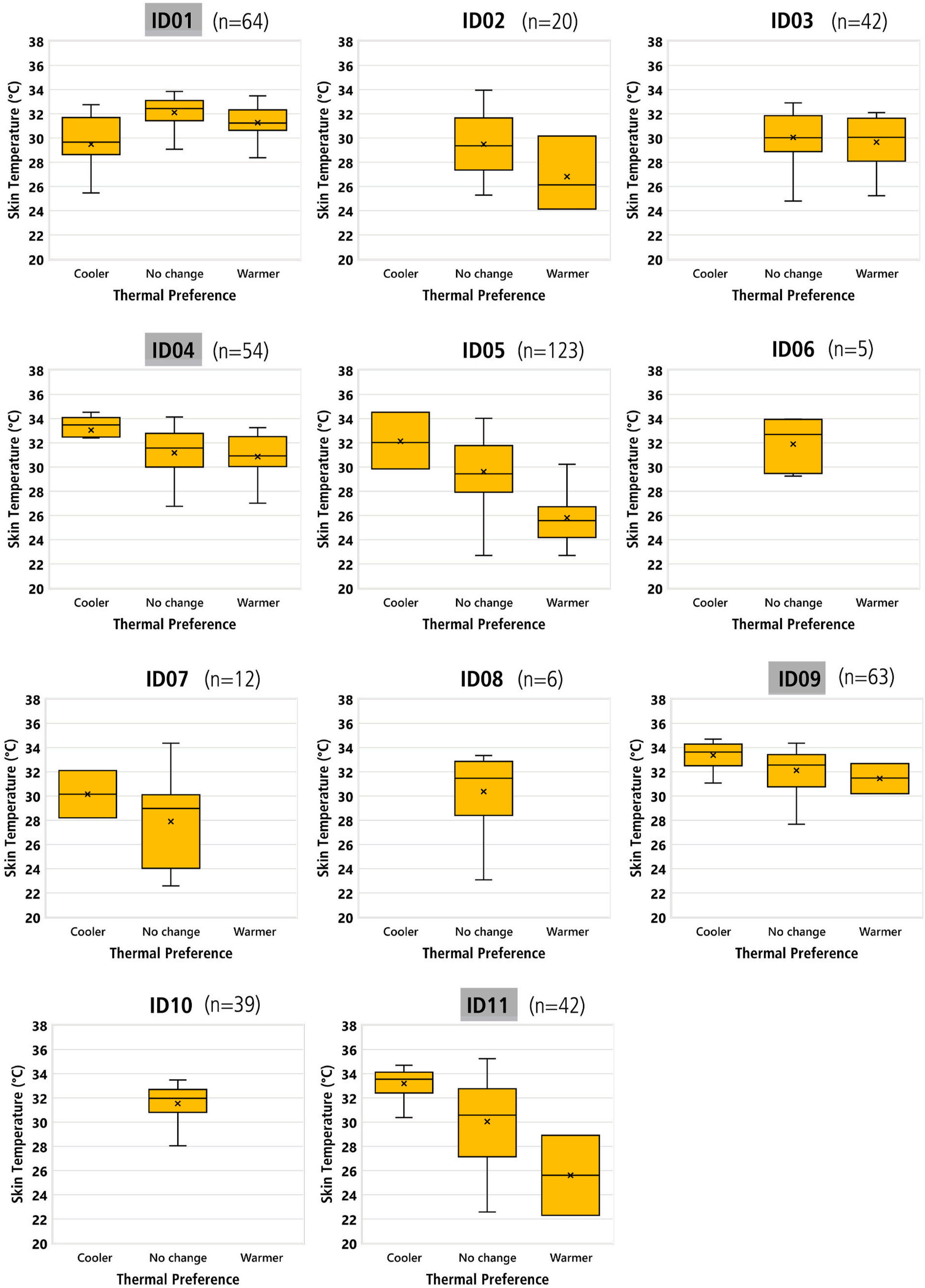
The accuracy of the personal thermal comfort models using skin temperature alone as the single predictor ranged from 33.33% to 66.67%, with a mean of 49.79%. The Cohen's Kappa indicator ranged from 0.00% to 50.00%, with a mean of 24.68%, and the AUC ranged from 0.5 to 0.75, with a mean of 0.62. These indicators suggest a relatively low performance, especially when considering individual AUC performances lower than 0.5 (i.e., worse than random guessing).

When adding dry bulb temperature, radiant temperature, relative humidity, and air speed (i.e., environmental factors) and the metabolic rate and clothing level (i.e., behavioural factors) – the combination called in this paper the 6PMV variables –, the individual models' performance increased, especially for ID04 and ID09, but not for ID01. The average accuracy increased to 66.72%, the average Cohen's Kappa to 50.08% and the average AUC to 0.77. These results are also similar to related studies, such as the work of Liu et al. (2019) [30], which reported an average Cohen's Kappa indicator of 24%, accuracy of 78% and AUC of 0.79 among a set personal models using physiological and environmental data.

Including health perception produces a slight decline in the average and individual models' performance indicators. This difference in averages, however, is not statistically significant ($p > 0.05$). With the inclusion of health perception as a predictor, the personal comfort models presented an average accuracy of 62.50%, an average Cohen's Kappa Coefficient of 43.75% and an average AUC of 0.75. From these results, the best performing personal thermal comfort models were the ones using physiological, environmental, and behavioural input variables.

When analysing the generalised models, on average, the PMV_C model predicted individual thermal preferences with an accuracy of 51.33%, a Cohen's Kappa indicator of 27.00%, and an AUC of 0.63. The WLS model presented an even lower performance, with a mean accuracy of 39.23%, a mean Cohen's Kappa of 8.85%, and a mean AUC of 0.54 (i.e., slightly better than random guessing). On average, therefore, this represents a superior predictive performance of the individualised models using both environmental and personal variables when compared with the generalised approaches, as represented by Fig. 8. These differences in mean predictive performance are statistically significant ($p < 0.05$).

It is also evident in Fig. 8 that ID04 and ID09's personal thermal models using only skin temperature underperformed, even when compared with the generalised models. Exploring in more detail these lower performances, Fig. 9 shows the probability density of the distributions of the thermal preference categories depending on the 8 input variables involved in the study, built using Kernel Density



(caption on next page)

Fig. 7. Box plots of skin temperatures for each thermal preference category, for each individual participant. Selected participants for personal thermal comfort modelling are highlighted in grey.

Estimation (KDE) [88]. When thermal preference categories have overlapping areas in these density plots, it suggests a participant is likely to prefer different thermal conditions when experiencing the same environmental conditions or having the same skin temperatures. Therefore, overlapping areas can represent the presence of events that are harder for the models to distinguish and predict. When analysing the density plots for skin temperature for ID04 and ID09, it is evident from the overlapping areas that adding this single variable as a predictor of thermal preference might not be ideal for them and could potentially compromise the models' predictive performance. ID11, on the other hand, has many fewer overlapping density regions for skin temperature, which could explain the higher performance of the personal model using this predictor. The skin temperature influence on thermal preference for ID11 has already been indicated by the box plot in Fig. 7.

The density plots can also help explain the relatively low impact that the health perception variable had on all individual models. Furthermore, it is noted that the four participants analysed in detail, although having varying health perception throughout the monitoring study, were either not frail or had low levels of frailty (as presented in Table 1), which could have limited the range and variability of the data collected related to health and wellbeing perception. The quality of data could also have been affected by the self-reported nature of the health assessment. Finally, although health perception could have impacted these participants' thermal preference, the weight of the other input variables certainly prevailed. This is evident for ID04 and ID09, for which the environmental factors played a much more distinguishable role in the models. In addition, it is possible to extract from the plots the reason for the higher impact that adding environmental factors such as dry bulb and radiant temperatures had for ID04 and ID09 than it had for ID01.

When analysing how well the personal comfort models and generalised alternatives predict each of the three thermal preference categories, shown in Fig. 10, the results suggest different misclassification patterns for each modelling method. The personal comfort models tended to present a higher predictive performance for 'prefer to be cooler' and 'prefer to be warmer' than for 'prefer to be neutral'. This meant that a preference for no change was being misclassified as preferring change more frequently than other possible misclassification options, which, in real scenarios where the models are used to control cooling and heating systems, would mean increasing the probability of unnecessarily cooling or heating the occupant's space. The generalised WLS model, however, presented the opposite tendency. This model's power for predicting the central category ('prefer no change') was generally better than its power for predicting the extremity classes ('prefer to be cooler' and 'prefer to be warmer'). This meant that a preference for change was misclassified as either preferring no change or preferring change in the wrong direction, more frequently than other possible misclassification options, which, in real scenarios, would mean leaving occupants either unattended during extreme events, or even more dissatisfied.

4. Discussion

The results of this study show that personal thermal comfort models can be considered appropriate tools to predict older people's thermal preferences, outperforming generalised approaches such as the PMV_C or a weighted regression model driven by skin temperature. It is also evident that, although to different degrees for each individual, hand skin temperature can be an indicator of thermal preferences for the cohort analysed. In addition, combining this physiological measurement with other environmental factors, especially air temperature and radiant temperature, along with behavioural factors, such as clothing level, has been proven to be beneficial for the model's predictive performance, although the best predictor combination may differ across individual older adults.

The key next step would be merging the following elements:

(1) physiological sensing technologies for **data collection**;
(2) individualised predicting models for **evaluation and decision-making**;
(3) and wearable comfort systems for **autonomous and automatic action.**

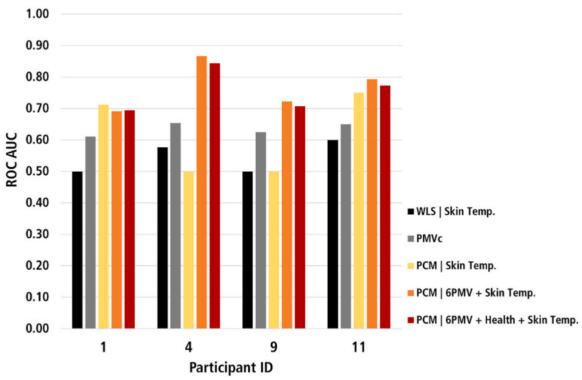


Fig. 8. Comparison between AUC for different models.

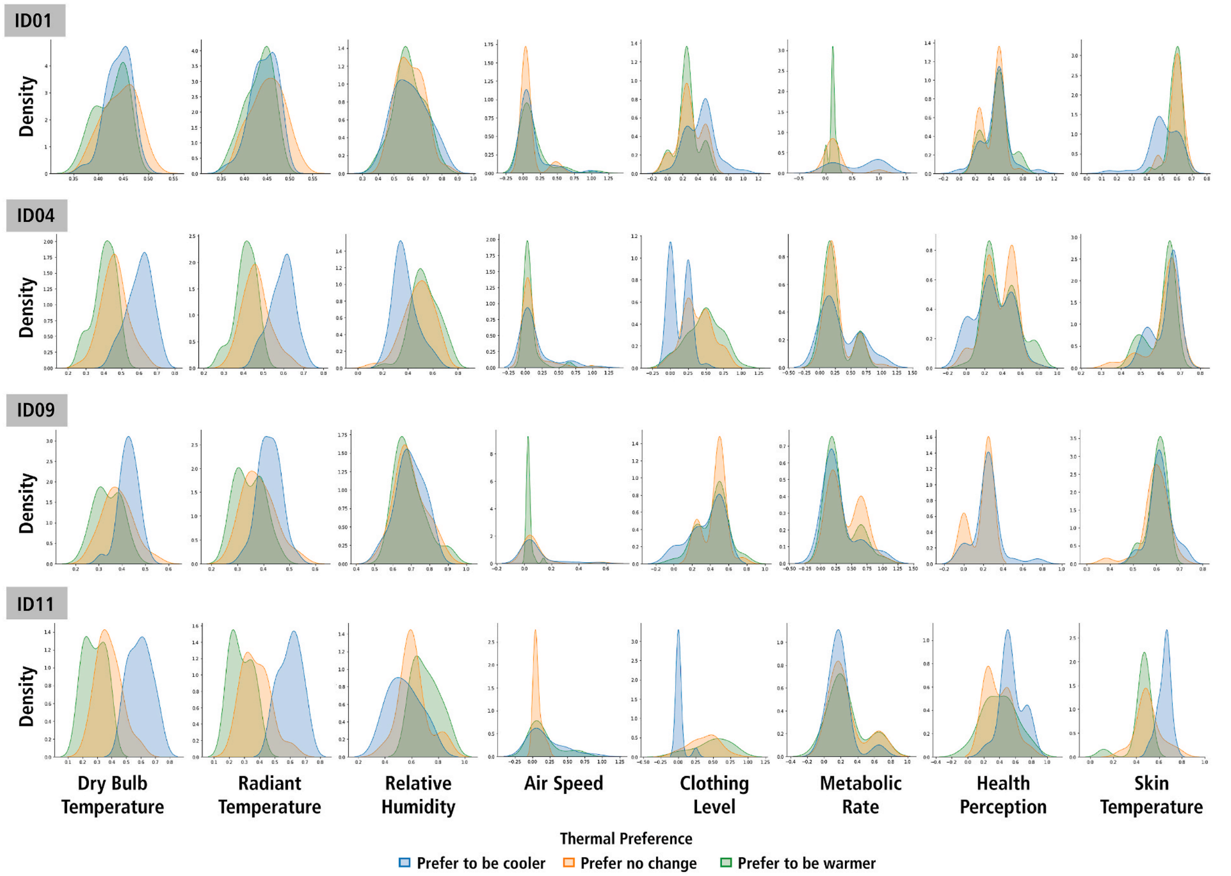


Fig. 9. Density plots for input variables used, for each thermal preference category, for each participant. Variables are normalized from 0 to 1, according to maximums and minimums presented in Table 2.

As physiological sensing could collect real-time proxy for comfort without the need for occupant feedback, individualised models could use this real-time proxy to allow more reliable predictions for change, and pass them to wearable actuators, which, in turn, could enable direct conditioning without the need for any manual activation. Although it could be beneficial for all ages, this automation process would particularly be relevant for older adults, enabling thermal comfort management without reliance on others, which is key for older people maintaining independence in their own homes.

Physiological sensing devices have been researched extensively over the last decades, with a wide range already available on the market. Sensors mounted on smart watches are one of the main solutions for physiological and environmental sensing in real time [89, 90]. On the other hand, heated clothing (e.g., gloves, socks, vests), neck and shoulder fans (also called wearable air-conditioning) [91], or heating or cooling wrist-bands [92] are common options for wearable actuators. Nevertheless, although hypothesized [30], combining the 3 facets, i.e., wearable sensing (data collection), prediction (evaluation) and conditioning (autonomous and automatic action), in a single solution is yet to be explored. In addition, these independent products tend to target a general and relatively homogeneous population, without considering the specific thermal comfort requirements and associated physiological responses of older people.

Nevertheless, it is important to highlight that the use of personal thermal comfort models, using not only physiological variables but also any type of input variable, requires non-interrupted and ideally infinite data collection, as well as constant update and re-learning to maintain accuracy and relevance through time for each individual. Furthermore, a wide range of thermal and situational conditions are essential to create enough deviations in the data collected to allow a balanced dataset and a statistically accurate and reliable analysis. Although real-time thermal comfort proxy data collection is currently being explored in studies involving personal comfort systems (PCS) [67], these requirements involving data size and structure, related directly to how data is collected, remain the main challenge of personal comfort models. Further efforts on solving these data collection requirements are needed in order to move personal comfort models from a mere research methodology paradigm to a real practical solution, feasible to be deployed.

Another point of consideration is that the monitoring of physiological factors, either through the use of wearable devices or non-contact sensors such as the ones used in this study, poses additional cost and data privacy concerns in comparison with stand-alone environmental sensors, as already highlighted by Aryal and Becerik-Gerber (2019) [23]. Choosing the best combination of inputs for the personal models relies, therefore, not only on the type of measurements' impact on predictive performance, but also on

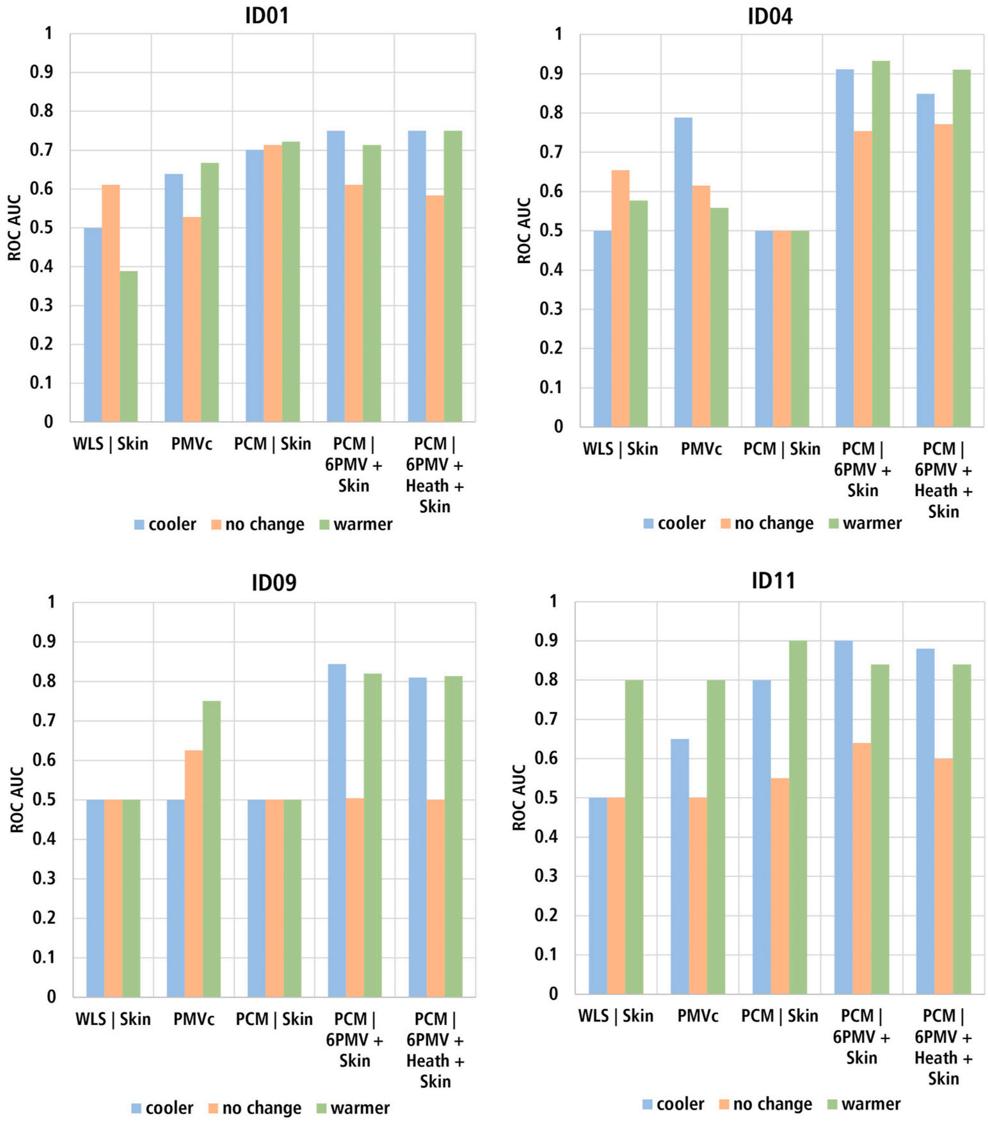


Fig. 10. Models' predictive performance for each thermal preference category, for each participant.

individuals' capability to afford the sensing and privacy costs. In addition, despite recent efforts to decrease the intrusiveness of sensor data collection by using wearable devices or PCS [26,30,67], personalised modelling would still require initial occupant feedback on their thermal preferences to allow minimum model training. Although the disruptions caused by monitoring would be an issue for all age cohorts, they may introduce additional barriers for frailer older adults' participation.

Furthermore, this study highlighted an important modelling limitation, still not entirely explored by studies on personal thermal comfort, which is the misclassification cost of thermal preference in general and specifically for older adults. The misclassification of each thermal preference category may represent different application consequences in real scenarios. While unnecessarily cooling or heating an occupant's space by misclassifying a preference for no change may result in an increase in energy use, leaving occupants unattended during extreme events by misclassifying a preference for change could result in heat related illnesses. In this context, not only are these misclassification costs complex to estimate, but they also involve different domains (e.g., energy use costs versus health costs). Applying different weights for each type of misclassification is potentially a more appropriate way to measure thermal preference models' performance than any of the indicators used so far (e.g., accuracy, Cohen's Kappa Coefficient or AUC). Lee et al. (2019) [78], for instance, have presented an alternative for generic metrics. Although they did not determine the exact cost for each case of misclassification, they estimated the cost ratio between cases. By assessing three cost matrices, a thermal satisfaction oriented, an energy-saving oriented and an equally weighted cost matrix, the authors explored different domains of cost (i.e., energy cost versus comfort cost) and highlighted that, apart from predictive performances, selecting the optimal model would depend on the intended application. The principles applied by the authors are in line with a sub-field of machine learning called cost-sensitive learning [93], and could be further investigated in future studies to deal with the un-even costs of thermal preference misclassification. Moreover, further studies should analyse whether the thermal preference misclassification costs differ between younger and older adults, considering the health, living and financial arrangements of each cohort.

5. Limitations and future studies

It is important to highlight that this study has limitations. Firstly, the data collection involving skin temperature was conducted between the months of September and February, covering only a warm and hot season in South Australia. Further data collection periods in cool and cold seasons are required to allow a broader understanding of the effects of thermal exposures on the skin temperature of older adults.

Secondly, although field studies provide a more accurate representation of reality than controlled climate chamber experiments, their use in this study also posed challenges to dataset sizes and distributions. Monitoring real thermal environments, where conditions vary without the influence of researchers, naturally resulted in imbalanced datasets, impacting the dataset sizes available for modelling, especially once undersampling was conducted. The authors, therefore, acknowledge the relevance of exploring the development of personal thermal comfort models under imbalanced dataset scenarios, especially considering the likelihood of these scenarios in thermal comfort field research. Furthermore, future studies by the authors plan to address other balancing strategies and overfitting reduction (e.g., dropout or batch regularization) in order to investigate the effectiveness of different sampling techniques in this specific context.

It is also noteworthy that the first data collection period was concluded in October 2019, before the declaration of COVID-19 as a pandemic in March 2020, and was not affected by the pandemic. The second data collection period, on the other hand, happened between September 2020 and February 2021. During this period, however, the State of South Australia implemented a strict response plan, which resulted in a relative low number of reported COVID-19 cases. In addition, none of the participants reported contracting the disease during or before this data collection. Normal activities, including research visits within the State were largely unaffected. Hence, the impacts of the pandemic on the data size or quality (especially related to health perception) were considered minimal by the authors. Nevertheless, an in-depth analysis of the effects of the pandemic on the cohort could be part of the scope of future studies.

Furthermore, although the older participants involved in this study represent a diverse cohort in terms of body composition, health and living environment, other socio-cultural and economic factors need to be addressed to build a more holistic image of their diversity. Moreover, the four participants whose individual dataset sizes allowed the development of personal thermal comfort models happened to be all female. The development of individual models for males is, therefore, required in future studies. In addition, although the models involve different environmental and personal inputs, other relevant input variables could be explored, such as seasonal thermal expectations or other physiological data, such as heart rates. Moreover, given the nature of the study, only self-reported health perceptions were used as inputs, which might lack the accuracy of records from healthcare providers.

Regarding the modelling methodology, it is important to highlight that the binning approach used for continuous variables in the weighted regression estimation can result in loss of information, depending on the granularity of the increments chosen. In addition, the use of k-Nearest-Neighbours for missing value imputation can impact the overall data structure and further studies are required to analyse the risk of distorting estimates despite an apparent optimal performance on other quality metrics. The impact of missing value imputation using data across two separate collection periods, although considered minimal in this study, should also be further analysed. Furthermore, other normalization techniques and standardization techniques could have been applied to determine the central tendency of the ordinal (and discrete) variables used in the models. Further studies will be developed by the authors to comprise not only different pre-processing techniques according to variable type, but also other methods for ordinal variable encoding.

Finally, the PMV scale conversion conducted in this study poses limitations in the comparisons, since thermal sensation and thermal preference scales cannot be considered interchangeable for all individuals. While neutral sensation and thermal preference for no change can be experienced simultaneously, it is still necessary to account for preferred sensations other than neutral. An alternative could be analysing different conversion rules for each individual participant, depending on their thermal sensation and thermal preference answers.

6. Conclusion

This paper presents an individualised modelling approach to predict older adults' thermal preferences in their living environments, based on environmental, physiological, and behavioural data, comparing the models' predictive performance with conventional aggregate modelling methods. From the analysis conducted, the study has pointed to the following findings and future pathways:

- When analysing the aggregate dataset, strong relationships were identified between skin temperature and dry bulb temperature, radiant temperature, clothing level and health perception for the older adults involved.
- Fitting a weighted least squares regression model for thermal preference prediction using skin temperature as the single predictor resulted in a R-squared value of 0.346 and a statistically significant independent variable coefficient ($p = 0.001$).
- On average, the PMV_C model predicted individual thermal preferences with an accuracy of 51.33%, a Cohen's Kappa indicator of 27.00%, and an AUC of 0.63. The WLS model presented a lower performance, with a mean accuracy of 39.23%, a mean Cohen's Kappa of 8.85%, and a mean AUC of 0.54.
- On average, the personal thermal comfort models using skin temperature as the single predictor showed an accuracy of 49.79%, a Cohen's Kappa indicator of 24.68%, an AUC of 0.62.
- When skin temperature data are combined with dry bulb temperature, radiant temperature, relative humidity, air speed (i.e., environmental factors), metabolic rate and clothing level (i.e., behavioural factors), the average accuracy of the prediction

increased to 66.72%, the average Cohen's Kappa to 50.08% and the average AUC to 0.77. This represents a superior predictive performance of the individualised models, using both environmental and personal variables, when compared with the generalised approaches.

- Including health perception as an input variable represents a slight decline in the average model's performance, but this difference is not statistically significant ($p > 0.05$).
- The results suggested different misclassification patterns for each modelling method and require further investigation into thermal preference misclassification costs in the context of older adults.

The key next step would be to combine physiological sensing technologies, individualised predicting models and wearable comfort systems. Although it would be beneficial for all ages, this automation process could be particularly relevant to assist older adults to maintain independence in their own homes.

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CRediT authorship contribution statement

Larissa Arakawa Martins: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Veronica Soebarto:** Conceptualization, Validation, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Terence Williamson:** Conceptualization, Software, Validation, Investigation, Data curation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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B. Ethics approval

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RESEARCH SERVICES
OFFICE OF RESEARCH ETHICS, COMPLIANCE AND INTEGRITY
THE UNIVERSITY OF ADELAIDE

LEVEL 4, RUNDLE MALL PLAZA
50 RUNDLE MALL
ADELAIDE SA 5000 AUSTRALIA

TELEPHONE +61 8 8313 5137
FACSIMILE +61 8 8313 3700
EMAIL hrec@adelaide.edu.au

CRICOS Provider Number 00123M

Our reference 32729

07 March 2018

Professor Veronica Soebarto
School of Architecture & Built Environment

Dear Professor Soebarto

ETHICS APPROVAL No:	H-2018-042
PROJECT TITLE:	Improving the thermal environment of housing for older Australians

The ethics application for the above project has been reviewed by the Human Research Ethics Committee and is deemed to meet the requirements of the *National Statement on Ethical Conduct in Human Research (2007)*.

You are authorised to commence your research on:	07/03/2018
The ethics expiry date for this project is:	31/03/2021

NAMED INVESTIGATORS:

Chief Investigator:	Professor Veronica Soebarto
Associate Investigator:	Professor Dino Pisaniello
Associate Investigator:	Dr Alana Hansen
Associate Investigator:	Professor Terence Williamson
Associate Investigator:	Associate Professor Jian Zuo
Associate Investigator:	Professor Renuka Visvanathan
Associate Investigator:	Dr Helen Bennetts
Associate Investigator:	Professor Joost van Hoof

CONDITIONS OF APPROVAL: Thank you for the detailed response dated 23.2.18 and 2.3.18 to the matters raised by the Committee.

Ethics approval is granted for three years and is subject to satisfactory annual reporting. The form titled Annual Report on Project Status is to be used when reporting annual progress and project completion and can be downloaded at http://www.adelaide.edu.au/research-services/oreci/human/reporting/. Prior to expiry, ethics approval may be extended for a further period.

Participants in the study are to be given a copy of the information sheet and the signed consent form to retain. It is also a condition of approval that you immediately report anything which might warrant review of ethical approval including:

- serious or unexpected adverse effects on participants,
- previously unforeseen events which might affect continued ethical acceptability of the project,
- proposed changes to the protocol or project investigators; and
- the project is discontinued before the expected date of completion.

Yours sincerely,

Professor Paul Delfabbro
Convenor

The University of Adelaide

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THE UNIVERSITY OF ADELAIDE

LEVEL 4, RUNDLE MALL PLAZA
50 RUNDLE MALL
ADELAIDE SA 5000 AUSTRALIA

TELEPHONE +61 8 8313 5137
FACSIMILE +61 8 8313 3700
EMAIL hrec@adelaide.edu.au

CRICOS Provider Number 00123M

Our reference 32729

31 July 2019

Professor Veronica Soebarto
School of Architecture & Built Environment

Dear Professor Soebarto

ETHICS APPROVAL No: H-2018-042
PROJECT TITLE: Improving the thermal environment of housing for older Australians

Thank you for providing the amended application dated the 31st of July 2019. The request to include an additional questionnaire and body composition testing with the consent of participants has been approved

The ethics amendment for the above project has been reviewed by the Human Research Ethics Committee and is deemed to meet the requirements of the *National Statement on Ethical Conduct in Human Research 2007 (Updated 2018)*.

You are authorised to commence your research on: 07/03/2018
The ethics expiry date for this project is: 31/03/2021

NAMED INVESTIGATORS:

Chief Investigator:	Professor Veronica Soebarto
Associate Investigator:	Professor Dino Pisaniello
Associate Investigator:	Dr Alana Hansen
Associate Investigator:	Professor Terence Williamson
Associate Investigator:	Professor Jian Zuo
Associate Investigator:	Professor Renuka Visvanathan
Associate Investigator:	Dr Helen Bennetts
Associate Investigator:	Professor Joost van Hoof
Student - Postgraduate Doctorate by Research (PhD):	Miss Larissa Arakawa Martins

Ethics approval is granted for three years and is subject to satisfactory annual reporting. The form titled Annual Report on Project Status is to be used when reporting annual progress and project completion and can be downloaded at http://www.adelaide.edu.au/research-services/oreci/human/reporting/. Prior to expiry, ethics approval may be extended for a further period.

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- previously unforeseen events which might affect continued ethical acceptability of the project,
- proposed changes to the protocol or project investigators; and
- the project is discontinued before the expected date of completion.

Yours sincerely,

The University of Adelaide

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THE UNIVERSITY OF ADELAIDE

LEVEL 4, RUNDLE MALL PLAZA
50 RUNDLE MALL
ADELAIDE SA 5000 AUSTRALIA

TELEPHONE +61 8 8313 5137
FACSIMILE +61 8 8313 3700
EMAIL hrec@adelaide.edu.au

CRICOS Provider Number 00123M

Our reference 32729

09 September 2020

Professor Veronica Soebarto
School of Architecture & Built Environment

Dear Professor Soebarto

ETHICS APPROVAL No: H-2018-042
PROJECT TITLE: Improving the thermal environment of housing for older Australians

Thank you for the revised version of your amended ethics application, submitted on the 7th of September 2020, for the addition of a skin-temperature sensor test to be appended to the follow-up study. This amendment has been approved.

The ethics amendment for the above project has been reviewed by the Human Research Ethics Committee and is deemed to meet the requirements of the *National Statement on Ethical Conduct in Human Research 2007 (Updated 2018)*.

You are authorised to commence your research on: 07/03/2018
The ethics expiry date for this project is: 31/03/2022

NAMED INVESTIGATORS:

Chief Investigator:	Professor Veronica Soebarto
Associate Investigator:	Professor Dino Pisaniello
Associate Investigator:	Dr Alana Hansen
Associate Investigator:	Professor Terence Williamson
Associate Investigator:	Professor Jian Zuo
Associate Investigator:	Professor Renuka Visvanathan
Associate Investigator:	Dr Helen Bennetts
Associate Investigator:	Professor Joost van Hoof
Student - Postgraduate Doctorate by Research (PhD):	Miss Larissa Arakawa Martins

Ethics approval is granted for three years and is subject to satisfactory annual reporting. The form titled Annual Report on Project Status is to be used when reporting annual progress and project completion and can be downloaded at http://www.adelaide.edu.au/research-services/oreci/human/reporting/. Prior to expiry, ethics approval may be extended for a further period.

Participants in the study are to be given a copy of the information sheet and the signed consent form to retain. It is also a condition of approval that you immediately report anything which might warrant review of ethical approval including:

- serious or unexpected adverse effects on participants,
- previously unforeseen events which might affect continued ethical acceptability of the project,
- proposed changes to the protocol or project investigators; and
- the project is discontinued before the expected date of completion.

Yours sincerely,

Professor Paul Delfabbro
Convenor

The University of Adelaide

C. Participant consent form

THE UNIVERSITY of ADELAIDE

CONSENT FORM

1. I have read the attached Information Sheet and agree to take part in the following research project:

Title:	**Improving the thermal environment of housing for older Australians**
Ethics Approval Number:	**H-2018-042**

2. I have had the project, so far as it affects me, fully explained to my satisfaction by the research worker. My consent is given freely.
3. I have been given the opportunity to have a member of my family or a friend present while the project was explained to me.
4. Although I understand the purpose of the research project it has also been explained that involvement may not be of any benefit to me.
5. I have been informed that, while information gained during the study may be published, I will not be identified and my personal results will not be divulged.
6. I understand that I am free to withdraw from the project at any time.
7. I agree to the discussion being audio recorded. Yes ☐ No ☐
8. I wish to receive a copy of the discussion. Yes ☐ No ☐
9. I agree to the interior and exterior of my house being photographed. Yes ☐ No ☐
10. I agree to provide my household's energy use records. Yes ☐ No ☐
11. If I am unable to provide information about my household's energy use I agree to give consent to the researcher to obtain such information from my utility company.
    Yes ☐ No ☐
12. I am aware that I should keep a copy of this Consent Form, when completed, and the attached Information Sheet.

Participant to complete:

Name: ____________________ Signature: ______________________ Date: __________

Researcher/Witness to complete:

I have described the nature of the research to ______________________________________
(print name of participant)

and in my opinion she/he understood the explanation.

Signature: _________________ Position: ________________________ Date: __________

D. Participant info sheet

THE UNIVERSITY *of* ADELAIDE

IMPROVING THE THERMAL ENVIRONMENT OF HOUSING FOR OLDER AUSTRALIANS - Household monitoring

The 3-year project funded by the Australian Research Council, *Improving the thermal environment of housing for older Australians* (ARC DP180102019) explores the connection between older people's well-being and the thermal conditions in their homes.

Main aims of project

- To understand the qualities of the living environment of older South Australians.
- To investigate the thermal environment of houses and the occupants' responses and behaviours during hot and cold weather.
- To understand the relationship between weather, the house construction and design, and the occupants' comfort, well-being and home energy use.
- To develop planning, design and operational guidelines to achieve thermal comfort in homes to support older people living independently.

('Older' refers to those aged 65 or over)

To help achieve these aims, we would like to know about the conditions of your house, how you achieve thermal comfort at home, your use of heating and cooling appliances, and how this impacts your energy use (and costs) as well as your health and well-being.

The research team

The project is being undertaken by the School of Architecture and Built Environment together with the School of Public Health from The University of Adelaide in conjunction with a Partner Investigator from The Hague University of Applied Sciences, The Netherlands, and the Director of the Aged and Extended Care Service at The Queen Elizabeth Hospital.

The project has approval from the University of Adelaide Human Research Ethics Committee: Approval number H-2018-042.

Household monitoring

An important aspect of the research is gathering data about the internal conditions (humidity, temperature, air movement) in 60 houses across SA where older people live independently.

The conditions in the homes will be combined with data about the occupants' comfort and their preferences, energy use and bills as well as information on their health and well-being.

The information gathered will be used to recommend to authorities possible economical improvements to houses that allow people to happily age-in-place.

What will I be asked to do?

Interview

Two members of the research team will visit your home to install the data loggers and conduct an interview with you and other members of the household.

The researchers will also collect information about the layout and construction of your house and, with your consent, take photographs of the house.

The interview will take about 30 minutes with questions about how you operate your house (e.g. use of heating and cooling, opening of windows) and your general health and well-being.

With your permission, an audio recording will be made of the interview. Afterwards we can provide a transcribed copy of the interview if you wish.

House monitoring

Following the interview, the researchers will install small data loggers to monitor the thermal conditions in the main living room and main bedroom of your house.

The loggers will record the conditions every 30 minutes, for up to 9 months covering a period of summer, winter and an in-between season.

Data loggers

The data logger to be placed in your main living room will look like the one illustrated in Figure 1.

The round ball (size of a ping pong ball) is to measure radiant temperature, and the small stick (as long as a pen) is to measure the air speed in the room. Other sensors will measure humidity, air temperature, VOC, CO and CO_2.

The loggers are battery operated and do not require any external connections and pose no health risks that we are aware of. To illustrate how small the data logger is relative to your furniture, please see Figure 2 for an example. The logger is the one on the corner table between the couches.

This logger needs to stay in the living room for the entire monitoring period. In discussion with the researchers it will be placed in a location that suits you.

A different data logger will be used in the bedroom (Figure 3) and is generally fixed to a vertical surface with tape. This one just measures air temperature and humidity.

The researchers may need to come back to your house during the 9-month period to replace the batteries and they will return to collect the loggers at the end of the monitoring period

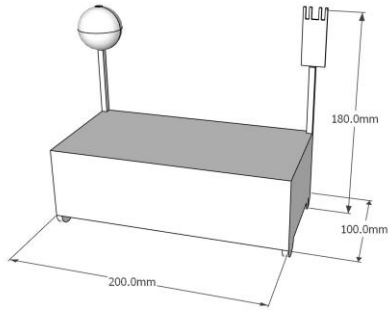

Figure 1: Living room data logger

Figure 2. Data logger (on the corner table between the sofas)

Figure 3: Bedroom data logger

Thermal comfort survey

During the 9 month period that the data loggers are installed, you will be asked to answer a thermal comfort survey at least twice a week. The more you respond to the survey, the more information we can learn from you. The survey will be available on an electronic notepad/tablet that will be provided to you (see below).

Figure 4. Survey tablet

The survey tablet does not need to stay in the same location the whole time. It can be stored away and brought out when you are doing the survey.

The survey will consist of about 12 simple questions about how you are feeling and whether you are using heating or cooling at the time. You touch the screen to record your response.

The survey tablet and the data logger will be synchronised to allow the researchers to match the conditions in the house with the time that the survey is done.

The internal conditions in the house will also be matched with external weather data obtained via the Bureau of Meteorology to allow the researchers to investigate how the house performs in different weather conditions.

Energy bills

With your consent we will look at your energy bills for the previous 3 years, if available, or at least for the previous year, to estimate how much energy has been used for heating and cooling. If you don't have the bills we will ask your permission to get them from your utility company.

What are the benefits for me?

Your participation will contribute to the development of policies and guidelines that will directly affect older people. You will also have the opportunity to discuss any issues that you think are relevant to thermal comfort in housing for older people.

Should you be interested, we will also send you regular brief summaries from the indoor monitoring results for your house.

Can I withdraw from the project?

Participation in this project is completely voluntary. Even if you agree to participate, you can with-draw from the study at any time.

What will happen to my information?

Your personal information and data collected will be held confidentially and your name will not be used in any analysis and publication from the study.

When the audio recording is transcribed, your name will be replaced by a code.

Your house will be identified by a code and no information about the address of the house will be used in any data analysis or publication of results.

Who do I contact if I have questions about the project?

For any information regarding this project, contact:
Professor Veronica Soebarto (Principal Investigator):
Phone 8313 5695 / email: veronica.soebarto@adealaide.edu.au
Or Dr Helen Bennetts:
Phone 0466 552 071 / email: helen.bennetts@adelaide.edu.au

If you wish to speak with an independent person regarding a concern or complaint, the University's policy on research involving human participants, or your rights as a participant, please contact the Human Research Ethics Committee's Secretariat:
Phone: +618 8313 6028
Email: hrec@adelaide.edu.au

Post: Level 4, Rundle Mall Plaza, 50 Rundle Mall, ADELAIDE SA 5000

Any complaint or concern will be treated in confidence and fully investigated. You will be informed of the outcome.

The University of Adelaide SA 5005 Australia

TELEPHONE +6 8 8313 7335

WEBSITE adelaide.edu.au

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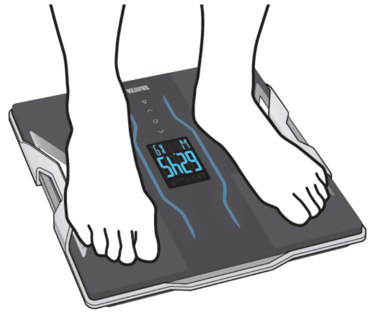

IMPROVING THE THERMAL ENVIRONMENT OF HOUSING FOR OLDER AUSTRALIANS – Additional questionnaire and body composition assessment

Further information

Since we started the house monitoring study, we have identified some additional factors that we think are important for understanding people's thermal comfort and well-being. These are:

- How people use outdoor spaces such as those around the house (e.g. gardens, courtyards, decks) and in the local neighbourhood;
- People's general health;
- Individual body composition.

What is body composition?

Body composition is used to describe the amount and distribution of the body's components including body water, fat, muscle and bone mass.

Recent studies have suggested that body composition is an important aspect of the body's ability to regulate temperature. Because of that, we are interested in whether this may influence people's thermal sensations and perceptions.

What will I be asked to do?

At the end of the monitoring period, our researchers will visit your house to retrieve the equipment that was installed earlier this year.

During this visit, **with your consent**, we will ask you to answer some questions about your use of outdoor spaces. We will also ask you to answer a quick questionnaire about your health that will allow us to calculate an individual's Frailty Score.

This will take approximately 15 minutes.

We would then like to measure your body composition. To do this, you will be asked to remove your shoes and socks and we will measure your height. You will then be asked to step on a scale, which quickly and automatically measures the body composition.

The Body Composition Scale is similar to those used by athletes and in gyms by people undertaking regular exercise. It measures:

- Body weight;
- Body water percentage;
- Body fat percentage;
- Muscle mass;
- Bone mass.

If you have a pacemaker or any mechanical implants, we will only measure your height and weight.

The body composition measurement will take less than 10 minutes.

Figure 1: Body Composition Scale

Main aims of project

The 3-year project funded by the Australian Research Council, Improving the thermal environment of housing for older Australians (ARC DP180102019) explores the connection between older people's well-being and the thermal conditions in their homes.

The main objectives are:

- To understand the qualities of the living environment of older South Australians.
- To investigate the thermal environment of houses and the occupants' responses and behaviours during hot and cold weather.
- To understand the relationship between weather, the house construction and design, and the occupants' comfort, well-being and home energy use.
- To develop planning, design and operational guidelines to achieve thermal comfort in homes to support older people living independently.

The research team

The project is being undertaken by the School of Architecture and Built Environment together with the School of Public Health from The University of Adelaide in conjunction with a Partner Investigator from The Hague University of Applied Sciences, The Netherlands, and the Director of the Aged and Extended Care Service at The Queen Elizabeth Hospital.

The project has approval from the University of Adelaide Human Research Ethics Committee: Approval number H-2018-042.

What are the benefits for me?

Your participation at this last stage of the study will complement the information already collected through the house monitoring process.

Ultimately, you are contributing to the development of policies and guidelines that will directly affect older people. You will also have the opportunity to discuss any issues that you think are relevant to thermal comfort in housing for older people.

Should you be interested, we will also send you a brief summary of the information gathered in this additional phase of the study.

Can I withdraw from the project?

Participation in this last phase of the project is completely voluntary. Even if you agree to participate, you can withdraw from the study at any time.

What will happen to my information?

Your personal information and data collected will be held confidentially and your name will not be used in any analysis and publication from the study.

When the audio recording is transcribed, your name will be replaced by a code. Your house will also be identified by a code and no information about the address of the house will be used in any data analysis or publication of results.

Who do I contact if I have questions about the project?

For any information regarding this additional stage of the project, contact:

Professor Veronica Soebarto (Principal Investigator):
Phone 8313 5695 / email:
veronica.soebarto@adelaide.edu.au
Or Larissa Arakawa Martins
Phone 0466 552 071 / email:
larissa.arakawamartins@adelaide.edu.au

If you wish to speak with an independent person regarding a concern or complaint, the University's policy on research involving human participants, or your rights as a participant, please contact the Human Research Ethics Committee's Secretariat:
Phone: +618 8313 6028
Email: hrec@adelaide.edu.au
Post: Level 4, Rundle Mall Plaza, 50 Rundle Mall, ADELAIDE SA 5000.

Any complaint or concern will be treated in confidence and fully investigated. You will be informed of the outcome.

The University of Adelaide SA 5005 Australia
TELEPHONE +6 8 8313 7335
WEBSITE adelaide.edu.au
CRICOS 00123M

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IMPROVING THE THERMAL ENVIRONMENT OF HOUSING FOR OLDER AUSTRALIANS

Skin Temperature Additional Study

Further information

Since we finished the house monitoring study, we have identified some additional factors that we think are important to understand people's thermal comfort and well-being. One of those factors is **skin temperature**, which, recent studies show, has a significant correlation with thermal comfort.

How are we measuring this?

The same data loggers that we used to monitor the temperature in your house will be used again for this additional study.

The only difference will be that the tablet that you used to answer the survey now has an **infrared temperature sensor** on the bottom (see Figure 1). The sensor is designed to measure the skin temperature of the back of your hand. The measurement is contactless, taking less than 1 second, and does not pose any harm to your skin.

What will I be asked to do?

Two members of the research team will visit your home to install the data loggers and explain this additional study to you.

The data logger will be placed in your main living room. It will measure, every 30 minutes, air temperature, radiant temperature, air speed and humidity.

As you know, the logger is battery operated and does not require any external connections and poses no health risks that we are aware of.

This logger needs to stay in the living room for the entire monitoring period. In discussion with the researchers it will be placed in a location that suits you.

During **a period of 2 weeks**, you will be asked to answer the comfort survey on the tablet **at least twice a day**. The more you respond, the more information we can learn from you.

The survey tablet does not need to stay in the same location the whole time. It can be stored away and brought out when you are doing the survey.

The survey will consist of 12 simple questions about how you are feeling and whether you are using heating or cooling at the time. You touch the screen to record your response.

After answering the last question of the survey, you will be asked to **place the back of your non-dominant hand close to the skin temperature sensor** located at the bottom of the tablet. You will hear a buzzer to let you know the measurement has been recorded. Figure 2 shows you how to place your hand for this measurement.

The survey tablet and data logger will be synchronised to allow the researchers to match the conditions in the house with the time that the survey and skin temperature measurement are completed.

Figure 1: Tablet and skin temperature sensor on the bottom

Figure 2: Placing the back of your hand close to the skin temperature sensor for measurement

Main aims of project

The 3-year project funded by the Australian Research Council, Improving the thermal environment of housing for older Australians (ARC DP180102019) explores the connection between older people's well-being and the thermal conditions in their homes.

The main objectives are:

To understand the qualities of the living environment of older South Australians.

To investigate the thermal environment of houses and the occupants' responses and behaviours during hot and cold weather.

To understand the relationship between weather, the house construction and design, and the occupants' comfort, well-being and home energy use.

To develop planning, design and operational guidelines to achieve thermal comfort in homes to support older people living independently.

The research team

The project is being undertaken by the School of Architecture and Built Environment together with the School of Public Health from The University of Adelaide in conjunction with a Partner Investigator from The Hague University of Applied Sciences, The Netherlands, and the Director of the Aged and Extended Care Service at The Queen Elizabeth Hospital.

The project has approval from the University of Adelaide Human Research Ethics Committee: Approval number H-2018-042.

What are the benefits for me?

Your participation at this last stage of the study will complement the information already collected through the house monitoring process.

Ultimately, you are contributing to the development of policies and guidelines that will directly affect older people. You will also have the opportunity to discuss any issues that you think are relevant to thermal comfort in housing for older people.

Should you be interested, we will also send you a brief summary of the information gathered in this additional phase of the study.

Can I withdraw from the project?

Participation in this additional phase of the project is completely voluntary. Even if you agree to participate, you can withdraw from the study at any time.

What will happen to my information?

Your personal information and data collected will be held confidentially and your name will not be used in any analysis and publication from the study.

Your house will be identified by a code and no information about the address of the house will be used in any data analysis or publication of results.

Note about the researchers

We strictly follow the SA Government instructions regarding COVID-19 restrictions and precautions. In addition, none of the researchers have been overseas or interstate in the past 6 months, and none have been exposed to people recently arrived from overseas or interstate. The researchers will only visit your house if they are in good health.

Who do I contact if I have questions about the project?

For any information regarding this additional stage of the project, contact:

Larissa Arakawa Martins

Phone 0466 552 071 / email: larissa.arakawamartins@adelaide.edu.au

or **Professor Veronica Soebarto** (Principal Investigator):

Phone 8313 5695 / email: veronica.soebarto@adelaide.edu.au

If you wish to speak with an independent person regarding a concern or complaint, the University's policy on research involving human participants, or your rights as a participant, please contact the Human Research Ethics Committee's Secretariat:
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Email: hrec@adelaide.edu.au Post: Level 4, Rundle Mall Plaza, 50 Rundle Mall, ADELAIDE SA 5000.

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TELEPHONE +6 8 8313 7335

WEBSITE adelaide.edu.au

CRICOS 00123M

E. Questionnaire

Improving the thermal environment of housing for older Australians:

Thermal comfort questionnaire

House number: Date: Interviewer:

☐ Person 1

☐ Person 2

The information you provide will remain strictly confidential. If you have any questions or concerns about the questionnaire, please contact Helen Bennetts on 0466 552 071 or helen.bennetts@adelaide.edu.au

A – About you

A.1 Gender

☐ Male

☐ Female

A.2 At your last birthday were you . . .

☐ 65-69 years

☐ 70-74 years

☐ 75-79 years

☐ 80-84 years

☐ 85 years or over

A.3 In which country were you born? _

A.4 What is your highest education level?

☐ Primary school

☐ Secondary or high school

☐ TAFE

☐ University

A.5 Are you (*more than one may apply*)

☐ Working part-time

☐ Receiving part or full pension

☐ Self-funded retiree

A.6 Do you live …

☐ Alone

☐ With spouse/partner

☐ Other, *please specify* :

A – About you *(cont)*

A.7 Which comment reflects you best?

- ☐ I generally prefer hot weather
- ☐ I generally prefer cold weather
- ☐ I do not like either hot or cold weather
- ☐ I have no preference
- ☐ Other, *please specify:* ____

A.8 What is the FIRST thing you do to keep cool on a very hot day?--

----

A.9 What else do you do to keep cool?---

A.10 What is the FIRST thing you do to keep warm on a very cold day?--

----

A.11 What else do you do to keep warm? --

A – About you *(cont)*

A.12 How concerned are you about the cost of running the **heating** in your home?

- ☐ Not at all concerned
- ☐ Somewhat concerned
- ☐ Concerned
- ☐ Very concerned
- ☐ Extremely concerned

A.13 How concerned are you about the cost of running the **cooling** in your home?

- ☐ Not at all concerned
- ☐ Somewhat concerned
- ☐ Concerned
- ☐ Very concerned
- ☐ Extremely concerned

B – Housing and the household

B.14 Approximately how old is this house? ____________________________

B.15 How long have you lived in this house? ____________________________

B.16 Is the home?

- ☐ Owned with mortgage
- ☐ Owned out-right
- ☐ Rented
- ☐ Other, *please specify* ________________________________
- ☐ Prefer not to say

B.17 Before tax is taken out, which category best describes your household income last year?

- ☐ Less than $30,000
- ☐ $30,000 - $70,000
- ☐ More than $70,000
- ☐ Prefer not to say

C – Quality of life

Under each heading, please tick ONE box that best describes your health TODAY

C.1 Mobility

- ☐ I have no problems walking about
- ☐ I have slight problems walking about
- ☐ I have moderate problems walking about
- ☐ I have severe problems walking about
- ☐ I am unable to walk about

C.2 Self-care

- ☐ I have no problems washing or dressing myself
- ☐ I have slight problems washing or dressing myself
- ☐ I have moderate problems washing or dressing myself
- ☐ I have severe problems washing or dressing myself
- ☐ I am unable to wash or dress myself

C.3 Usual activities (e.g. housework, family or leisure activities)

- ☐ I have no problems doing my usual activities
- ☐ I have slight problems doing my usual activities
- ☐ I have moderate problems doing my usual activities
- ☐ I have severe problems doing my usual activities
- ☐ I am unable to doing my usual activities

C.4 Pain/discomfort

- ☐ I have no pain or discomfort
- ☐ I have slight pain or discomfort
- ☐ I have moderate pain or discomfort
- ☐ I have severe pain or discomfort
- ☐ I have extreme pain or discomfort

C.5 Anxiety/depression

- ☐ I am not anxious or depressed
- ☐ I am slightly anxious or depressed
- ☐ I am moderately anxious or depressed
- ☐ I am severely anxious or depressed
- ☐ I am extremely anxious or depressed

C – Quality of life *(cont)*

C.6 Do you have any health problems that require you to stay at home?

- ☐ Yes
- ☐ No

C.7 In case of need can you count on someone close to you?

- ☐ Yes
- ☐ No

C.8 To get about do you regularly use

- ☐ Nothing
- ☐ Walking stick
- ☐ Walking frame
- ☐ Wheelchair
- ☐ Gopher

C.9 How often do people close to you tell you that you are forgetful?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Quite often
- ☐ All the time

D – Health

D.1 We'd like to know how good your health is today. Imagine a scale of 0 to 100 where 100 is the best health you can imagine and 0 is the worst – where on the scale would you mark your health today? Please indicate with a cross.

0: worst health | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100: best health

D.2 In the last few years have you had any of the following symptoms during COLD weather?

☐ Colds and coughs

☐ Flu

☐ Shortness of breath or trouble breathing

☐ Painful joints

☐ Cold sores

☐ Numbness, pain or change of colour of fingers or toes

☐ Dry skin

☐ Diarrhoea

☐ Winter blues or worsening of depressive condition

☐ Other, *please specify*:

☐ None of the above

D.3 In the last few years have you had any of the following symptoms during HOT weather?

☐ Dizziness

☐ Headaches

☐ Falls

☐ Fatigue or tiredness

☐ Increased thirst or dry mouth

☐ Low volume or urine or darker coloured urine

☐ Red or hot skin

☐ Reduced sweating despite the heat

☐ Muscle cramps or muscle weakness

☐ Nausea or vomiting

☐ Palpitations

☐ Breathlessness or shortness of breath

☐ Sleeplessness

☐ Other, *please specify*:

☐ None of the above

D – Health *(cont)*

D.4 In the last few years, have you ever been told by a doctor that you have any of the following conditions?

- ☐ Asthma
- ☐ Chronic bronchitis, or other respiratory illnesses
- ☐ Coronary heart disease or angina
- ☐ Renal or kidney condition
- ☐ Dehydration or heat stroke
- ☐ Pneumonia
- ☐ High blood pressure (hypertension)
- ☐ Allergy, such as rhinitis, hay fever, eye inflammation, dermatitis, food allergy or other allergy (not asthma)
- ☐ None of the above

E – Information and advice

E.1 In the last 12 months have you received or seen any information or advice about how hot and cold weather can affect your health?

☐ Don't know

☐ No

Yes, *from*

☐ Local council
☐ Family or friends
☐ TV
☐ Newspaper/magazine
☐ Internet/social media
☐ Energy or utility company
☐ Other, *please specify*: ______________________________

E.2 In the last 12 months have you received or seen any information or advice about how to improve your comfort during hot or cold weather?

☐ Don't know

☐ No

Yes, *from*

☐ Local council
☐ Family or friends
☐ TV
☐ Newspaper/magazine
☐ Internet/social media
☐ Energy or utility company
☐ Other, *please specify*: ______________________________

E.3 In the last 12 months have you received or seen any information or advice about reducing energy consumption?

☐ Don't know

☐ No

Yes, *from*

☐ Local council
☐ Family or friends
☐ TV
☐ Newspaper/magazine
☐ Internet/social media
☐ Energy or utility company
☐ Other, *please specify*: ______________________________

F. Additional questionnaire

THE UNIVERSITY of ADELAIDE

Improving the thermal environment of housing for older Australians:

Additional questionnaire

House number: Date: Interviewer:

☐ Person 1

☐ Person 2

The information you provide will remain strictly confidential. If you have any questions or concerns about the questionnaire, please contact Larissa Martins on 0466 552 071 or larissa.arakawamartins@adelaide.edu.au

A – About your outdoor spaces and neighbourhood

A.1 Do you spend time outdoors (e.g. in gardens, backyards, courtyards, decks or patios and around the neighbourhood)?

☐ Yes

☐ No

A.2 What activities do you do outdoors?

☐ Eating

☐ Drinking

☐ Cooking

☐ Work/study

☐ Reading

☐ Sports and recreation

☐ Relaxing

☐ Sunbathing

☐ Playing with children

☐ Playing with pets

☐ Socializing

☐ Entertaining

☐ Undertaking hobbies

☐ Gardening

☐ Smoking

☐ Walking

☐ Walking the dog

☐ Jogging

☐ Cycling

☐ Swimming

☐ Other, please specify ____

Improving the thermal environment of housing for older Australians
Additional questionnaire

A.3 How often do you spend time outdoors?

Time of the year/day	Frequency
Summer hot days (>30°C)	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
Summer hot nights (>30°C)	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
Summer cool nights	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
spring/autumn days (20°-30°C)	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
spring/autumn nights	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
winter days (<20°C)	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always
winter nights	☐ Never ☐ Very rarely ☐ Sometimes ☐ Frequently ☐ Always

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Improving the thermal environment of housing for older Australians

Additional questionnaire

A.4 Do you use different areas of the outdoor space around your house depending on the season or weather conditions?

☐ Yes

☐ No

If Yes, which areas and when?

A.5 Do you use the outdoor spaces as a way to stay warm during cold days/nights?

☐ Yes

☐ No

Comments

A.6 Do you use the outdoor spaces as a way to stay cool during hot days/nights?

☐ Yes

☐ No

Comments

Improving the thermal environment of housing for older Australians

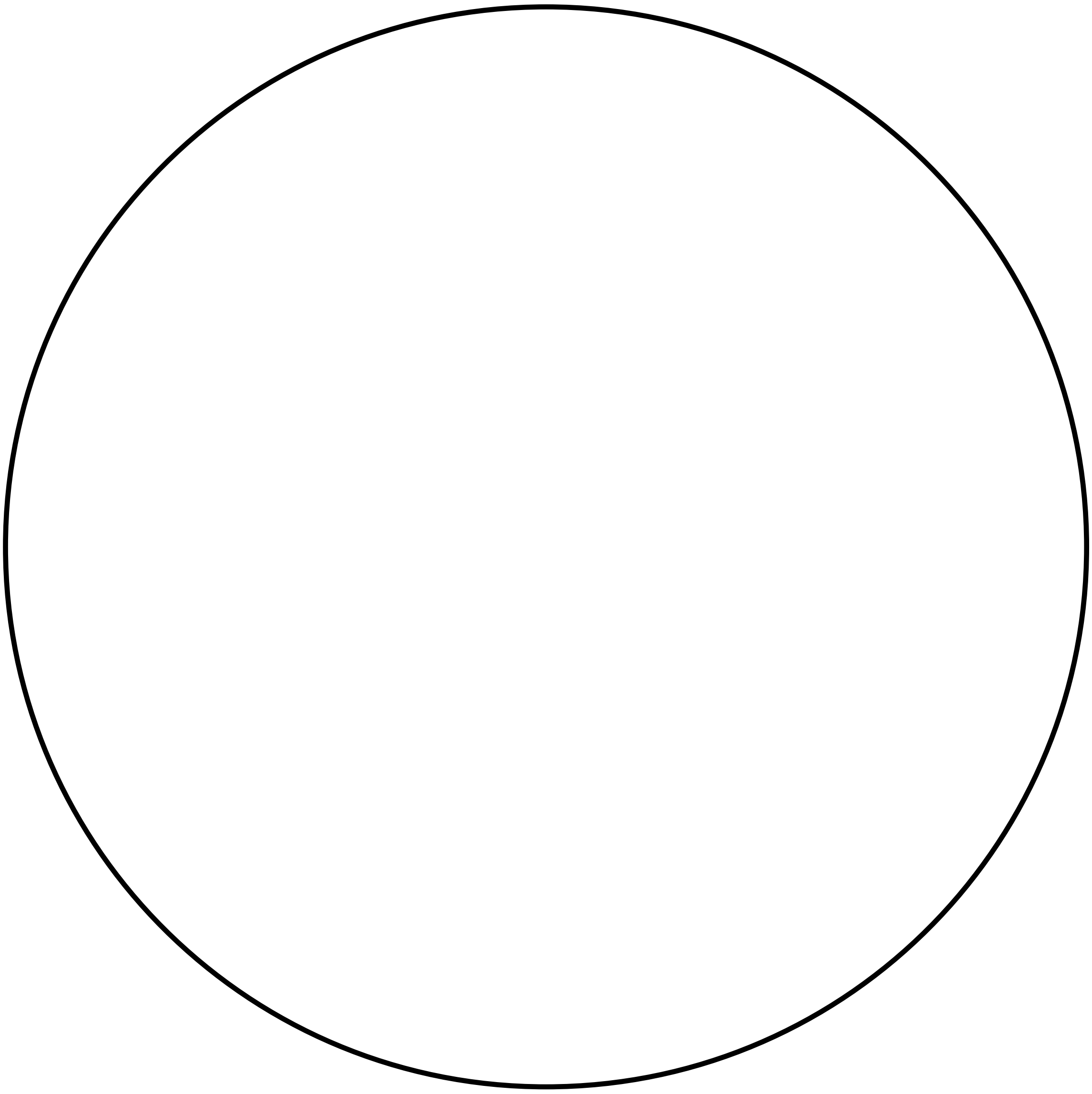
Additional questionnaire

B – Reported Edmonton Frail Scale (REFS)

B.1 Please imagine this pre-drawn circle is a clock.

First, write all the numbers of the clock in the correct positions.

Then, draw the hands of the clock to indicate a time of **'ten after eleven'**.



Improving the thermal environment of housing for older Australians
Additional questionnaire

B.2 In the past year, how many times have you been admitted to a hospital?

- ☐ 0 time
- ☐ 1 to 2 times
- ☐ More than 2 times

B.3 In general, how would you describe your health?

- ☐ Excellent
- ☐ Very good
- ☐ Good
- ☐ Fair
- ☐ Poor

B.4 Which of the following activities do you require assistance with (more than one may apply)?

- ☐ Meal preparation
- ☐ Shopping
- ☐ Transportation
- ☐ Telephone
- ☐ Housekeeping
- ☐ Taking medication
- ☐ Managing money
- ☐ Laundry
- ☐ None

B.5 When you need help, can you count on someone who is willing and able to meet your needs?

- ☐ Always
- ☐ Sometimes
- ☐ Never

B.6 Do you use five or more prescription medications on a regular basis?

- ☐ No
- ☐ Yes

Improving the thermal environment of housing for older Australians

Additional questionnaire

B.7 At times, do you forget to take your prescription medications?

☐ No

☐ Yes

☐ Not applicable

B.8 Have you recently lost weight such that your clothes have become looser?

☐ No

☐ Yes

B.9 Do you often feel sad or depressed?

☐ No

☐ Yes

B.10 Do you have a problem with losing control of urine when you do not want to?

☐ Always

☐ Sometimes

☐ Never

B.11 Two weeks ago, were you able to do heavy work around the house such as washing windows, walls or floors without help?

☐ No

☐ Yes

B.12 Two weeks ago, were you able to walk up- and downstairs to a/the second floor without help?

☐ No

☐ Yes

B.13 Two weeks ago, were you able to walk 1 km without help?

☐ No

☐ Yes

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Improving the thermal environment of housing for older Australians

Additional questionnaire

C – About your body composition

C.1 Do you have a pacemaker or other mechanical implants (e.g. hips and knees implants)?

☐ Yes

☐ No

For participants who answered positive to question C1, use WEIGHT ONLY MODE.

Ask participant to **take off socks and jewellery** (if any).

Measurements Tanita RD-953

Gender	
Age	
Ht	
W	
BMI	
BF	
MM	
MQ	
PR	
BM	
VF	
BMR	
MA	
TBW	

G. House construction check-list

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Improving the thermal environment of housing for older Australians:
Construction, heating and cooling checklist

House Number -------------------------------------- Date ---

Researcher ---

Logger & Tablet Number---

HOBO Number ---

Type of dwelling:

- ☐ Separate house
- ☐ Semi-detached house, row or terrace house, townhouse
- ☐ Flat, unit or apartment
- ☐ Other, *please specify:* _

In a retirement village?

- ☐ Yes
- ☐ No

Drawings?

- ☐ Provided
- ☐ We are doing
- ☐ Other, *specify*: _

Energy bills?

- ☐ Provided
- ☐ Consent obtained for us to source

Utility company: ------------------------------------- Customer no. ------------------------------

GENERAL CONSTRUCTION

		Comment or enter thickness / colour / type / size/ value if known
Roof		
Tile		
Metal		
Other		
Insulation		
Ext Wall		
Brick veneer		
Cavity brick		
Solid brick		
Stone		
Framed		
Other		
Insulation		
Int Wall		
Brick		
Framed		
Other		
Insulation		
Floor		Note floor coverings
Concrete slab on ground		
Suspended concrete		
Timber		
Other		
Insulation		
Ceiling		
Plasterboard		
Timber		
Other		
Insulation		

Windows		
Timber Frame		
Aluminium Frame		
Glass		
Skylight		
Timber Frame		
Aluminium Frame		
Glass/Other		
External blinds		
Material		
Which rooms		
Use schedule		
Internal blinds/ curtains		
Material		
Which rooms		
Use schedule		
Solar panels		
Hot water system		
Cook top (gas/electric)		
Oven (gas/electric)		
Leakiness that needs following up		
Air quality that needs following up		
Send copy of consent form		
post		
email		
text		
Send copy of audio file		

LIVING ROOM

Logger	Location:
Heater	Comments
Type	
Location	
Capacity	
Thermostat	
Other rooms heated	
When used	
Problems/comments	
Cooler	
Type	
Location	
Capacity	
Thermostat	
Other rooms cooled	
When used	
Problems/comments	
Fan	
Type	
Location	
When used	
Problems/comments	

BEDROOM

HOBO	Location:
Heater	Comments
Type	
Location	
Capacity	
Thermostat	
Other rooms heated	
When used	
Problems/comments	
Cooler	
Type	
Location	
Capacity	
Thermostat	
Other rooms cooled	
When used	
Problems/comments	
Fan	
Type	
Location	
When used	
Problems/comments	

HEATING

Heater	Comments
Type	
Location	
Capacity	
Thermostat	
Rooms heated	
When used	
Problems/comments	
Heater	
Type	
Location	
Capacity	
Thermostat	
Rooms heated	
When used	
Problems/comments	
Heater	
Type	
Location	
Capacity	
Thermostat	
Rooms heated	
When used	
Problems/comments	

COOLING

Air-con	Comments
Type	
Location	
Capacity	
Thermostat	
Rooms cooled	
When used	
Problems/comments	
Air-con	
Type	
Location	
Capacity	
Thermostat	
Rooms cooled	
When used	
Problems/comments	
Air-con	
Type	
Location	
Capacity	
Thermostat	
Rooms cooled	
When used	
Problems/comments	

FANS

Fans	Comments
Type	
Location	
When used	
Problems/comments	
Fans	
Type	
Location	
When used	
Problems/comments	
Fans	
Type	
Location	
When used	
Problems/comments	
Fans	
Type	
Location	
When used	
Problems/comments	

Walk-through with owner with conversation recorded, photos of key factors & discussion of

- Any changes to the house for thermal comfort
- Reason for heating / cooling (other than their own thermal comfort)
- Use of blinds, curtains
- Use of doors & windows for ventilation
- Whether / how the weather, heating & cooling affect their well-being
- How comfortable their house is in summer and winter

IMPORTANT: If necessary and the occupant gives consent, take photos of the rooms using the Infrared camera to identify cracks around the room.

H. Thermal comfort survey tablet screens

Welcome

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NEXT

1

Identification

☐ Person 1

☐ Person 2

NEXT

2

Which room are you in?

☐ Living room

☐ Bedroom

NEXT

3

How are you currently dressed?

☐ Very light

☐ Light

☐ Moderate

☐ Heavy

☐ Very heavy

NEXT

4

Describe your activity in the last 15 minutes in this space:

- [ ] Very relaxed
- [ ] Relaxed
- [ ] Light
- [ ] Moderate
- [ ] Active

NEXT

5

How do you feel right now?

- [ ] Cold
- [ ] Cool
- [ ] Slightly cool
- [ ] Neutral
- [ ] Slightly warm
- [ ] Warm
- [ ] Hot

NEXT

6

Would you prefer to be...

- [ ] Cooler
- [ ] No change
- [ ] Warmer

NEXT

7

How satisfied are you with the temperature in this room?

- [ ] Very satisfied
- [ ] Satisfied
- [ ] Partially satisfied
- [ ] Dissatisfied
- [ ] Very dissatisfied

NEXT

8

The air conditioner in the room is…

- [ ] On
- [ ] Off

NEXT

9

A heater in this room is…

- [ ] On
- [ ] Off

NEXT

10

A fan in this room is…

- [ ] On
- [ ] Off

NEXT

11

Curtains / blinds in this room are…

- [ ] All open
- [ ] Some open/ closed
- [ ] All closed

NEXT

12

In this room, windows and door(s) to outside are:

- [ ] All open
- [ ] Some open/ closed
- [ ] All closed

NEXT

13

In this room, door(s) to other room(s) are:

- [ ] All open
- [ ] Some open/ closed
- [ ] All closed

NEXT

14

Do you think the air in this room is...

- [ ] Stuffy
- [ ] OK
- [ ] Draughty

NEXT

15

Do you feel that the air quality in this room is:

- [ ] Very good
- [ ] Good
- [ ] OK
- [ ] Poor
- [ ] Very poor

NEXT

16

How would you describe your health and well-being at the moment?

- [ ] Very good
- [ ] Good
- [ ] Reasonable
- [ ] Poor
- [ ] Very poor

NEXT

17

The conditions in this room influence my health and well-being:

- [ ] Definitely yes
- [ ] Probably yes
- [ ] Unsure
- [ ] Probably not
- [ ] Definitely not

NEXT

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Finished

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Thank You

NEXT

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I. Thermal comfort survey tablet booklet

How to use the thermal comfort tablet

Welcome

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The thermal comfort survey provides an opportunity for you to provide information to the researchers about how you 'operate' your house and about your thermal comfort.

The survey tablet has an internal battery and does not need to be plugged in to a power source or connected to the internet. We will need to come and change the battery after about 4 months.

Completing the survey should take no more than a couple of minutes. Ideally we would like you to complete it every day, at different times, but twice a week will be fine.

If you have been outside, wait for at least 15 minutes before doing the survey so that you have adjusted to being inside.

To register your responses: Select the option that suits best by touching it with your finger. If you change your mind, just select another option. This will over-ride your former choice as only one option can be selected on each screen. The tablet automatically turns off if you don't select anything within 2 minutes. If you want to continue, just press the white button and start again.

When you have made your selection, touch the 'Next' button to go to the next screen.

Please do the survey in either the Living room or Bedroom (the rooms where the temperature loggers are located). Your responses will be connected to the temperature and other data measured at the same time. This way we can understand the indoor conditions at the time you responded to the survey.

For general queries about the monitoring or to request data about your house, contact Helen Bennetts:
helen.bennetts@adelaide.edu.au
Mob: 0466 552 071

Queries about the overall project should be directed to the Principal Researcher, Veronica Soebarto.
veronica.soebarto@adelaide.edu.au

Technical queries about the tablet or loggers should be sent to:
Terry Williamson:
terry.williamson@adelaide.edu.au

Either one or two people can complete the survey. If you live alone, this is easy – you are always Person 1.

If more than one person might do the survey, we'd like to know who you are. We will put a sticker with your name on the logger, but, in case it comes off:

Person 1..........................

Person 2..........................

Identification

☐ Person 1

☐ Person 2

NEXT

Knowing where you are when you do the survey will let us know which temperature logger is relevant at the time.

The logger in the Bedroom measures air temperature and humidity while the one in the Living Room measures air temperature, radiant temperature, humidity, carbon dioxide (CO_2) and Volatile Organic Compounds (VOC).

Which room are you in?

☐ Living room

☐ Bedroom

NEXT

Your clothes can affect how warm or cool you feel. Some examples of the categories are given below:

Very light:
- sleeveless, lightweight pyjamas
- bathers and lightweight sarong
- underwear and t-shirt or lightweight sleeveless top and shorts or light skirt with no shoes or sandals

Light:
- short-sleeved pyjamas
- underwear and shorts or skirt with lightweight short-sleeved top and sandals

Moderate:
- long-sleeved pyjamas with dressing gown and slippers
- underwear and skirt, dress or trousers with long-sleeve shirt, sleeveless vest or light pullover and shoes and socks

Heavy:
- as for **Moderate** plus thick sweater *or* light jacket

Very heavy:
- as for **Moderate** but thick trousers or thick skirt and tights, thick pullover *and* sleeveless vest or jacket

How are you currently dressed?

☐ Very light

☐ Light

☐ Moderate

☐ Heavy

☐ Very heavy

NEXT

This question gives us some idea about your metabolic rate. If you've been outside you should wait at least 15 minutes before doing the survey so that your body has adjusted to being inside.

Each individual will vary but some examples of what the categories mean are given below.

Very relaxed: Lying down either on a couch or the bed, snoozing, listening to music, the radio or a Podcast, meditating

Relaxed: either standing quietly perhaps looking out the window watching the world go by, or else sitting reading, playing solitaire or watching TV, talking on the phone

Light: sitting doing something such as eating a meal, knitting, sewing, writing, using the computer.

Moderate: perhaps you're getting ready to go out or you're doing some light housework such as dusting or tidying up, ironing.

Active: Stretching or yoga in a chair or on the floor, making the bed, cooking, more vigorous housework such as sweeping or vacuuming

Describe your activity in the last 15 minutes in this space:

- ☐ Very relaxed
- ☐ Relaxed
- ☐ Light
- ☐ Moderate
- ☐ Active

NEXT

How hot or cold do you feel?

Remember there is no incorrect answer because how you react to the weather is very personal and subjective.

We just want to know what you are feeling . . .

How do you feel right now?

- ☐ Cold
- ☐ Cool
- ☐ Slightly cool
- ☐ Neutral
- ☐ Slightly warm
- ☐ Warm
- ☐ Hot

NEXT

. . . and also whether you would prefer to feel differently. . .

Would you prefer to be...

- ☐ Cooler
- ☐ No change
- ☐ Warmer

NEXT

. . . and we just want to know how satisfied you are with the temperature. You may feel slightly cool, prefer to be warmer and still be Satisfied with the temperature

How satisfied are you with the temperature in this room?

- ☐ Very satisfied
- ☐ Satisfied
- ☐ Partially satisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

NEXT

These questions relate only to an air conditioner (cooler) or heater that is in the room where you are completing the survey. If there is an air conditioner or heater that is working in another room, it doesn't count, even if the doors between the two rooms are open.

Knowing what equipment is operating in the room will help us work out how your house is performing.

In the long term, this will also give us information about what conditions prompt people to use heaters, coolers or fans.

The air conditioner in the room is...

- ☐ On
- ☐ Off

NEXT

A heater in this room is...

- ☐ On
- ☐ Off

NEXT

We like to know if there is a ceiling fan or portable fan operating because it will change the air movement in the room.

A fan in this room is...

- ☐ On
- ☐ Off

NEXT

When curtains or other window coverings are closed it changes the amount of heat entering or leaving the room.

Knowing if some or all of the curtains or blinds are open or closed will help explain the temperature data at the time.

Curtains / blinds in this room are...

- ☐ All open
- ☐ Some open/ closed
- ☐ All closed

NEXT

If windows and / or doors are open to the outside environment it will affect conditions in the room. Knowing whether they are open or not will help us understand the conditions in the room. This information will also help build a picture of when and how people use their windows and doors for ventilation.

In this room, windows and door(s) to outside are:

- ☐ All open
- ☐ Some open/ closed
- ☐ All closed

NEXT

The conditions in the space will change depending on whether doors between this room and other rooms are open or closed.

In this room, door(s) to other room(s) are:

- ☐ All open
- ☐ Some open/ closed
- ☐ All closed

NEXT

Low air movement, lack of ventilation or lots of people in the room may make a room feel stuffy.

You may feel the amount of ventilation or air movement is about right for you at the time.

Sometimes a room may feel too draughty due to air leakage from gaps around windows and doors or down unsealed chimneys.

Do you think the air in this room is...

- ☐ Stuffy
- ☐ OK
- ☐ Draughty

NEXT

You may feel the air in the room seems fresh, clean and pleasant and that air quality is good or very good.

Often we don't particularly notice the air quality in our rooms - it is perfectly acceptable or OK.

There are many things that might make the air quality seem poor including the presence of chemicals, gases or dust from inside the house or from outside. Dust storms, building or roadworks, smoke, chemical spills, paints or other materials, damp or mustiness can all contribute to poor air quality.

If there are any unusual conditions affecting the air quality, please make a note at the back of this booklet.

Do you feel that the air quality in this room is:

- ☐ Very good
- ☐ Good
- ☐ OK
- ☐ Poor
- ☐ Very poor

NEXT

We'd like a general idea of how you are feeling at the time of doing the survey. Your response may be affected by long-term and on-going conditions or concerns or by unusal and one-off events.

You can make a note of particular health and well-being concerns at the back of this booklet.

How would you describe your health and well-being at the moment?

- ☐ Very good
- ☐ Good
- ☐ Reasonable
- ☐ Poor
- ☐ Very poor

NEXT

Do you think the conditions in the room at this time contributed to your previous response?

The conditions in this room influence my health and well-being:

- ☐ Definitely yes
- ☐ Probably yes
- ☐ Unsure
- ☐ Probably not
- ☐ Definitely not

NEXT

If you wish, you can make a note of events or things that may have affected your responses (for example an unusual smell in the room from a bushfire or nearby roadworks that affects the air quality, concerns with the equipment, health concerns that you have at the time of the survey, the presence of visitors that cause you to operate the house differently etc).

Date/time	**Comment**

Date/time	**Comment**

Date/time	Comment

Date/time	Comment