Human-centered predictive control in buildings using personalized comfort data-driven models

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DOCTORAL DISSERTATION

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Sveučilište u Zagrebu

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DOKTORSKI RAD

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Abstract

The drive for improved building energy performance has led to increased automation levels in building control systems, challenging the balance between energy efficiency and comfort. This has often resulted in decreased user satisfaction with indoor environments for two main reasons, occupants are unable to adjust conditions to their preferences, resulting in discomfort, and the lack of control causes psychological dissatisfaction. Since people spend approximately 90% of their time indoors, shifting from technology-centric to human-centric control (HCC) systems in buildings is crucial. HCC allows the integration of user preferences into the building control system for indoor environmental control. This approach not only improves occupant comfort but also enables occupants to change their energy consumption behaviour towards more efficient and sustainable behaviour. This is particularly beneficial for demand-response actions in imbalanced grids, where load fluctuates during peak and off-peak hours, and there is a higher participation of renewable energy sources, sometimes resulting in a surplus of generated electricity. As buildings account for about 75% of electricity consumption in developed countries, with 80% of that occurring during peak hours, engaging users in grid flexibility actions through advanced control systems like HCC shows significant potential for supporting grid efficiency and stability.

However, this integration of user preferences into controllers requires occupants to interact with the system and share data or feedback on their perceived comfort or to engage in grid flexibility actions, which can be inconvenient for users. Data-driven personalized comfort models (PCMs) offer an optimal solution by learning occupant preferences (e.g., if one wants warmer or cooler, dimmer or brighter, comfortable or not) and representing their comfort levels without requiring continuous interaction. Nonetheless, this still demands some effort from users until sufficient data is collected to learn their preferences. In HCC research, seamless user interaction and continuous data sharing are often assumed, leading to a lack of user-provided data when deployed in real scenarios.

This thesis explores user perspectives on interacting with HCC, using a survey-based study to examine their opinions and perceptions and their willingness to share data or feedback for indoor environmental control and grid flexibility interaction. It developed a method to create PCMs for multiple comfort aspects and multiple occupants during two field experiments, including indoor air quality, thermal, and visual comfort PCMs. During the second field experiment, the impact of implementing HCC in an actual building is tested, providing important insights from the real experiences of 24 building occupants interacting with HCC. Additionally, through simulations, the study investigates how user-building interaction facilitated by HCC coupled with advanced controllers like Model Predictive Control (MPC) can be leveraged for grid flexibility and the impact of HCC on grid flexibility, energy consumption, costs, and comfort.

The research methods include a survey-based study with almost 1 000 respondents, a behavioural science theory, two field experiments, and simulations. This emphasizes the interdisciplinary nature of this thesis, which bridges technical and social sciences. The survey was conducted in Zagreb, Croatia, with occupants from six educational buildings consisting of a diverse target group. The first field experiment involved four participants in a faculty office over three weeks, gathering data to develop PCMs. The second experiment took place in a high school building (RCK Ruder Boskovic) in Zagreb, Croatia, with 24 participants over two weeks, aiming to test the findings from the first experiment in real scenarios and integrate user preferences into the open code building control system. A mixed-method approach consisting of mini-surveys and semi-structured interviews evaluated the impact of implementing HCC on user satisfaction during the school field experiment. Lastly, simulations compared the effects of integrating user preferences into conventional PID control and advanced systems like MPC. More importantly, the impact of combining HCC with MPC and engaging users in demand response or grid flexibility actions was analyzed and quantified.

The survey-based research revealed that 75.7% of nearly 1 000 occupants want access to building controls, but only 55.6% are willing to interact with HCC by sharing data. Indoor air quality was the most important comfort aspect for 85% of occupants, followed by thermal comfort (84%) and visual comfort (74%). A behavioral science model with 64% prediction accuracy was developed to predict occupants' willingness to share data with HCC. This study also elicited that the key factors influencing data sharing with HCC, ranked by impact, are beliefs about its usability and benefits, ease of use, social influence, and privacy security. The survey also indicated that 66% of respondents prefer using smartphones as interfaces and primarily interact with controls only when discomfort arises. Field experiments, designed based on these preferences, collected data from actual building occupants in natural environments. The results from these experiments show that tree-based models, like Decision Trees and Random Forest, are the best-performing machine learning models for developing

PCMs, depending on the varying levels of occupant engagement in providing data. The school field experiment indicated that integrating user preferences into the control system increased user satisfaction with the indoor environment by 16.7%. Regarding grid flexibility, 59.5% of survey respondents were willing to engage in grid flexibility or demand response actions. About 47.7% preferred interacting for 1 – 2 hours daily, with varying expectations for financial incentives, even if it meant adjusting indoor temperatures to unfavourable conditions during grid overloads to reduce energy usage. Simulations combining HCC and MPC with grid flexibility actions while prioritizing occupant preferences achieved 44.6% energy savings, 60.6% load shifting, and 59.4% cost savings during peak hours compared to the baseline PID scenario with standard setpoints. Comfort improved by 38% compared to the baseline, yet the improvement was lower compared to scenarios that primarily focus on occupant preferences without engaging in grid flexibility, which is expected and assumed to be agreed upon by occupants. These findings are valuable for HCC designers, practitioners, and stakeholders aiming to create control systems prioritizing occupants and their preferences. Additionally, insights on leveraging user-building interaction through HCC for grid flexibility are crucial for the future role of buildings in smart and sustainable grids.

Keywords: Human-centered control, advanced control systems, MPC, smart buildings, occupant comfort, personalized comfort models, grid flexibility.

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Nomenclature

ACC	Accuracy	%
$D(t_0, t_f)$	Discomfort between start and end time	Kh
EC	Electricity cost	EUR
E_{flex}	Energy consumption for flexibility scenario	kWh
E_{ref}	Energy consumption of reference baseline	kWh
$E_{scenario(i)}$	Energy consumption of other scenarios	kWh
E_{total}	Total energy consumption	kWh
El_{price}	Electricity price	EUR/kWh
F1 score	Prediction potential	%
ΔF1 score	Difference of F1 scores	%
N	Number of zones	-
PRE	Precision	%
Q^2	Predictive relevance	%
Q_{int}	Internal heat gains	W
Q_{sol}	Solar heat gains	W
Q_{w}	Water inlet heat in the heat pump	W
R^2	Explained variance or predictive potential	%
REC	Recall	%
s_z	Temperature deviation outside comfort boundaries	℃
T_{amb}	Ambient temperature	℃
T_{z}	Zone temperature	℃
x	Mean setpoint for all users (temperature)	℃
α	Cronbach's alpha	-
β	Path coefficient	-
μ_i	Mean setpoint for each user (temperature)	℃
σ_i	Standard deviation for each user (temperature)	℃

Acronyms and abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
ASHRAE	American society of heating, refrigerating and air conditioning engineers
AVE	Average variance extracted
BIM	Building information modeling
CIBSE	Chartered institution of building services engineers
CR	Composite reliability
CV	Convergent validity

DGP	Discomfort glare perception
DV	Divergent validity
DR	Demand response
DR-HR-MPC	Demand response human-centered model predictive control
DSM	Demand side management
EPBD	Energy performance of buildings directive
FL	Factor loading
FN	False negatives
FP	False positives
HCC	Human-centered control
HC-MPC	Human-centered model predictive control
HC-PID	Human-centered PID
HTMT	Heterotrait-monotrait ratio
HVAC	Heating, ventilation and air conditioning
IAQ	Indoor air quality
IEQ	Indoor environment quality
IoT	Internet of things
IPMA	Importance performance map analysis
KDE	Kernel density estimation
KNN	K-nearest neighbor
KPI	Key performance indicator
LSTM	Long short term memory
ML	Machine learning
MPC	Model predictive control
OSHA	Occupational safety and health administration
PCM	Personalized comfort model
PCS	Personalized comfort systems
PDF	Probability density function
PI	Proportional integral
PID	Proportional-integral-derivative control strategy
PLS	Partial least squares
RF	Random Forest
RNN LSTM	Recurrent neutral network with long short term memory
SCADA	Supervisory control and data acquisition
SEM	Structural equation modeling
SRI	Smart readiness indicator
SRMR	Standardized root mean square residual
SVM	Support vector machine
TN	True negatives
TP	True positives
TPB	Theory of planned behaviour

Definitions

Human-centered control—An advanced control system in buildings that primarily focuses on users' needs and preferences, intending to improve user experience while maintaining the energy efficiency of the building. Synonym: Occupant-centered control.

Personalized Comfort Model – A model trained on user-provided data that can predict the comfort level of individuals based on their previous experiences in indoor environments.

Theory of Planned Behaviour – A well-established psychological theoretical framework that enables predicting future action or behavior or the intention to exhibit that behaviour based on believed outcomes, social influences, and self-perceived ability.

Behavioral Intention – The intention, tendency, or willingness to exhibit an action or behaviour now or in the future based on intrinsic motivations.

Attitude – The viewpoint or belief people have toward an action or behaviour and what possible outcome they expect from that action.

Perceived Behavioral Control – The self-perceived capability to exhibit an action or behaviour.

Social Norms – The social impact of the exhibited action or behavior from the target (user) to society or vice versa.

Grid flexibility – "The ability of a power grid to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales, from ensuring instantaneous stability of the power system to supporting long-term security of supply" as defined by Energy Agency (IEA).

Demand-response actions - "Demand response refers to balancing the demand on power grids by encouraging customers to shift electricity demand to times when electricity is more plentiful or other demand is lower, typically through prices or monetary incentives." As defined verbatim by Energy Agency (IEA).

Chapter I.

1. Introduction

Recent dynamic lifestyle changes have led people to focus their daily activities and work primarily in indoor environments. It is estimated that most people spend around 90% of their time indoors [1]. The importance of proper indoor conditions was emphasized, especially during the pandemic. In highly automated modern buildings, the lack of accessible controls that operate on standardized settings in a "one-size-fits-all" fashion frequently compromises occupant satisfaction, rendering individual preferences obsolete [2], [3]. Striving for energy efficiency in modern buildings sometimes takes precedence over comfort when aiming for sustainability goals. However, the paramount importance of occupant well-being and comfort has shifted the priorities to balance efficiency and comfort in buildings [4]. This emphasizes the importance of integrating the human dimension into building control systems, giving rise to human-centered control (HCC) systems. These systems prioritize the needs and preferences of building occupants without compromising energy efficiency targets. HCC facilitates the integration of occupant preferences for indoor climate control [5], [6] and engagement in grid flexibility interactions. The integration of user preference as a direct input has been reported in various control systems, such as diverse predictive controllers [7], [8], [9], Model Predictive Control (MPC) [10], [11], [12], [13], [14], or more conventional ones like PI control [7], [15], and PID control [16], BMS [17], heuristic rules control [18], [19], [20], and self-developed frameworks [21]. However, implementing HCC using advanced data-driven methods to allow user-led control in automated buildings and how it affects occupants remains underexplored. This highlights the need for further research into how such systems that integrate user preferences into control systems can be effectively implemented and evaluated for their impact on occupant satisfaction and overall comfort.

Smart buildings are characterized by their energy performance and operation, response to the occupants' needs, and energy flexibility. This is stated in the revised Energy Performance of Buildings Directive (EPBD)) [22], which introduced the Smart Readiness Indicator (SRI) to evaluate the smart readiness of a particular building. The impact criteria that the smart services should meet include energy savings, maintenance, grid flexibility, comfort, convenience, health and well-being, and providing information to occupants. Notably, the last four criteria are related to occupants, emphasizing the importance of integrating the human dimension when aiming to design smart and sustainable buildings, as it weighs more on the smart readiness scale of buildings. In line with the energy-saving criteria of the SRI, HCC systems demonstrate the potential for achieving energy-savings [23] while improving user comfort [24],[25]. For instance, personalized comfort settings enabled by HCC allow for localized energy usage, leading to energy savings in multifunctional buildings. Furthermore, HCC facilitates grid flexibility by enabling occupants to engage in demand response programs to adjust energy use based on grid load or electricity pricing. These benefits extend beyond occupant satisfaction, encompassing energy efficiency and grid flexibility; hence, it is paramount to conduct further investigations on the impact of HCC on building energy performance and grid flexibility.

Integrating user preferences into the control framework of HCC is facilitated through two primary methods: direct user input and personalized comfort models (PCMs). PCMs are data-driven models that learn user preferences under different conditions, predict comfort without constant interaction, and serve as digital representations of occupants [26]. Unlike traditional group-based comfort models like Predicted Mean Vote (PMV) or Percentage of People Dissatisfied (PPD), PCMs consider individual comfort preferences and physiological responses [27]. The increase in the availability of IoT (Internet of Things) and ICT (Information and Communication Technology) in modern buildings enables extensive data collection, empowering the development of data-driven PCMs through predictive models using artificial intelligence (AI) or, more specifically, machine learning (ML) models. Despite its promising potential in control systems, the integration of PCMs into actual building control system algorithms remains limited in current research. Hence, there is a need for a framework or a “know-how” to integrate the predicted outputs of PCMs as inputs into control algorithms for indoor environment control.

PCMs are developed using diverse input features: physiological data (e.g., skin temperature, heart rate) [28], [29], environmental measurements (e.g., air temperature, relative humidity) indoors and outdoors, and subjective self-reported data from occupants, regarding their states, activities, preferences, perceptions, or environmental sensations [7], [30], [31]. PCMs can address various comfort aspects, including Indoor Air Quality (IAQ), thermal, visual, and acoustic comfort. However, the predominant focus in existing literature has been on thermal comfort [28], [32], [33] often neglecting other vital aspects such as IAQ, visual [34], or acoustic comfort [28] for building occupants [35]. The bias toward thermal comfort stems from the relatively well-understood nature of thermal comfort and its immediate detectability by occupants. In contrast, IAQ comfort is complex, involving numerous pollutants and factors, and poor IAQ is not easily detected by occupants. Conversely, visual comfort is heavily influenced by occupants' spatial positions and is typically more adaptable. Consequently, this oversight highlights the need for a more comprehensive approach encompassing all comfort aspects in building environments. Figure 1.1 presents the trend of research regarding comfort-related studies with PCMs and occupants in buildings that were yielded by analyzing over 300 studies regarding occupant comfort in buildings.

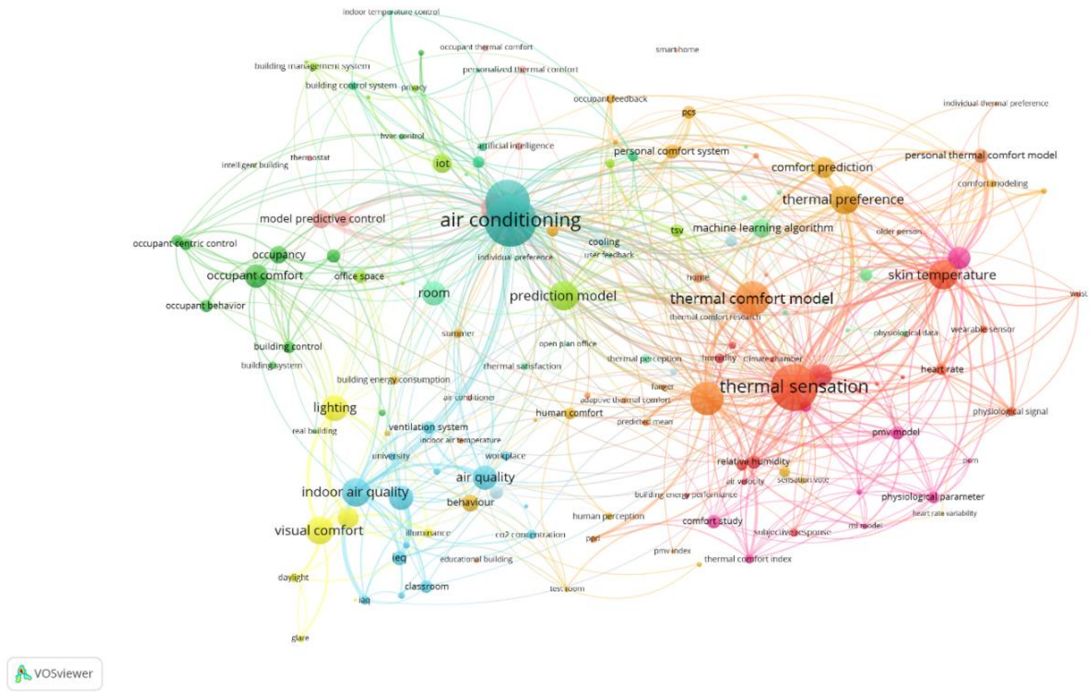

Figure 1.1. Cluster visualization of existing research on PCMs and human-centered control. The thermal comfort (cluster depicted in orange color) is the most researched compared to IAQ (blue cluster) and visual comfort (yellow cluster)

Introducing new technologies like HCC that depend on user inputs and interaction to work properly, without considering the user's willingness to interact with them, can be unproductive and impede the long-term operation of such systems. PCMs need subjective inputs from users, such as preferences or perceptions of indoor conditions, alongside measured environmental or physiological data to enhance predictive accuracy. Due to their subjective nature, psychological features like preferences cannot be directly measured and are challenging to quantify. The primary data sources for these aspects are the occupants themselves, as the "mind" holds irreplaceable information for perceived comfort [36]. Meaning that they need to share data or feedback (e.g., through an interface [37]), which is generally perceived as a hassle by occupants if requested frequently. Therefore, studies often report a shortage of data supplied by occupants to substantiate their findings. For instance, a study by [37] revealed that when using feedback-dependent controllers, 71% of participants in the experiment experienced a decrease in their thermal comfort, compared to only 21% who experienced an increase. This outcome is attributed to insufficient data collected from user feedback, highlighting the importance of evaluating user acceptance and their willingness to engage with such controllers by sharing data. Therefore, by leveraging theoretical frameworks from behavioral sciences, such as the Theory of Planned Behavior (TPB) [38], the willingness or intention of occupants to interact with HCC can be predicted. This theory also enables the identification of influencing factors that drive or hinder the interaction. This approach fosters interdisciplinary collaboration by combining advanced building control methodologies with behavioral sciences.

To ensure the HCC design aligns with occupant preferences and provides a more convenient interaction experience, it is essential to ask occupants for feedback on their preferences using surveys or interviews [39]. This approach helps tailor the system to meet their needs effectively. This includes asking occupants about their desired automation levels [40], interaction frequencies, preferred interfaces, motivating factors, and more. Given that HCC facilitates grid flexibility actions within buildings, understanding occupants' willingness to engage in demand response actions is also crucial. This entails identifying preferences regarding participation in demand response actions, including the potential need for financial incentives and the preferred duration for such involvement during the day. While current studies highlight the importance of integrating user preferences in HCC systems, there is a lack of comprehensive research on how these preferences impact the effectiveness and acceptance of HCC in real-world scenarios. Furthermore, the specific aspects of user interaction, such as frequency and interface preferences, and their influence on engagement and satisfaction with HCC remain underexplored. This indicates a need for further studies to understand these dynamics better and develop more user-led HCC designs.

Considering the significant potential for leveraging buildings in demand-response or grid flexibility actions during periods of grid overload, it is crucial to align occupants' preferences and readiness to engage in such actions. Therefore, the participatory role of occupants in grid flexibility needs more exploration. Power grids struggle to balance fluctuating demand and generation from renewable energy systems, making grid flexibility essential for maintaining grid stability and efficiency. Furthermore, it is important to evaluate the impact of HCC systems on energy flexibility. It is necessary to understand how control strategies, from conventional PID to advanced MPC, affect energy consumption, costs, load shifting, and comfort. These insights can help HCC developers and stakeholders design demand-side management strategies that leverage HCC for more sustainable power grids. By aligning these strategies with occupant preferences, a more effective and user-led approach to grid flexibility and building performance can be ensured.

1.1 Motivation

From the literature review (a detailed literature review is provided for each specific chapter later in the thesis), the research gaps that are addressed in this thesis are aggregated into:

- The human aspect of HCC is often overlooked in research. More attention is needed to understand user preferences, their willingness to engage with building control, and motivating factors. Interdisciplinary studies incorporating behavioral science theories are essential to gain insights into user-system interactions, especially in HCC, where user input is critical for design, development, and operation.
- Research on PCMs with multi-comfort aspects for multiple building occupants is limited, with most studies focusing on thermal comfort rather than visual or IAQ comfort. The lack of field implementations of HCC systems shows the need for integration frameworks of PCMs for multi-comfort aspects and multi-occupants in advanced building control systems.
- Due to the novelty, the impact of HCC on grid flexibility needs to be further investigated by defining and quantifying its effects.

1.2 Thesis objective and structure

This thesis aims to address an important gap in building control systems by developing a comprehensive framework that facilitates the integration of the human dimension into automated controls to regulate the indoor environment according to user preferences using PCMs. This entails the development of multi-comfort (including IAQ, thermal, and visual comfort) and multi-occupant data-driven PCMs using ML. Furthermore, the thesis provides a theoretical framework to analyze the human perspective of using control systems in buildings from an interdisciplinary approach. Adapting existing psychological theories, this thesis also explores occupants' willingness to interact with such control systems and elucidates their preferences, motivations, and drivers regarding interaction. Finally, leveraging the capabilities of advanced predictive control, the thesis evaluates the impact of HCC on grid flexibility to estimate the broader implications of HCC implementation on load shifting, energy saving, cost and comfort.

This research hypothesizes that deploying human-centered predictive control in a building by developing personalized data-driven comfort models significantly increases the occupants' indoor comfort satisfaction.

The thesis follows the structure outlined in Figure 1.2. The introduction provides an overarching view of the subtopics, while each subsequent chapter includes its detailed literature review, methods, results, discussion, and conclusion sections.

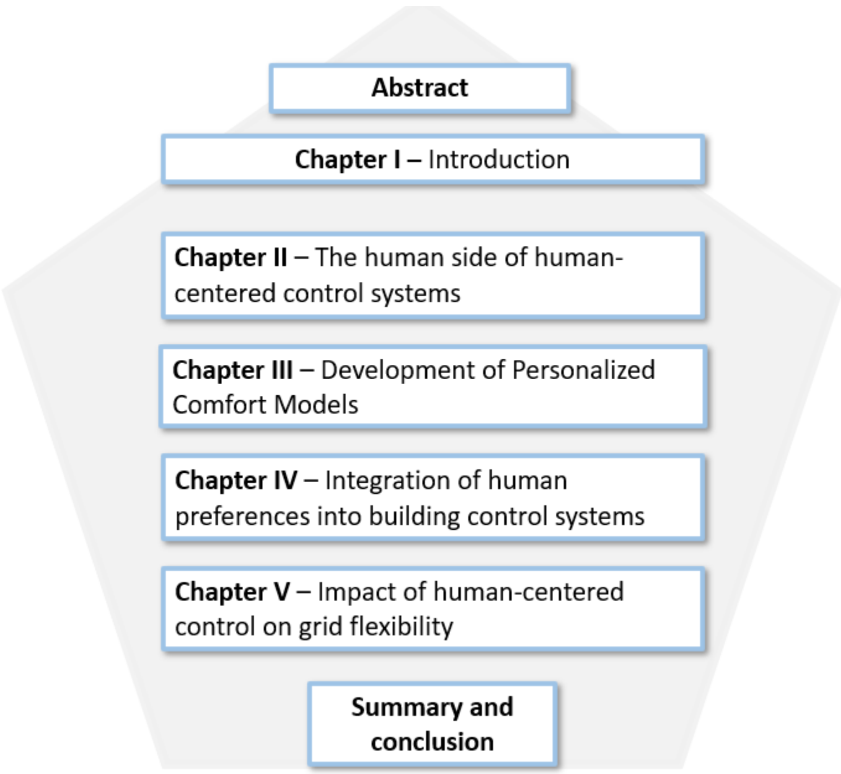

Figure 1.2. Thesis outline

1.3 Research questions and scientific contributions

The scientific contributions of this research are as follows:

- A framework based on a behavioural science approach, namely the Theory of Planned Behaviour (TPB), that can be used to predict the willingness of users to report feedback on the perceived comfort conditions in a human-centered control system.
- A method for developing personalized comfort models using multi-aspect comfort data collected as direct feedback from the occupants on their perceived indoor comfort. The developed models will enable the deployment of human-centered predictive control in buildings.
- Definition and quantification of the impact of human-centered predictive control on grid flexibility.

The following sections outline the scientific contributions and insights elucidated by each chapter; more detailed information can be found in the respective chapters.

Chapter II – The human side of human-centered control systems. This chapter presents the first scientific contribution of providing a framework based on a behavioural science approach, namely the TPB, that can be used to predict occupant behaviour or willingness to report feedback on the perceived comfort conditions in an HCC system. It also answers these research questions:

- What are the user preferences regarding control systems, including control access, comfort prioritization, user interface, duration, frequency of interacting with HCC, etc.?
- Can we predict the willingness of building occupants to interact with HCC (by sharing data on their perceived comfort)? If so, are they willing to interact, and what motivates their interaction?
- Are occupants inclined to participate in grid flexibility actions, and what are the underlying motivators?

To address these inquiries, a survey involving nearly 1 000 participants was conducted. The research is structured using a well-established psychological theory called TPB, and the data is analyzed using Structural Equation Modelling through Smart PLS software as a statistical tool.

Chapter III – Development of Personalized Comfort Models. This chapter elaborates on the scientific contribution of providing a method for developing PCMs using multi-comfort aspect data collected as direct feedback from the occupants on their perceived indoor comfort. The developed models will enable the deployment of human-centered predictive control in buildings. Some of the research questions answered in this section of the thesis include:

- How can data be effectively collected to develop data-driven PCMs?
- How can multi-comfort PCMs for multiple occupants be developed using ML models?
- Which is the most reliable ML model for PCM? How many data points are needed for an optimal PCM? How to overcome the lack of data?

This is addressed by presenting evidence from two experiments conducted in actual buildings, incorporating site measurement data and participant subjective feedback. Based on the collected data, different ML models are developed and compared to find the best performing model for PCMs.

Chapter IV – Integration of user preferences into building control systems. This chapter focuses on one of the key objectives of this research, which is to provide a framework for integrating the human dimension into the control algorithm of an actual pilot building, using user preferences as a proxy to regulate the indoor environment. Furthermore, this chapter shows how deploying HCC in a building impacts occupant comfort and satisfaction. The research questions answered in this section include:

- How to integrate PCMs into control systems in buildings?
- Does integrating user preferences through PCMs into control systems increase user satisfaction?
- How do occupants experience and accept the interaction with HCC during and after deployment?

These analyses are provided through a case study in which the outputs of PCMs are integrated into the control system of a school building.

Chapter V – Impact of human-centered control on grid flexibility. This chapter elaborates on the last scientific contribution of defining and quantifying the impact of HCC on grid flexibility. The research questions elaborated on in this chapter include:

- What is the impact of HCC on grid flexibility?
- How do different control systems impact grid flexibility, including user preferences and dynamic electricity pricing?

The methods used in this chapter include simulating various scenarios using the TRNSYS software, one of the most advanced tools for dynamic simulation of buildings.

Chapter II.

2. The human side of human-centered control systems

Parts of this chapter are based on:

A. Bresa, T. Žakula, and D. Ajduković, “Occupant preferences on the interaction with human-centered control systems in school buildings,” *Journal of Building Engineering*, p. 105489, Nov. 2022, doi: 10.1016/j.jobe.2022.105489.

A. Bresa, T. Zakula, and D. Ajdukovic, “A framework to predict the willingness and influencing factors of building Occupants to interact with advanced control systems in buildings,” *Energy Reports*, vol. 10, pp. 4078–4086, Nov. 2023, doi: 10.1016/j.egyr.2023.10.071.

A. Bresa, T. Zakula, and D. Ajdukovic, “Occupant-centric control in buildings: Investigating occupant intentions and preferences for indoor environment and grid flexibility interactions,” Energy and Buildings, p. 114393, Jun. 2024, doi: 10.1016/j.enbuild.2024.114393.

"We shape our buildings; thereafter, they shape us."

W. Churchill

Human-centered control (HCC) allows occupants to shape their environmental conditions according to their preferences and needs. However, the design, development, and functioning of such controllers do not always adhere to occupant preferences. Therefore, harnessing their opinion and preferences on designing and operating HCC is crucial, as HCC relies on occupant-provided data and their interaction. Many research studies assume seamless interaction between individuals and advanced controls reliant on occupant data, which results in a lack of data in real-world applications due to low engagement levels of occupants. An interdisciplinary research approach is needed to understand the willingness of occupants to interact with control systems, the influencing factors that drive or hinder this interaction, and overall occupant preferences for control systems. The use of interdisciplinary research in the control system domain is very scarce, as mentioned by [41] and in a review on the use of behavioural theories for user-building interactions [42], therefore, it is paramount to investigate HCC from a behavioural science perspective. This chapter focuses on eliciting occupant preferences and opinions on HCC for indoor environmental control and grid flexibility interaction. This creates grounds for reconsidering some of the occupant-related misconceptions and assumptions in current building control studies. It provides survey-based insights from 959 participants with varying levels of technical knowledge across six educational buildings in Zagreb, Croatia. It is one of the rare interdisciplinary studies that combine behavioral science and technical science in building control systems, offering practical guidance for practitioners and designers who seek to create HCC and assess user engagement with such systems.

2.1 Literature review

User preferences regarding control systems have been analyzed in previous research studies, such as in [39], where they aim to develop a user-led design and operation of building control, or separately, preferences for automation levels in [40]. Research [43] explored the correlation between perceived control in adjusting indoor conditions and comfort using interviews with 170 occupants in 23 institutional buildings in Canada. While a thorough review [42] emphasizes the need to consider occupant behaviour and preferences in building systems. However, there is a gap in comprehensive reporting on user preferences for control access, the designing of HCC, and grid flexibility interaction combined in one study. Hence, it is beneficial to have a well-rounded preference overview, such as control access preference, comfort prioritization, data-sharing interface, the process of sharing data, and grid flexibility engagement, which is imperative to empowering the occupant-in-the-center tenet of HCC.

To better analyze occupant behavior regarding building control systems, behavioral science theories such as the Theory of Planned Behavior (TPB) [38] can be employed. Predicting human behavior, particularly the willingness or intention to perform a specific action, is inherently complex [44]. This complexity extends to predicting occupant willingness to share their data or interact with HCC systems. By viewing this willingness as a planned action, established psychological theories like Ajzen's TPB [38] can provide a predictive framework. Despite providing predictions, this theoretical framework is also used to uncover the drivers and motivators behind human actions. TPB simplifies the prediction of an individual's willingness to act (Behavioral Intention) by weighing their attitude toward the action (Attitude), societal perceptions (Subjective or Social Norms), and their perceived ability to perform it (Perceived Behavioral Control). TPB has been effectively used to predict various behaviors in many scientific domains [45], [46], [47]. For instance, it has been used for research on energy conservation by users [46], [47], [48], [49] and pro-environmental-related behaviour [50], [51], [52], [53]. Furthermore, it was used for smart appliance adoption [54], [55], [56] and miscellaneous topics such as green exercise [57], tourism [58], consumption of local beverages [59], etc. The TPB was also employed in [60] where they analyzed the occupant behaviour to manual adjustments of the Heating, Ventilation, and Air Conditioning (HVAC) system thermostat and its impact on energy savings. Apart from that, TPB was also used to analyze the behaviour for lighting and shading operations [61], [62].This shows that TPB can be easily tailored to represent a specific behaviour, such as in our study, where it is used to predict the willingness of occupants to report feedback or to interact with advanced control systems (HCC), a situation not previously encountered in the existing literature.

2.1.2 Extended Theory of Planned Behaviour

The TPB [63] suggests behaviour can be predicted once the motivation and intention exist, how much of a factor the social impact is on them, and whether the ability to perform the action exists. However, these subjective measures do not always suffice to describe the behaviour or the intention altogether [53]. Extending the scope of TPB by incorporating external influencing factors has shown promise in predicting behaviors [59]. Hence, many research studies involving TPB have added external or additional variables on TPB as the foundation. The literature review shows that the exogenous variable type depends on the observed behaviour. The variables were chosen either by adopting them from other “surrogate” research studies and tailoring them according to their need, or they were elicited from interviews and surveys from people. Some added variables are moral norms, past behaviour, self-identity, habit, self-efficacy, environmental awareness and values, socioeconomic and demographic factors [46], etc. For instance, research [52] predicted how green buildings dictate pro-environmental behaviour to their occupants. This was analyzed with the additional variable to the TPB, which was the impact of informational background factors added to the building, such as passive instructions. In research [64], they predicted the intention of the users to adopt hybrid electric vehicles, and the external variables added to the TPB were the moral norm and environmental concern. In research [55], the consumer acceptance of smart home services was predicted, and the added variables were automation, mobility, interoperability, security and privacy risks, physical risks, and trust in the service provider. Research [46] elaborated on saving intentions using additional variables such as income and education. A similar study was conducted in research [65], which analyzed occupants’ behaviour toward energy conservation in university buildings. Research [54] and [66] show the intention to use green and environmentally friendly products and technologies. The exogenous variables used include social impression, environmental ethics, and consciousness. Research [67] and [68] used personal traits as exogenous variables to predict the intention to adopt pro-environmental behaviour and household energy conservation, respectively. In addition to employing exogenous variables, research [69] combined three theoretical frameworks: TPB, Drivers, Needs, and Action System (DNAS), and Social Cognitive Theory (SCT)[41]. In conclusion, it is seen from the literature that the possibility of expanding the TPB with additional variables facilitates capturing a more comprehensive range of phenomena affecting the observed behaviour, increasing the TPB model prediction potential. However, the scarcity of studies addressing the prediction of users' willingness to share data and engage in grid flexibility actions, particularly in the context of HCC systems, remains an open gap that needs to be addressed.

2.2 Methods

This chapter aims to get occupant feedback on their preferences and willingness to interact with control systems, specifically with HCC, which relies on occupant-provided data. This survey-based study uses a qualitative and quantitative approach. This was done using surveys, where one part of the questionnaire collected user preferences, and the other used the TPB method to predict the willingness of users to interact with HCC. The data and the hypothesis testing were analyzed using Structural equation modeling (SEM) through SmartPLS software. In the following sections, the survey design, the theoretical framework, and the data analysis method are presented.

2.2.1 Survey design and data collection

The survey was conducted in Zagreb, Croatia, in six educational buildings, two of which were high schools and the rest university faculty buildings. These buildings were selected to achieve diversity in the target group in terms of age, gender, background, levels of technical knowledge, and interests. Furthermore, since HCC will be implemented in one of the surveyed high school buildings, it was important to gather the occupant preferences and their intention to interact with such controllers. Figure 2.1 shows the process of the conducted research, which includes two phases: Phase I, where only one high school building was surveyed, and Phase II, where five additional educational buildings were added, reaching a cumulative number of six educational buildings with a total of 959 respondents.

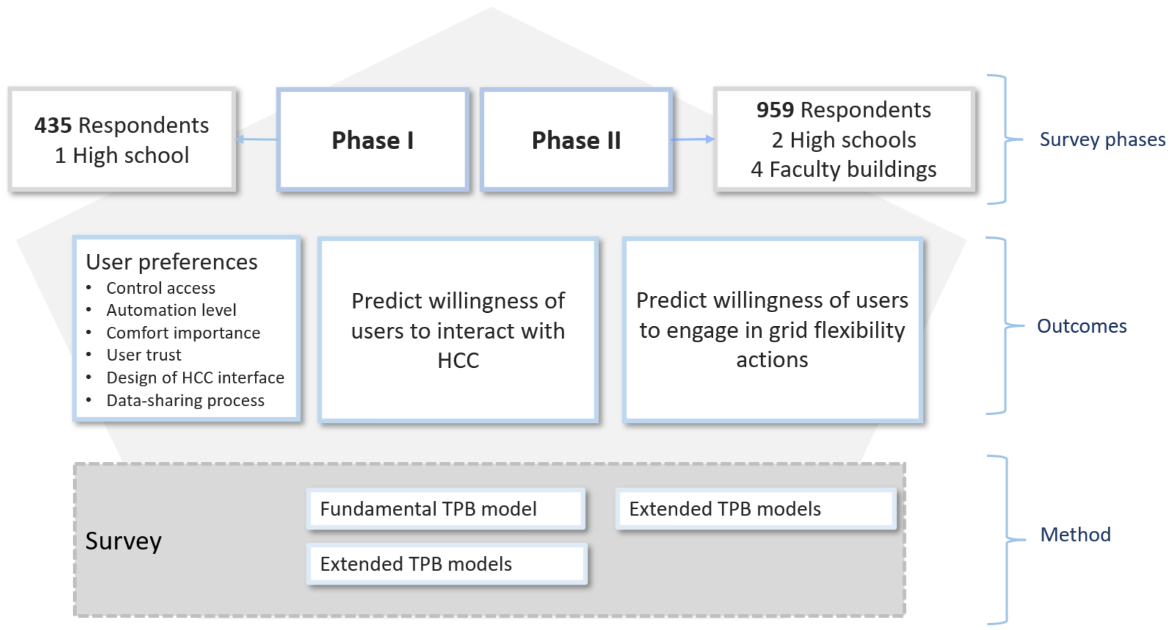

Figure 2.1. The process of conducting the survey-based research in educational buildings

The questionnaire consists of three parts. The first part addresses the respondents' demographic details, such as age, sex, and occupation. The second part presents the section with questions to elicit control-related user preferences, and it is presented in Annex A, Table A.1. This section includes questions to show occupants' preferences on access to control, automation level preference, engagement in grid flexibility, HCC interface design, etc. Lastly, the third part of the questionnaire is presented in Annex A, Table A.2, and is structured according to the TPB guidelines [70], [71]. Most questions (also called items) are adopted and tailored from prior studies, and the answers are structured on a 5-point Likert scale. Initially, the survey was tested through a piloting phase with 43 respondents outside the target group. The survey was distributed online using Google Forms through the snowball sampling technique. Due to the highly technical nature of the questionnaire, as the survey topic contains technical terms and concepts that might be new to the participants, an informative video was shared along with the link to the questionnaire. The aim was to give the respondents basic information regarding the technical concepts for HCC and what it means to provide feedback, by taking careful consideration to maintain a neutral tone to avoid biased responses. The questionnaire is given in Annex A, also published in [72]. The current study includes an extensive sample group, reaching 959 respondents. The respondent details are shown in Table 2.1.

Table 2.1. Demographic details of the respondents from six educational buildings

Building	Sex		Age range				Percentage
	Female	**Male**	**Up to 18**	**19-30**	**31-50**	**Over 50**	**%**
Technical high school	74	361	410	1	10	14	**45.4**
Gymnasium high school	66	32	86	9	0	3	**10.2**
Faculty of Humanities and Social Sciences	105	30	3	127	5	0	**14.1**
Faculty of Economics	84	45	0	129	0	0	**13.5**
Faculty of Mechanical Engineering and Naval Architecture	32	81	2	102	5	4	**11.8**
Faculty of Sciences	40	9	0	24	16	9	**5.1**
Percentage %	**41.8**	**58.2**	**52.2**	**40.9**	**3.8**	**3.1**	

2.2.2 Theory of Planned Behaviour

TPB (a theoretical psychological framework) is used to express the relationship between the factors that impact the willingness of users to share data or report feedback and how well those factors enable to predict the feedback-reporting intention of users. This theory states that once the willingness to perform an action exists, the action is highly likely to be exhibited as well. In our research, if the willingness of the occupants to interact with the control system exists, there is a level of certainty that they will interact with the controller as active participants or data providers. The framework of the fundamental form of TPB is presented in Figure 2.2. TPB suggests that people’s intention to perform a specific action is based on three fundamental pillars, also called constructs. The first pillar presents the Attitude, which shows that someone with a positive attitude toward an action is more likely to exhibit that action. In other words, if they think they will get a positive outcome (e.g., if they interact with the controller, they will save energy), they will be more prone to interact with the controller. The second pillar presents the Subjective Norms or the social impact. It states that if someone puts a high value on the opinion of others, then they are wired to act according to others’ expectations or to follow their example. For instance, if occupants know they would set an excellent example for others to interact with the controller, they are more likely to commit to the interaction. The third pillar presents the Perceived Behavioural Control. It states that if someone thinks they are capable of performing the action, they are more prone to do so. For instance, if someone thinks using a smartphone to report feedback on the perceived indoor temperature is easy, they are more likely to interact with the controller.

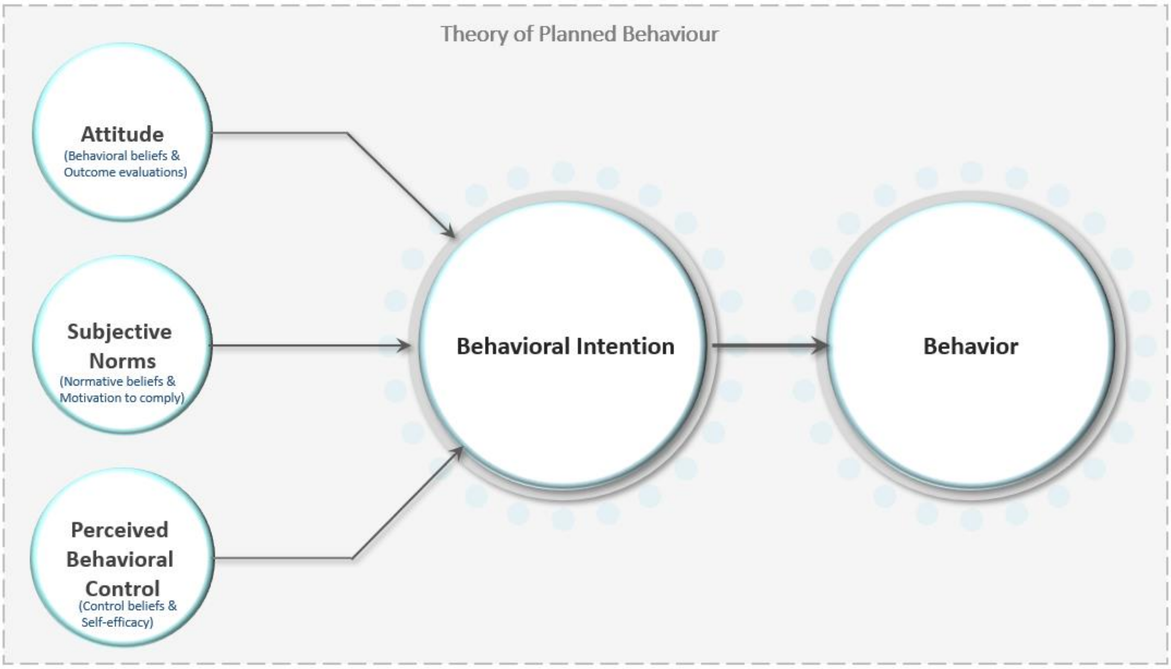

Figure 2.2. The fundamental TPB layout consisting of three pillars or constructs, according to Ajzen

Three different variations of the TPB models are developed in this research, called models M1, M2, and M3, for simplicity. Models M1 and M2 are used to predict the willingness of users to interact with HCC by sharing data. In contrast, model M3 is used to predict the willingness of users to engage in grid flexibility actions and how this is correlated to the intention to use HCC. Model M1 presents the fundamental TPB according to the original framework proposed by Ajzen [73]. The model design or what questions were used are presented in Figure 2.3. The second TPB model, M2, presents an extended version of the fundamental TPB and is also used to predict the willingness of users to share data. The difference is in the inclusion of additional external or exogenous variables to the model that can impact the willingness of users to interact with HCC, such as user trust, user preferences, etc. Model M2 is based on the proposed framework in Figure 2.4 meaning that this model includes model M1 plus the additional exogenous variables depicted in yellow circles. Lastly, model M3 also presents an extended version of TPB, and the framework is presented in Figure 2.5.

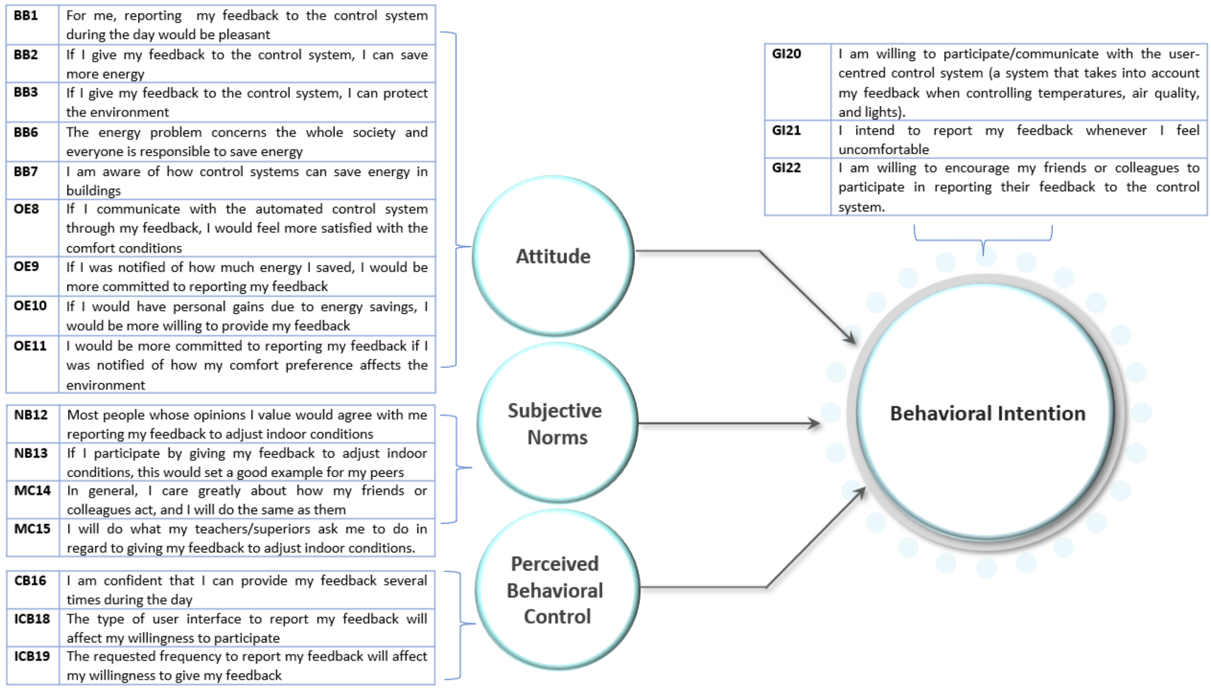

Figure 2.3. The framework of the fundamental TPB model (model M1), where the boxes show the questions from the questionnaire with their acronym, the circles show the basic constructs (latent variables), and the big circle shows the target to be predicted

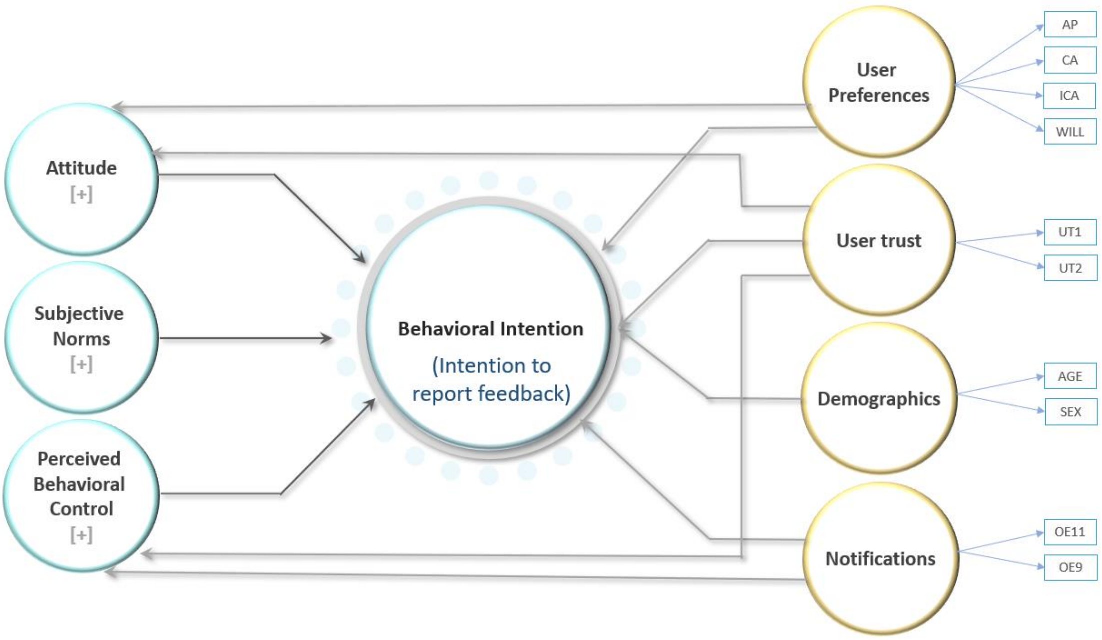

Figure 2.4 The extended TPB (a proposed framework) predicts occupants' willingness to interact with HCC. Yellow circles present the additional exogenous variables. The plus sign ([+]) shows that each construct has its own set of questions. The question-coded acronyms are given in Annex A

2.2.3 Data analysis with Structural Equation Modeling to quantify survey findings

A statistical approach was used to quantify the strengths of the relationships between the considered variables (e.g., how much the user trust impacts the willingness to interact with HCC or intention to report feedback). Specifically, the data collected from the TPB survey was analyzed using the Structural Equation Modelling (SEM) method [74] with Partial Least Squares (PLS) computing [46] using Smart PLS software [75], [76] as a statistical tool.

The SEM analysis [77] consists of measurement and structural modelling. The first one helps to assess the reliability and validity of the constructs; in other words, it shows how well the questions in the questionnaire present the construct, namely, whether they are valid and reliable representations to measure that construct. Specifically, it evaluates if the survey is a good tool to measure the willingness of users to interact with HCC by sharing data or reporting feedback. Structural modelling helps to assess the relationship between variables and to define how one variable affects the other.

The measurement model is assessed through Convergent Validity (CV) and Divergent Validity (DV) indices. The CV reflects how each question presents the construct or the correlation of items in a construct. According to [78], the CV can be assessed by (1) the Factor Loading (FL) that should be greater than 0.5 for each question to be significant, (2) the Average Variance Extracted (AVE) greater than 0.5, (3) the Composite Reliability (CR) greater than 0.7, and (4) the Cronbach's Alpha (α) greater than 0.6. On the other hand, the DV is calculated to elicit which questions placed in different constructs are correlated with one another or to show whether they perform well in their mother constructs (e.g., if an item better represents an Attitude rather than a Subjective Norm). The DV results show how the constructs are statistically different. The DV is evaluated using the FL criterion [78] and the heterotrait-monotrait (HTMT) ratio.

The structural model is calculated to test the statistical significance of the path coefficients, showing the importance of the hypothesized relationships between variables. For example, whether Attitude affects Behavioural Intention or not is evaluated through the structural model used to generate t-statistics that show the significance of the paths. The structural model in Smart PLS software is calculated using the Bootstrapping technique, which is a method to test statistical significance by recreating samples of the dataset. During this analysis, the bootstrapping setup in the software was two-tailed with 5000 subsamples with parallel processing. The t-value of a path (t-statistic) should be higher than 1.96 to show a strong influence of one variable on the other. Whether the hypotheses of the relationships are supported or rejected can be determined by the p-value or the probability value, which shows the probability that the yielded data would have occurred by random chance. A smaller p-value shows that the model paths are significant, meaning that there is a correlation between the dependent (Behavioural Intention or willingness to interact with HCC) and independent variables (Attitude, Subjective Norms, and Perceived Behavioural Control) or that one of them impacts the other. In this study, for example, the p-value determines whether the hypothesis that Attitude impacts Behavioural Intention is supported. If the $p\text{-value}<0.05$, the relation between the variables (Attitude and Behavioural Intention) is significant, and the hypothesis is supported.

The fundamental constructs of TPB, namely, the Attitude, Subjective Norm, and Perceived Behavioural Control, were presented as indirect variables, whereas their respective questions show the direct variables. The nature of the proposed TPB constructs is reflective, which is common for behavioural science constructs, indicating that each question has a specific meaning reflecting the construct (e.g., the Attitude). The measurement model was modelled as a composite using PLS-SEM, considering that the primary purpose of the model is explanation and prediction [79]. It should be noted that using PLS for reflective measurement models is still an open discussion in the field because the results are biased; however, according to Hair et al. [80] the PLS-SEM is suitable for measurement models regardless of the nature of the constructs. Furthermore, it is stated that the bias does not have practical relevance in most applications [80], and if the aim of the model is prediction and explanation, as in this case, PLS-SEM should be considered.

The predictive accuracy of the proposed models is measured using the explained variance R^2, the predictive relevance Q^2, and the predictive potential using the PLSpredict analysis [81]. The detailed measurement and structural model results are presented in Annex B for brevity reasons. Furthermore, 2.5% and 97.5% confidence intervals are also given for each hypothesis. The confidence interval value different from zero shows a significant relationship between the constructs. The model fit was also evaluated using the SRMR (Standardized Root Mean Square Residual) measure computed with SmartPLS [82]. The acceptable results of SRMS range in values that are less than 0.1 [83] and for a more conservative threshold, it is 0.08 [84]. However, the quality of the model in PLS-SEM is represented more with the predictive potential (R^2) and relevance (Q^2) and less with the model fit indices, as argued in [85].

Lastly, another analysis in SmartPLS4 software [82] is used to assess the influencing factors that can highly improve the willingness of users to interact with HCC and engage in grid flexibility. This analysis is called the Importance Performance Map Analysis (IPMA) [86], [87]. It is a graphical representation that places all the influencing factors in a graph and determines which influences have the highest potential to improve the willingness of users to share data and engage in grid flexibility. The IPMA map consists of four quadrants: I, II, III, and IV. Quadrant I is the "Keep up the good work" section. It shows the influencing factors that have a high impact and high performance, meaning that practitioners and designers of HCC should focus on developing or maintaining these factors. Quadrant II is the "Concentrate here" section, which shows the factors that have an impact and require improvement to meet the desired level of performance. Quadrant III shows the "Low priority" section with low impact and low performance, meaning they are unimportant. Quadrant IV is the "Possible overkill" section, which shows influencing factors with low impact. Their improvement does not make a difference in the willingness of occupants to interact with HCC.

Hypothesis testing. To establish a relationship between two variables, their relationship must be initially hypothesized. The $p-value$ and $t-statistics$ indices are used to confirm whether a hypothesis is supported or rejected. The hypotheses tested for the first model, M1, are presented below, whereas the rest are in Annex B:

H1a: Attitude influences the intention of the occupants to interact with HCC systems by sharing comfort-related data in the form of feedback.

H1b: Subjective Norms influence the intention of the occupants to interact with HCC systems by sharing comfort-related data in the form of feedback.

H1c: Perceived Behavioural Control influences the intention of the occupants to interact with HCC systems by sharing comfort-related data in the form of feedback.

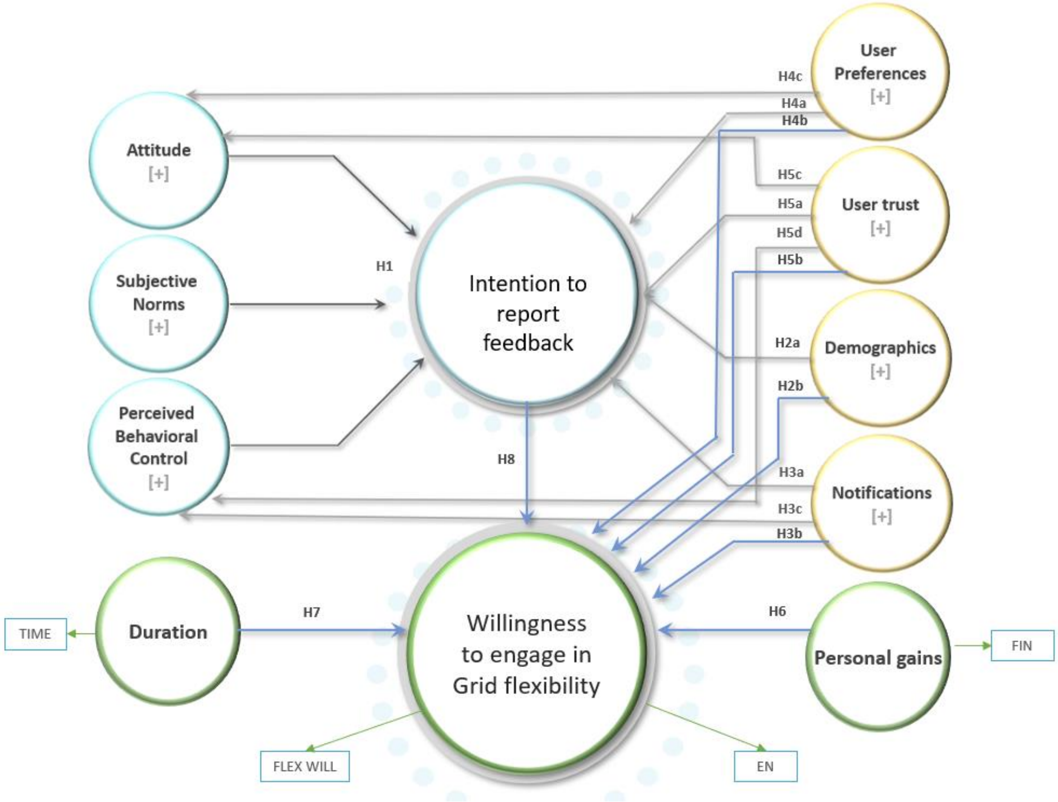

Figure 2.5. The framework and hypotheses formulation based on the relationship between variables for model M3

2.3 Results

The results of this research are two-fold; on one side, the user preferences regarding control systems are elicited. On the other hand, their willingness to share data with HCC for indoor climate control is predicted, including their willingness to engage in grid flexibility actions and their correlation. In this study, the “user preferences” include various aspects such as the user preference to have control access either in the traditional concept (e.g., by regulating the thermometer) or through HCC. The latter means providing data to a system that creates a data-driven comfort model and uses the outputs to regulate the indoor environment based on user comfort preferences. Other user preferences considered include the automation scale preference (whether occupants like more manual or more automated controllers) and which comfort aspect they prioritize (e.g., indoor air quality, thermal comfort, visual comfort). Additionally, what are the preferred design features in HCC? For instance, what kind of interface do they like to use? What is the tolerated frequency of reporting feedback? Do occupants accept notifications and reminders, or do they prefer to report only when uncomfortable? Do they trust HCC with their data and location in terms of privacy? Lastly, are occupants open to engage in grid flexibility actions? If yes, do personal financial benefits play a crucial role? What daily duration would they accept to engage in grid flexibility? These and other findings are presented in the following sections.

2.3.4 Findings on user preferences to interact with human-centered control

Figure 2.6 presents user preferences for control systems and automation levels. It includes the preference for control access or the ability to adjust indoor parameters like temperature, lighting, and ventilation for manual or automated control. Furthermore, the preference related to involvement in the decision-making algorithm for automated control was also evaluated (e.g., whether occupants want their preferences to be considered when a building manager or equivalent adjusts indoor parameters in automated control systems). Lastly, among the preferences was whether occupants like to share their data to control the indoor environment using HCC, which includes their comfort perceptions reported as feedback. The findings in Figure 2.6 indicate that:

- As expected, occupants want access to control systems (to regulate indoor conditions). A cumulative response rate incorporating *very important* and *important* answers shows that 75.7% of the surveyed occupants want access to controllers.
- Only 60.8% of occupants want to be involved or have their preferences taken into consideration when indoor conditions such as temperature, lighting, or the amount of fresh air indoors are set up automatically in controlled environments.
- Only 55.6% of the surveyed occupants are willing to interact with HCC controllers by sharing feedback on perceived comfort. It suggests that the participation of occupants in data-sharing activities cannot be assumed to exist seamlessly, meaning it can result in a lack of data. This situation can impede the proper functioning of HCC, which relies on user input. Therefore, predicting user willingness to share data when implementing HCC is beneficial and is further discussed in Section 2.3.6.
- The discrepancy between 75.7% of occupants wanting control access, of whom only 55.6% are open to interacting with HCC through data sharing, suggests that occupants prefer not to make an effort to regulate the indoor climate. This significant discrepancy

may also be attributed to a lack of knowledge of the functionality of HCC. Hence, the willingness to interact might change with an increasing awareness of how HCC operates. Other factors impacting this discrepancy are given in Section 2.3.6.

- The results show that the majority (46.7%) of respondents want a higher level of automation, while only 26.9% prefer manual control.

Figure 2.7 shows the distribution of responses for control preferences across different age groups and sexes. The scale on the y-axis shows a 5-point Likert scale from *not at all important* to *very important*, and for the preference level of automation, it is a 5-point Likert scale from *more manual* to *more automated*. The results indicate that demographic factors do not significantly impact user preferences regarding control systems. However, it is seen that the desire to control indoor conditions is more prevalent in older age groups who also want more manual control systems. In contrast, younger groups wish to access controllers and prefer more automated control systems.

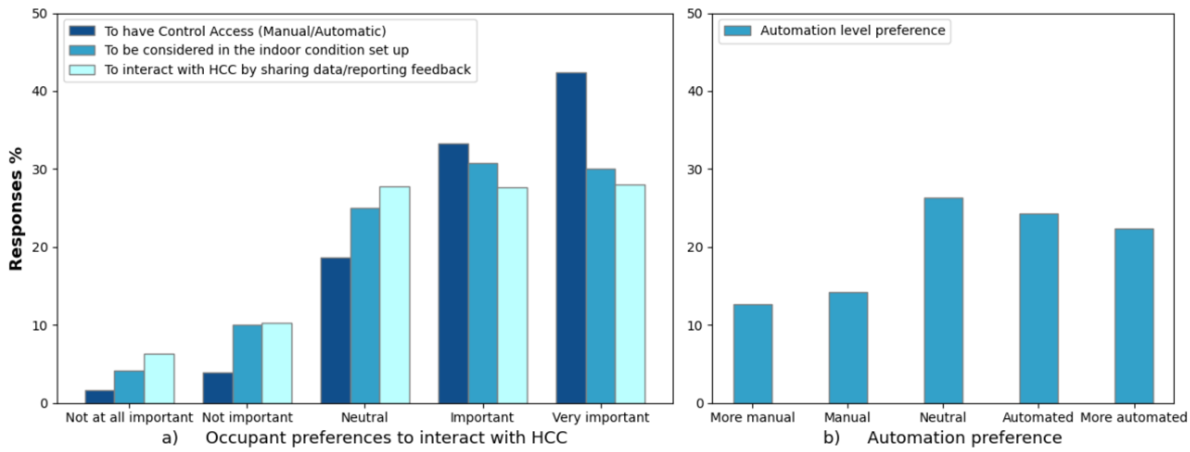

Figure 2.6. Occupant preferences on a) control access, desire to be considered when regulating indoor conditions in automatically controlled environments, and openness to share data or interact with HCC, and b) automation level preference

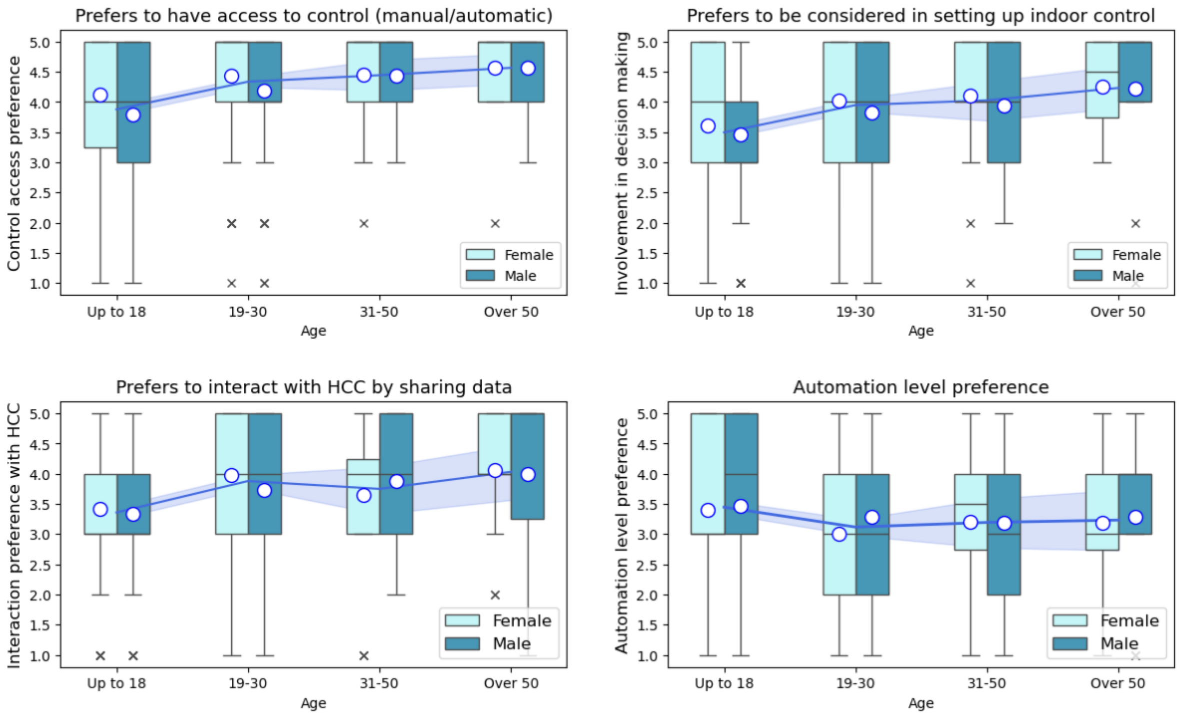

Figure 2.7. Occupant preferences based on demographic details: control access (top left), desire to be considered in automated control (top right), openness to share data or interact with HCC (bottom left), and automation scale preference (bottom right)

HCC systems can manage multiple comfort aspects, such as IAQ, thermal, and visual comfort. The results in Figure 2.8 show that 85% of respondents found IAQ as the most important comfort aspect (based on cumulative responses of *very important* and *important*). This outcome is closely followed by thermal comfort (84%) and visual comfort (74%). This finding is important considering that most studies dealing with comfort focus primarily on thermal comfort, when the results here show that IAQ is as much or even more important to building occupants. Hence, when aiming for human-centric design, the focus should also be on IAQ.

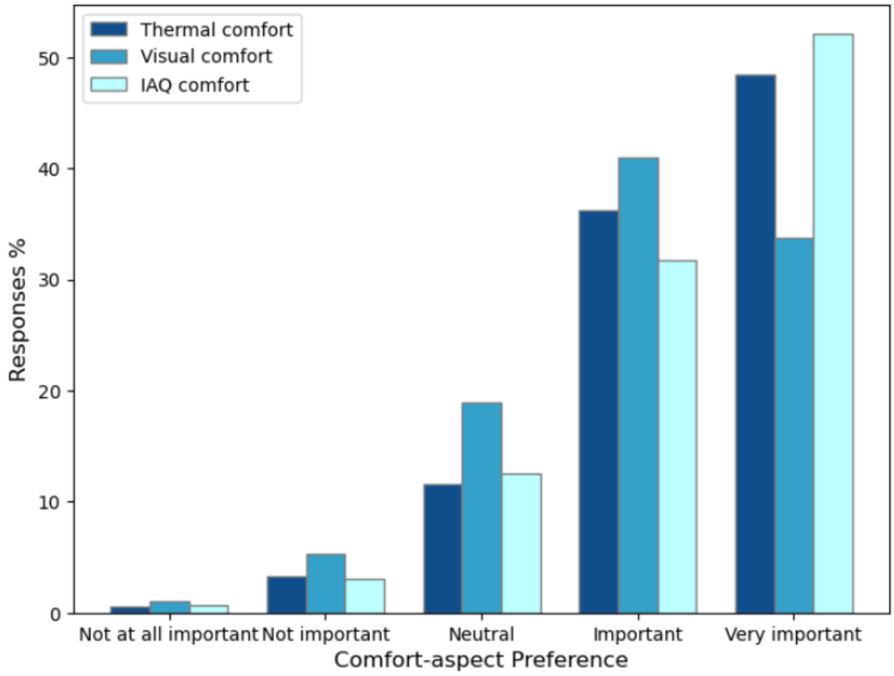

Figure 2.8. Comfort aspect preference showing which comfort aspect occupants prioritize (IAQ, thermal, or visual comfort)

However, the perceived importance of the comfort aspect might vary depending on the demographics of the individual respondent. Figure 2.9 shows the variance of the perceived importance for different age groups and occupants in different educational buildings (different technical knowledge and interests). It shows that occupants perceive IAQ as the most important comfort aspect, followed closely by thermal comfort for all age groups. However, visual comfort is perceived as less important for younger groups than older groups.

This study also explores user preferences regarding interface design and the data-gathering process, which is important when designing HCCs. Figure 2.10 shows the survey results regarding occupant preferences when using HCC interfaces. The results indicate:

- Smartphones are the most convenient tool for reporting feedback, specifically smartphone applications (65.9%). This is likely due to the widespread ownership of smartphones today, while fewer people own or prefer to carry smartwatches or another similar gadget.
- Concerning the frequency of data sharing throughout the day, occupants only want to interact with the controller when feeling uncomfortable (73.3%), and some can compromise by interacting once every few hours (14.4%).

– In all, 53.3% of respondents are open to interacting with HCCs only on their terms, usually when discomfort arises, and only 29.5% want to receive reminders or nudges to share data.

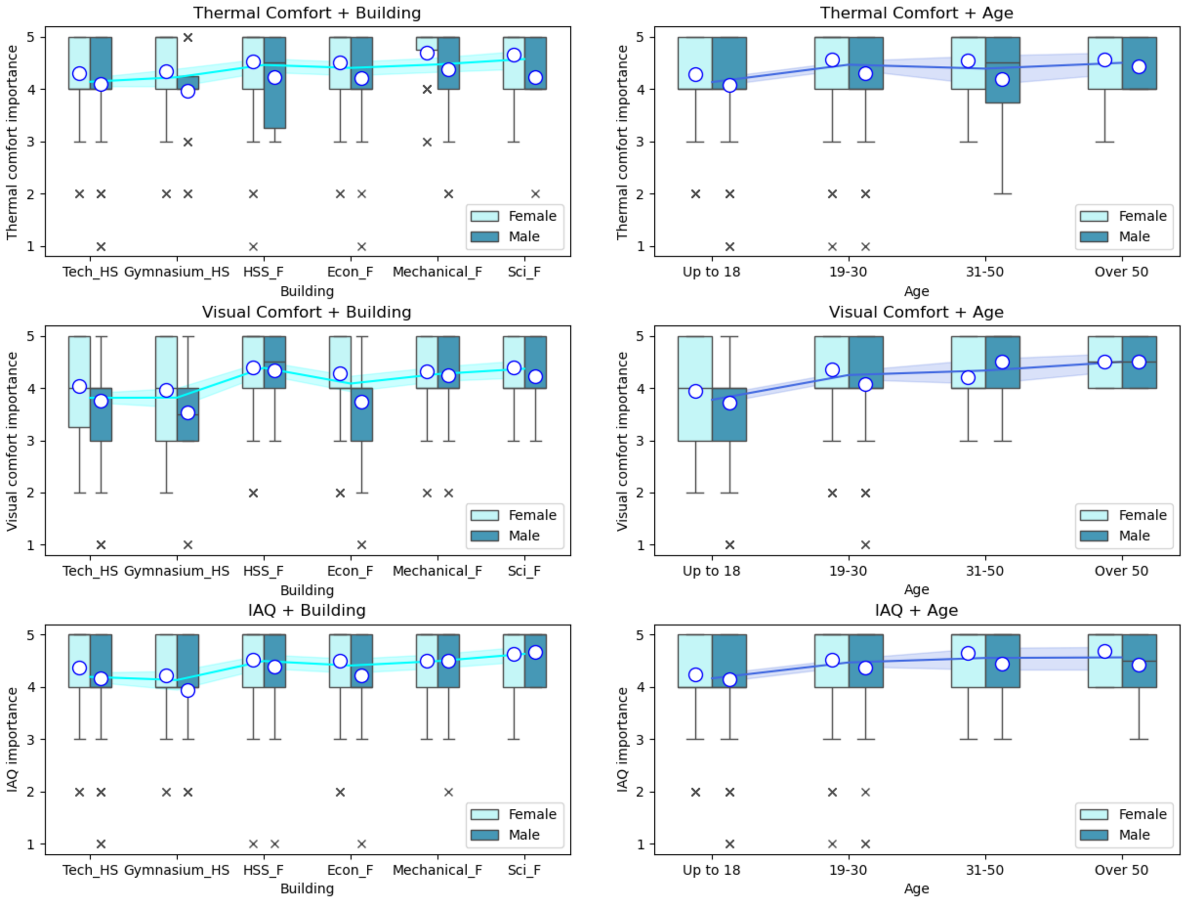

Figure 2.9. Comfort aspect preference showing which comfort aspect occupants prioritize based on age group, sexes, and occupant background (or technical knowledge)

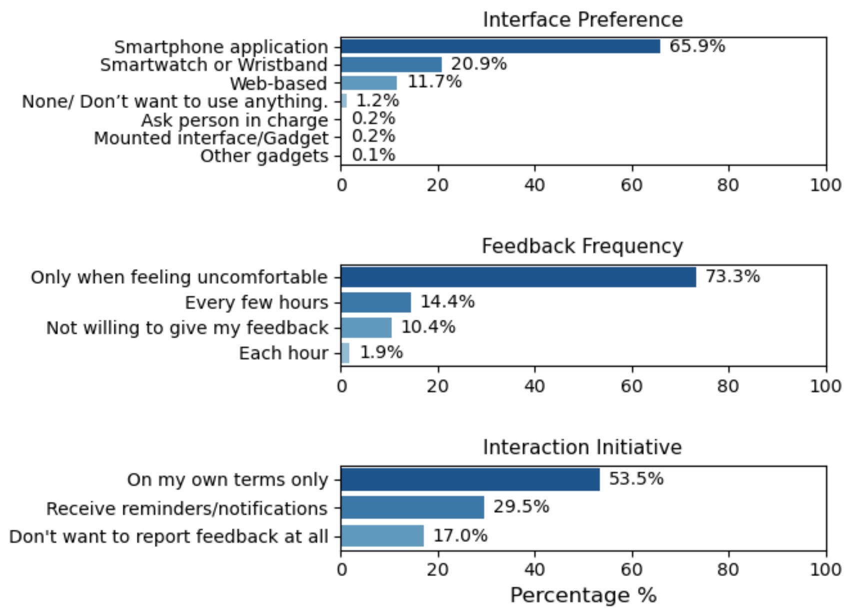

Figure 2.10. User preferences on the interface type for sharing data with HCC, feedback frequency, and preferred manner of initiating interaction

Given that HCC requires occupants to share data, user trust should be considered. The results presented in Figure 2.11 show that:

– Occupants are divided regarding their trust in privacy when sharing data with the HCC. Overall, 40.8% would trust the HCC with their data (basic personal information and location), whereas 32.9% of respondents would most likely not trust the controller even when it was emphasized that all privacy measures had been ensured.
– Although it is a novel concept, 60.9% of occupants trust the operability of HCC, i.e., they trust they will benefit from using HCC or it will make a positive difference.

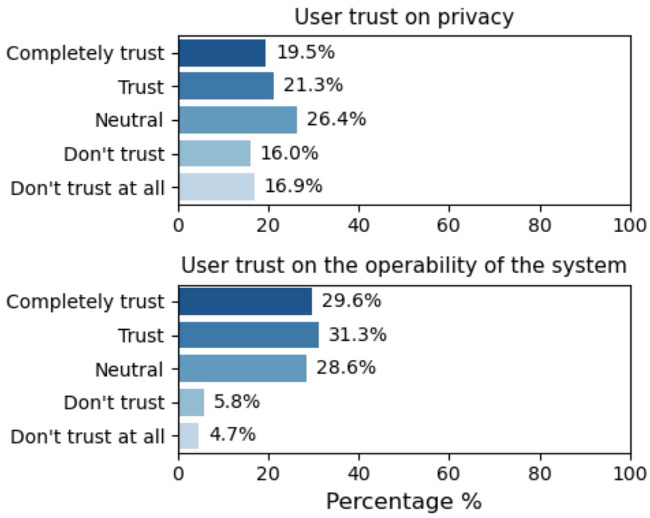

Figure 2.11. User trust in privacy security (top) and user trust in HCC operability (bottom)

HCC can facilitate the engagement of occupants in grid flexibility actions, such as notifying users of an overloaded grid, allowing them to reduce energy consumption (dim lights, adjust the temperature, unplug unnecessary appliances). However, it is important to determine whether occupants are open to engaging in actions that can potentially compromise their comfort, for instance, when reducing the indoor temperature during the heating season to alleviate energy demand in the grid. Occupant preferences regarding their engagement in grid flexibility are shown in Figure 2.12. The results suggest that:

- If given the opportunity, 59.5% of occupants are open to engaging in grid flexibility actions.
- 14.6% prioritize their comfort and would not engage in grid flexibility actions if they had to compromise their comfort (e.g., decrease the indoor temperature).
- Higher financial gains do not necessarily motivate occupants to engage in such actions. Most (30.9%) would adopt curtailment actions for grid flexibility even without obtaining personal monetary gains, as their actions are driven by other intrinsic values (such as high energy-saving or environmental awareness).
- Most occupants (47.7%) would engage in curtailment actions (i.e., dim the lights or reduce the indoor temperature if informed of an overloaded grid) but only for a short period of time, i.e., 1 – 2 hours a day. Only 22.1% would do so for a more extended period of time, i.e., more than 2 hours daily, while some are willing to interact all the time if necessary (21.6%).

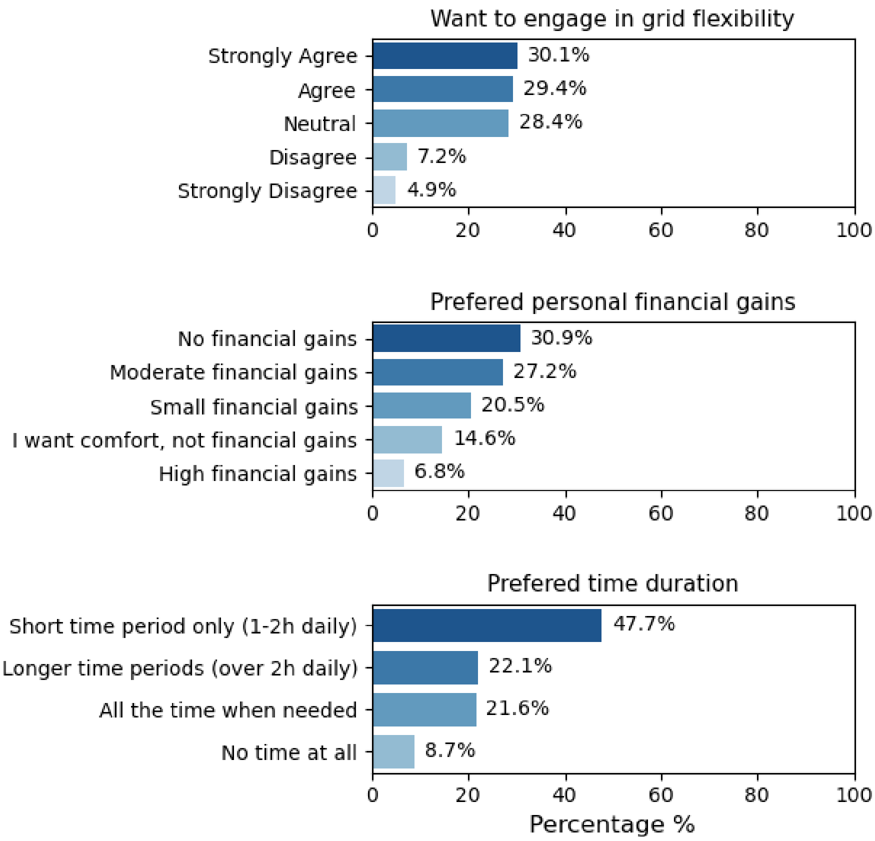

Figure 2.12. User preferences on grid flexibility engagement. Openness to participate in grid flexibility actions (top), personal financial gains as motivation to participate (middle), and the time duration for which they are willing to participate (bottom)

2.3.5 Findings on the model performance to predict occupant willingness to interact with human-centered control

One of the aims of this research is to provide a model based on behavioural science theory to predict the willingness of occupants to interact with HCC by reporting feedback. Three TPB models were developed and analyzed using the SEM method. The first model (M1) was built upon the fundamental form of TPB to predict occupant willingness to interact with HCC for indoor environmental control. The second model (M2) was built upon a proposed framework that uses the fundamental form of TPB and adds more influencing factors. The target of this model was the same as M1. Lastly, the third model (M3) used another proposed framework with additional inputs, and the target was to predict the willingness of occupants to interact with HCC for grid flexibility (to be engaged in demand response). These models enable us to estimate if building occupants are predisposed to share data, which creates a degree of certainty that they will provide data.

The results show that the willingness of users to interact with HCC can be predicted with a satisfactory prediction potential. The yielded predictive potential of the models is M1 ($R^2 = 0.62$), M2(0.64) and $M3(0.64)$. The R^2 shows the prediction potential or the percentage of the covered influencing factors that explain why a phenomenon happens. The higher the value of R^2, the more the model explains the observed phenomena. The reached value in all three models is above 60%, which is satisfactory as the model predicts a human behaviour, which has an unpredictable nature. For reference, in social and behavioural sciences, as a rule of thumb, an R^2 of 0.75 is a relevant prediction, 0.5 is moderate prediction and 0.25 is a weak prediction potential of the model [88]. Hence our values are in the upper bound of moderate which is acceptable. To strengthen these findings, predictive potential of the models was also measured using other metrics, like the model fit using SRMR (Standardized Root Mean Square Residual) and predictive relevance using Q^2, the results again complied with the thresholds [84] and are shown in more detail in Annex B.

The results of the path coefficients (coefficients that show the strength of the relationship between two variables) from the measurement models are presented in Figure 2.13 only for model M1. The higher the path weight and value of the t-statistic, the greater the influence of the factor on the observed phenomena. The R^2 is also shown in the same figure indicating the predictive potential of the model $R^2 = 0.62$ for model M1. Furthermore, Table 2.2 shows the results from the structural model and confirms the posed hypotheses for model M1, that attitude or beliefs, social norms and ease of use or perceived control, significantly impact the willingness of occupants to interact with HCC. For the other models (M2 and M3), the path coefficients, as well as other numerical results of CV and DV are presented in the respective tables in Annex B, for brevity.

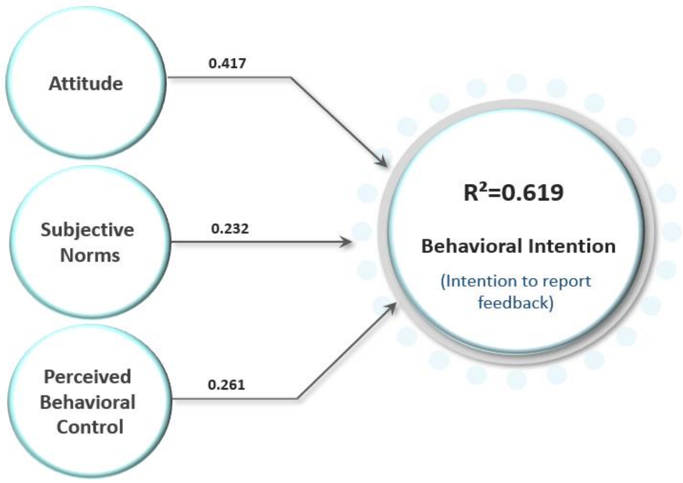

Figure 2.13. Measurement model result of the path coefficient for the fundamental TPB (M1)

Table 2.2. Structural modeling results and hypothesis testing of model M1

	Relationship	Path weight β	T statistics	P values	Confidence intervals 2.50%	97.50%	Hypothesis
H1	Attitude →Behavioral Intention	0.419	12.513	0.000	0.352	0.483	Supported
	Perceived Control → Behavioral Intention	0.262	8.812	0.000	0.202	0.319	Supported
	Social Norms → Behavioral Intention	0.229	8.016	0.000	0.173	0.285	Supported

2.3.6 Predictions on the willingness of users to interact with the HCC

The most important findings from the M1 and M2 models predicting user willingness to share data to interact with HCC or the intention to report feedback (i.e., a willingness to interact with HCC), shown Table 2.2 and for M2 in Annex B, Table B.5., are as follows:

- The willingness to interact with HCC can be predicted using the M1 and M2 models. The explained variance or the prediction potential of the M1 model is $R^2 = 61.9\%$, and for the M2 model it is $R^2 = 63.9\%$. It means that this model explains almost 64% of all influencing factors and that the respondents are willing to participate.
- The main influencing factors impacting the willingness to interact with HCC are user attitudes (beliefs in the advantages of using HCC, whether users will save energy, mitigate the environmental impact, and feel more satisfied with indoor conditions). This

is measured in both M1 ($\beta=0.42$, p-value<0.05, t-statistic=12.51) and M2 ($\beta=0.26$, p-value<0.05, t-statistic=6.67). The metric β is the path coefficient that shows the intensity or strength of the relationship, the higher the value the stronger the correlation. The p-value shows if the relationship is significant (the threshold is p-value<0.05) and t-statistic>1.96 also measures significance and the quality of the relationship. In the following findings, only the path coefficient β is presented in the text, the other values can be seen in their corresponding tables.

- Subjective norms significantly impact a willingness to interact with HCC, i.e., social norms and the impact of other people's opinions or motivation to comply (e.g., a group of colleagues reporting feedback would motivate other people to do the same). This was measured in M1 ($\beta=0.23$) and M2 ($\beta=0.216$).
- Perceived behavioral control (the ease of use or perceived user ability to interact with HCC), significantly impacts the willingness to interact with HCC, as shown in M1 ($\beta=0.26$) and M2 ($\beta=0.23$).
- User preferences for control systems (control access preference, automation level) slightly impact the willingness to interact with HCC (M2, $\beta=0.079$).
- User trust (in terms of privacy issues and trust in the operability of the system) significantly impacts the willingness to interact with HCC (M2, $\beta=0.13$)
- Demographic characteristics (age and gender) do not have a notable impact on the willingness to interact with HCC (M2, $\beta=0.028$).
- Notifications or nudges sent to inform users on how their actions (e.g., dimming the lights or reducing the indoor temperature) affect energy usage or the environment have an impact on user willingness to interact with HCC (M2, $\beta=0.79$).

2.3.7 Predictions on the willingness to engage in grid flexibility actions

If occupants are willing to share data or report feedback with HCC, does this mean they are also willing to engage in grid flexibility actions? This correlation was tested in the M3 model, and the results are shown in Annex B, Table B.6. The results suggest that:

- Occupants willing to interact with HCC are more likely to engage in grid flexibility actions. It was measured in the M3 model showing a significant correlation between these two actions (M3, $\beta = 0.17, p - value < 0.05, t - statistic = 4.64$)
- User preferences (M3, $\beta = 0.10$) and user trust (M3, $\beta = 0.07$) significantly impact the willingness to engage in grid flexibility. Other numerical values shown in Annex B.
- There is an impact on the willingness to engage in grid flexibility from occupant demographic characteristics (M3, $\beta = 0.12$). It means different age groups perceive engaging in grid flexibility actions differently.
- Notifications or nudges positively impact the willingness to engage in grid flexibility actions (M3, $\beta = 0.27$).
- Personal financial gains (financial benefits that occupants gain when engaging in grid flexibility actions) have an impact on their willingness to engage in grid flexibility actions (M3, $\beta = -0.09$). Surprisingly, the findings indicate that more occupants are open to engaging in grid flexibility for lower rather than higher financial gains. It suggests that increasing financial gains is not necessarily a source of motivation for users, but their drive to interact comes from other intrinsic values.
- The time span or duration in the day when occupants would accept curtailment actions (e.g., dimming the lights or reducing the indoor temperature) if the grid is overloaded significantly impacts their willingness to engage in grid flexibility actions (M3, $\beta = 0.23$). It means that occupants like shorter periods rather than longer ones for interaction.

To strengthen the findings of using the extended TPB model M3, another approach was tested using a heatmap correlation matrix for the survey data. The insights yielded from Figure 2.14 are in line with the findings from the TPB and they suggest that:

- If occupants are prone to interact with HCC, they are more likely to engage in grid flexibility actions.
- Energy saving awareness of occupants has a high impact on the willingness of users to share data and their willingness to engage in grid flexibility actions.
- People are willing to engage in grid flexibility actions (such as dimming the lights or decreasing the temperatures in winter) for a short period ($1 - 2$ hours) but not for more extended periods.

– Financial gains do not have a positive correlation, meaning that an increase in financial gains does not necessarily mean people will be more prone to engage in grid flexibility.

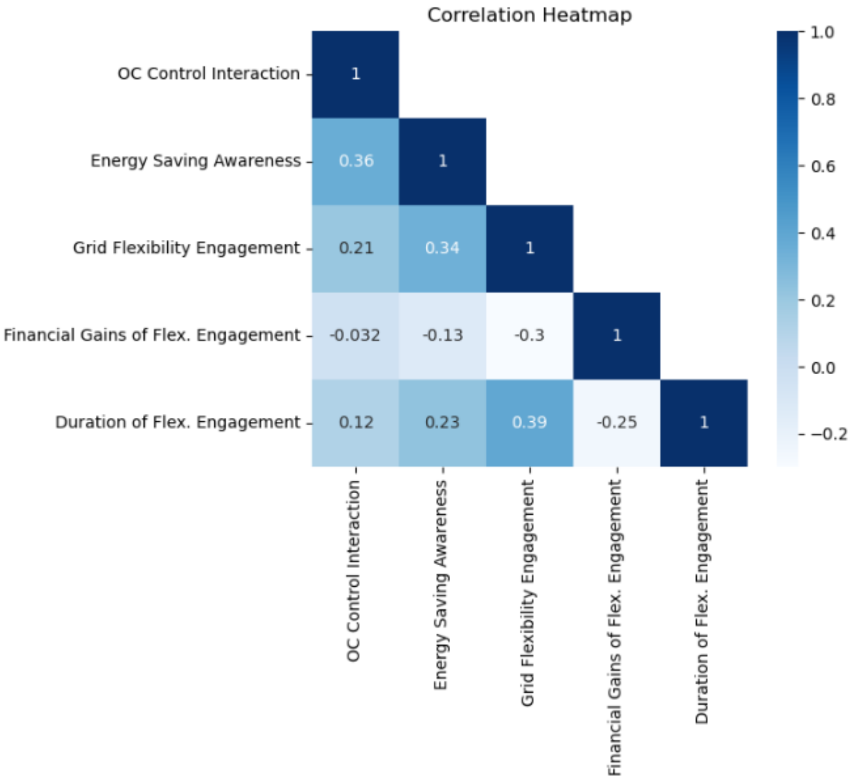

Figure 2.14. Heatmap correlation matrix of the willingness of occupants to share data with HCC and their willingness to engage in grid flexibility actions

2.3.8 Influencing factors when engaging occupants in grid flexibility actions

The impact of individual influencing factors on grid flexibility engagement was also assessed using the Importance Performance Map Analysis (IPMA) [87] and is presented in Figure 2.15. The results suggest the following:

– Notifications have the highest potential to increase user willingness to engage in grid flexibility. This means that once occupants receive information (either through a smartphone application or another interface) about how their actions lead to higher energy savings, a lower environmental impact, and other benefits, they will become more motivated to interact with HCC for grid flexibility.
– The time duration of the grid interaction is important and needs more in-depth consideration. More specifically, the shorter the duration of grid flexibility actions, the higher the user readiness to engage in such actions.

- User trust is also an important influencing factor, meaning that transparent data privacy measures can bolster user engagement to share data when needed.
- Personal gains, in line with the findings from the extended TPB model, are attributed as "Low Priority" according to the IPMA (Quadrant III). In other words, this corroborates our previous finding that financial gains are not a top priority when motivating occupants to engage in grid flexibility actions.

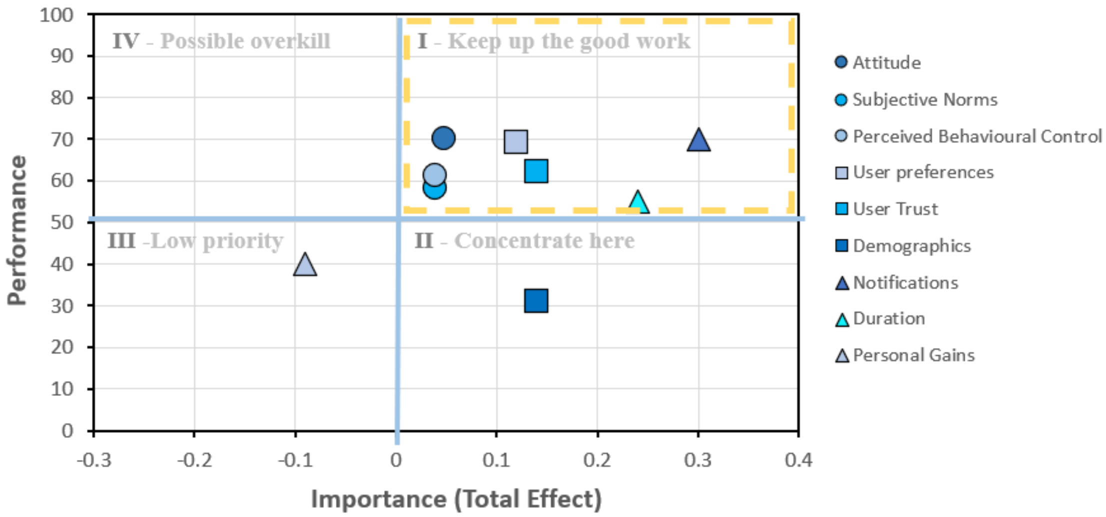

Figure 2.15. The IPMA analysis diagram shows the distribution of the influencing factors towards grid flexibility based on importance

2.4 Discussion and Conclusion

This study investigates HCC systems in buildings, focusing on the integral role of user preferences regarding control systems and user willingness to participate in the successful implementation of HCC through sharing data on perceived user comfort and engaging in grid flexibility actions. The survey-based research was conducted in six different educational buildings with a diverse target group in terms of age, sex, and technical knowledge, totaling 959 respondents. The results offer valuable insights into user preferences for interacting with control systems. It includes their preferences on control access, automation level, willingness to interact with advanced controllers that utilize user data in the form of reported feedback on the comfort conditions, and user willingness to engage in grid flexibility actions. Furthermore, it also offers insight into preferences on the interface design for sharing data and the actual process.

Although HCC opts to prioritize users, some aspects, like user willingness to share data and user preferences, are often overlooked in research. The findings from this study show that occupants want control access, but, unsurprisingly, their engagement diminishes when effort or data sharing on their part is involved. Therefore, user interaction with controls dependent on user-reported data cannot be seamlessly assumed but can be predicted to increase the level of certainty that users will interact with controllers through data sharing in the form of reported feedback. Furthermore, 46.7% of the occupants prefer higher automation levels, which goes in line with findings of research [40]. Also, in compliance with research [39], the results show that they also want control access (75.7%), but only 55.6% would like to interact with the controller by reporting feedback. This indicates that almost 20% of occupants would rather not have control access at all than interact with an advanced controller through active inputs. This finding is important as it shows that the occupants' involvement as active data providers cannot just be assumed, even if the interaction of users is needed for a short time to develop personalized models.

HCC systems enable the management of multi-dimensional comfort aspects like IAQ, thermal comfort, and visual comfort. The results from the survey show that IAQ holds the most importance among occupants (85%), followed by thermal (84%) and visual comfort (74%). This outcome may be due to the pandemic, which placed paramount importance on air quality. Interestingly, the perceived significance of these comfort aspects remains somewhat consistent across different age groups, except for visual comfort, which seems less important for younger individuals (up to 18 years old). Therefore, in addition to thermal comfort, IAQ control should also be given priority in building control systems.

The study also emphasizes the importance of understanding user preferences to optimize HCC design. The results show that the preferred tool for occupants reporting feedback is a smartphone application (65.9%), which most likely stems from its widespread use and convenience. Users are willing to interact or share data in most cases only when discomfort arises (53.5%), and some are open to accepting reminders (29.5%), indicating the significance of nudges or notifications. These results support the concept that feedback sharing needs to be effortless and infrequent to avoid overwhelming occupants [89]. Hence, if user data is used to develop PCM, historical data or data transfer and tailoring from other groups can be used to avoid the need for too much data from users. Using cohort-based models to adapt data by groups of similar comfort preferences is well used in some research studies [4], [90].

In an attempt to predict user willingness to interact with HCC through data sharing and identifying a possible correlation of this willingness with user readiness to engage in grid flexibility actions, three versions of the Theory of Planned Behaviour (TPB) model were developed and evaluated (M1, M2, M3). The moderate predictive potential or explained variance for the M1 and M2 models ($R^2 = 61.9\%$, and $R^2 = 63.9\%$, respectively), suggests that occupant willingness to share data can be predicted and occupants are willing to interact with HCC.

The major motivators to interact with HCC for all three models resulted to be occupant attitudes ($\beta = 0.264$, believing in the benefits of sharing data in terms of energy savings or the environment), perceived control ($\beta = 0.231$, occupants pondering on whether they are capable of reporting feedback or whether the task is easy, means they are more prone to do the task) and lastly, the social aspect ($\beta = 0.216$, how other occupants interact with the controllers or their opinion on the matter highly impacts their behavior). This goes in line with other TPB-related research studies [91], [92], [93]. The yielded results for all three fundamental TPB constructs in model M1 show ($p<0.001$), hence supporting the posed hypothesis (H1) that attitude, subjective norms, and perceived control significantly impact the willingness of users to interact with HCC. These findings suggest that knowing what motivates and drives the occupants is beneficial when planning to implement HCC systems in actual buildings. As a result, appealing interventions to the occupants can be tailored, such as nudges or prompts through the feedback interface. For example, if the awareness for energy saving is high, then prompts may be tailored to include information on how much energy was or can be saved. Increasing environmental and energy-saving awareness through campaigns or education enhances the belief of occupants in the usability of such systems, thereby improving their willingness to engage in HCC, which can lead to significant energy savings.

On the other hand, when considering Perceived Behaviour Control and Subjective Norms, the results show that the perceived ease and ability to report feedback and the social impact (opinion of others, peer pressure) significantly influence the Intention to report feedback. These findings comply with research [93] where higher perceived control determined higher intention to perform the studied behaviour of using smart meters. On the other hand, the results show that the social impact is also an important driver of the occupants' intention to report feedback, meaning that there is ground for possible interventions e.g. comparison among peers or gamification [94]. Additionally, due to the early stage of development and adoption of

HCC, people tend to rely more on the opinion of others when it comes to interacting with new technologies as asserted by [55], which justifies the current results of high social impact.

The results on the impact of user trust (the privacy concerns of users when sharing data and their belief that the system is beneficial) suggest that user trust significantly impacts their willingness to interact with HCC. This goes in line with the findings of other TPB [45], [55] where the impact of user trust was assessed for the intention to adopt smart home services and internet banking, respectively.

The third TPB model, M3, explores the correlation between user willingness to share data with HCC and the readiness to engage in grid flexibility actions. All relationships resulted to be significant with $p - value < 0.05$. The findings show that those willing to share data are more likely to engage in grid flexibility actions ($\beta = 0.17$). The shorter the required time duration during the day, the higher the willingness of occupants to interact with the grid ($\beta = 0.23$). Surprisingly, although financial benefits have a significant impact ($\beta = -0.09$), higher financial gains do not always equate to higher levels of engagement. The results suggest that 30.9% of occupants would interact even without any financial benefit and a smaller portion for small financial benefit (20.5%). Some would interact for moderate financial gains (27.2%), and fewer occupants for high financial gains (6.8%). Lastly, there are those who, regardless of financial gains, want to prioritize their comfort (14.6%). Results also suggest that demographics impact the willingness to engage in grid flexibility actions ($\beta = 0.12$), but not the overall willingness to interact with HCC ($\beta = 0.028$).

Lastly, the findings mentioned above were confirmed using a correlation heatmap, reiterating that occupants are prone to interact with HCC for indoor environment control and are more likely to interact with it for demand response actions. Moreover, the IPMA analysis used to identify critical factors that can improve interaction with HCC and engagement in grid flexibility shows that notifications, time duration, and user trust are pivotal areas that can boost participation. The theoretical and practical implications elicited from this survey are discussed in the following sections.

2.4.9 Theoretical implications

This research developed three TPB models, namely M1, M2 and M3. Model M2 and M3 present novel frameworks not encountered in previous research studies to the best of the author's knowledge. The framework can be a foundation for future research studies on user willingness towards other control-related actions (either for indoor climate control or grid flexibility actions), and it can be expanded with additional exogenous variables. It is also a significant contribution to broadening the use of TPB in multidisciplinary fields beyond social sciences.

2.4.10 Practical implications

The concept of HCC indicates that its design should be rooted in occupant preferences and needs. However, user willingness to interact with HCC or their preferences in the data-sharing process and interface design are not often considered. In opting towards an occupant-centered approach, the findings of this research are presented below and can be used as guidelines for HCC practitioners and designers:

- Automation and interaction: most users favor an automated control system with interaction capabilities or a system giving them control over it. However, they prefer not to spend too much time or effort interacting with it. This occupant attitude highlights the need for adaptable control systems that customize indoor conditions to user comfort preferences.
- Data sharing and feedback: users are willing to share data with HCC predominantly when discomfort arises. However, proactive nudges and reminders are important in motivating interaction, although only around 30% of occupants said they would like to receive such nudges. Notifications that illustrate user actions environmental and energy impact enhance user engagement to share data or participate in grid flexibility actions.
- Influencing factors and motivators: intrinsic values such as user beliefs and awareness of the possible benefits of HCC significantly impact user willingness to interact with HCC. Accordingly, there should be a greater focus on educating people about the benefits of HCC and grid flexibility to increase awareness, ultimately leading to higher engagement levels. Social impact is also an important indicator, suggesting that behavioral approaches (comparison, gamification) can motivate people to participate on a larger scale. These approaches were used in different energy efficiency actions in [95], [96], [97]. Lastly, the ease of sharing data with HCC is very important, meaning that intuitive, easy-to-use interfaces make the reporting process less burdensome for users.
- Feedback mechanism: users prefer smartphone applications for reporting feedback, possibly due to the widespread use of smartphones. The findings suggest that smartphone

applications should be simple, easy to use, and require less frequent feedback, and a high degree of privacy security should be ensured.

– Grid flexibility engagement: the findings suggest that users inclined to interact with HCC are more inclined to participate in grid flexibility actions. If higher user engagement is expected, a shorter duration of curtailment actions should be planned. Higher financial benefits for the users do not always equate to higher levels of user engagement; therefore, although financial incentives are important, other motivators also need to be considered.

2.4.11 Limitations and future research directions

Although the findings cover a wide range of the population regarding age groups, there is a relatively limited number of elderly respondents because the survey was conducted on educational facilities. However, the current respondents are the most likely users of HCC, given that a broader implementation of such systems is still in the development phase. In the future, it will be interesting to compare the occupant behavior while interacting with HCC after implementation in real-world settings compared to their expressed willingness to interact. Furthermore, it is also interesting to explore the long-term impact of HCC data collection interfaces on occupant engagement. Despite the various aspects considered in this research, several other influencing factors impact user willingness to share data and are worth analyzing, such as the personality traits of occupants. Lastly, other means of soliciting occupant preferences should be explored (e.g. from interviews) to extract additional insights that otherwise are harder to predict.

Chapter III.

3. Development of Personalized Comfort Models

Parts of this chapter are based on:

A. Bresa, T. Zakula, and B. Omerzo, "Indoor Air Quality Comfort Model Development Using Machine Learning," *18th SDEWES Conference, Dubrovnik, Croatia*, Sep. 2023

"When I enter most intimately into what I call ***myself****,*
I always stumble on some particular perception or other, of heat or cold,
light or shade, love or hatred, pain or pleasure."

D. Hume

The development of personalized comfort models (PCMs) plays a pivotal role in understanding people's perceptions of their indoor surroundings, which is crucial for creating environments that meet their needs and preferences. By learning user preferences over a short period, PCMs reduce the need for constant user input, addressing the challenge of obtaining user-provided data for human-centered control (HCC) systems. PCMs can be developed for different comfort aspects such as thermal, visual, acoustic, and indoor air quality (IAQ) [27]. These models integrate personal characteristics (age, gender, clothing, activity level), subjective feedback, physiological measurements, and environmental data to learn user comfort levels for varying indoor conditions. Although the use of PCMs is still developing, they hold great potential when integrated into advanced control systems. This chapter focuses on creating PCMs that enable user-building interaction without continuous user input. The goal is to develop PCMs for multiple users and comfort aspects. Drawing from two experiments – one in a faculty laboratory and one in a school building – this chapter demonstrates how to develop PCMs, effectively collect data, determine the necessary data points, handle data scarcity, and identify an optimal machine learning model for various comfort aspects and users.

3.1 Literature review

Occupant comfort in the building industry has recently gained significant attention, but there is a significantly higher focus on thermal comfort compared to IAQ, visual, and acoustic comfort [35]. This is because thermal comfort is relatively well understood, and building occupants can immediately sense the lack of thermal comfort. For instance, Liu et al. predicted the thermal comfort of 14 occupants by collecting data for 2 – 4 weeks [32]. Salamone et al. [33] conducted a field experiment with eight office workers to assess their thermal comfort using an ML technique. Research [98] predicted thermal comfort using ML in an office building in France by collecting user feedback. Kim et al. [27] developed thermal PCMs for 38 occupants in an office building. Quintana et al. [99] present data on thermal comfort collected for over four weeks in a faculty building in Singapore from 17 occupants. This dataset was used to develop thermal PCMs in combination with spatial data imported from Building Information Modelling (BIM) in [100] and [31], where the models showed higher accuracy. Research [101] focused on IAQ in a hotel building and collected measurement and subjective data from occupants to develop thermal comfort models. There are some studies dealing with a multi-comfort aspect such as thermal, visual, and acoustic comfort, such as in research [28] where data from 30 occupants for over two weeks were collected to develop multi-aspect comfort models and also show the correlation between thermal comfort and other comfort aspects. The correlation of the multi-comfort aspect is also studied in research [102], where the impact of visual stimuli on the thermal comfort perception of users in real and virtual environments using ML was tested. Although these studies have made significant efforts in thermal comfort predictions, the other comfort aspects are not as researched, which is important to improve overall occupant comfort.

Data-driven ML models are widely used in the building sector, as stated in [103] and can be leveraged for comfort-related predictions in buildings [104]. These models are becoming increasingly popular as they outperform traditional comfort models. For instance, research [105] used ML models in naturally ventilated buildings to predict thermal comfort and sensation. Furthermore, [106] stated that their ML models outperform traditional group-based models like Predicted mean vote (PMV) by 13.1%, up to 17.8%. Research [107] also employs ML models for thermal comfort prediction. The use of ML models in comfort-related studies was extensively discussed in the review [108]. Some of the most used ML models for comfort-related predictions are Random forest [109], [110], [111], Decision trees [112], Support Vector Machine (SVM) [113], [114], ANN [115], [116], [117], [118], [119], Deep learning [24], [120], [121], [122], [123], [124], Reinforcement learning (RL) [125], [126], [127], [128], [129], Logistic regression, K-nearest neighbor (KNN) [130], Bayesian networks [131], [132], [133], etc. The choice of model depends on the target and data availability, and it is important to compare various ML models on the same dataset to identify the best-performing model for a specific target.

Developing data-driven PCMs using ML models requires a lot of user-provided data that ideally would have sufficient variability to avoid an imbalanced dataset. The data collection process in actual buildings is challenging. While more data is better for the models, it also means increasing survey fatigue and burden for the data providers, in this case, building occupants. Furthermore, ensuring a balanced dataset collected from users is difficult in natural settings because feedback data cannot always be sufficiently balanced (e.g., one cannot expect the same amount of reported “Comfortable” and “Uncomfortable” feedback responses) as it would mean that the building is poorly managed [134]. To address this, scheduled feedback-reporting times are often used, such as participants are asked to report their feedback once every half-hour or hour, but this can disrupt occupants’ daily tasks. If feedback reporting is left entirely to occupants, the data collection process can become prolonged, as evidenced by a study where 77% of participants only reported 1 – 2 times over six months [135]. To overcome this challenge, various methods have been developed, like Cohort-based models, that develop PCMs by grouping people with similar characteristics and using data from other occupants from the same group [4], [90]. Additionally, algorithms such as comfortGAN [134] can augment imbalanced datasets. Another method involves leveraging data collected from peers in similar indoor settings to address gaps in individual datasets. This approach enables the initial development of PCMs, which can be refined and adjusted as more personalized data becomes available. Despite these efforts, the question of how to collect sufficient data for proper PCM development remains an ongoing quest.

Several studies have outlined the necessary data points for PCM development. For instance, some research suggests that 250 – 300 data points are needed for reliable PCM development [136], while other studies have achieved 80% classification accuracy with just 50 data points, representing 60% of the collected data [20]. Daum et al. [137] reported that 90 data points are needed for the model to converge. Kim et al. [27] developed stable predictions of comfort models with around 60 data points. Research [138] used 110 and 150 data points for two users, respectively, and achieved an overall accuracy of > 94% to predict thermal preference. In [139], they used two weeks of data collected from wearable technology for at least 20 hours/day and achieved 75% accuracy. The required number of data points varies based on the ML model used (e.g., neural networks, logistic regression, random forests), the classification classes (e.g., binary vs. multi-class classification), and the indoor conditions during data collection (data variability) etc. Generally, binary classification (e.g., Comfortable vs. Uncomfortable) requires fewer data points and offers higher predictive potential [134]. However, this can confuse users when asked to provide feedback on their comfort level for different aspects (e.g., IAQ, thermal, visual comfort). In contrast, multi-class classification (e.g., want warmer, no change, want cooler) might require more data but is easier and more intuitive for users to answer. The question of whether preference-based models (multi-class classification) or comfort-based models (binary classification) are better for PCMs is still debated.

Due to the challenges of collecting data from occupants, there is a lack of openly available measured datasets accompanied by user-reported comfort data. Some studies provide valuable data, such as Quintana et al. [99] sharing four weeks of data from 17 collected participants, as well as Gao et al. [140] sharing data in a K-12 private school in Australia from 23 students and six teachers for four weeks. Both studies included indoor and outdoor measurements, physiological data, and subjective feedback on occupant perception. However, these studies focused primarily on thermal comfort and did not include multi-comfort aspects such as temperature, air quality, and lighting. Therefore, it would be highly beneficial for the whole research community and the industry to provide data sets that entail multiple comfort aspects for multiple users.

3.1.1 Thermal personalized comfort models

Thermal comfort is a state of mind [141], making it challenging to quantify and predict due to its subjective nature. While various mathematical models (PMV, PPD) and physiological measurements (heart rate, skin temperature) are used to assess thermal comfort, they are incomplete without involving the "mind" or subjective feedback from users [36]. Thermal comfort is among the most studied comfort aspects. Table 3.1 shows the reported studies that developed thermal PCMs by using occupant votes or feedback on their perceived comfort, and some of them combined the feedback with physiological measurements.

PCMs are developed using various input variables and predict different outputs depending on the researchers and the aim of the model. This was also emphasized in a review of comfort models [146]. Kim et al. [26] mentioned that there is a need to unify the input variables to avoid unnecessary complications that come from gathering additional data. Figure 3.1 shows some of the most used inputs and outputs in PCM based on the number of studies analyzed, such as indoor air temperature, relative humidity, and air velocity. It also includes physiological measurements of the human body, such as temperature on the wrist, forehead, face, nose, etc. Then, there are others like occupancy status and subjective inputs like preferred temperature, sensations, etc.

Table 3.1. Literature review on thermal PCMs

Ref.	Author	Year	Title	PCM, target	ML model
[109]	Chaudhuri	2018	Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology	Thermal sensation, thermal preference, and thermal comfort votes, also uses PMV.	RF
[27]	Kim	2018	Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning	Thermal preference	CTree, GPC, GBM, kSVM, RF, regLR
[10]	Lee	2019	Implementation of a self-tuned HVAC controller to satisfy occupant thermal preferences and optimize energy use	Thermal preference	Bayesian clustering
[112]	Jiang	2019	Personalized Thermal Comfort Model with Decision Tree		Decision tree
[142]	Zhang	2020	Coupled thermal comfort control of thermal condition profile of air distribution and thermal preferences	Thermal condition profile	Possibility analysis, Sequential coupling
[143]	Wang	2020	Dimension analysis of subjective thermal comfort metrics based on ASHRAE Global Thermal Comfort Database using machine learning	Thermal acceptability, thermal preference, thermal sensation, comfort	Logistic regression, SVM
[144]	Dimara	2021	Personalized thermal comfort modeling through genetic algorithm		Genetic algorithm
[145]	Suman	2021	Towards Personalization of User Preferences in Partially Observable Smart Home Environments	Activity-based	Bayesian, LSTM, RL
[4]	Quintana	2021	Cohort-based personal comfort models for HVAC occupant-centric control	Thermal preference modeling and prediction,	RF

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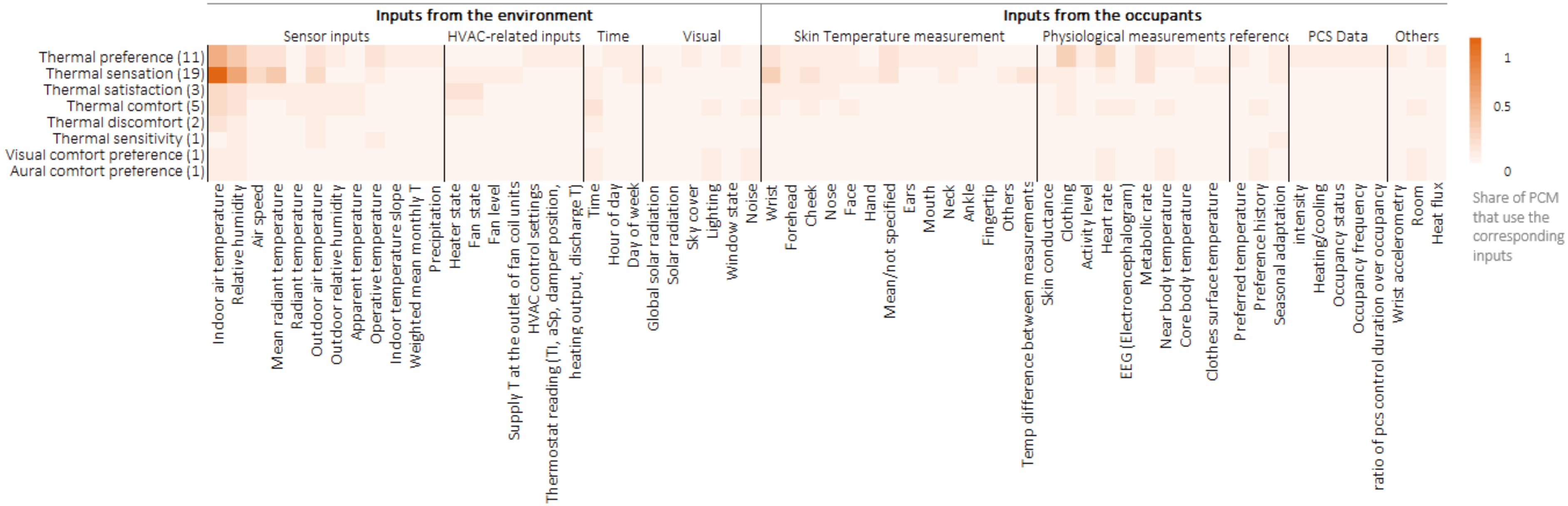

Figure 3.1. Input variables and outputs used for PCMs in the literature. The scale presents normalized values of the used variables in the aggregated number of studies shown in brackets

3.1.2 IAQ personalized comfort model

IAQ significantly impacts the health and well-being of occupants. It involves multiple pollutants and factors, making IAQ comfort a complex issue. Its effects can be subtle, often not showing immediate symptoms, which makes it challenging to point out clear cause-and-effect relationships. Additionally, IAQ is often not adequately considered through quantifiable metrics, as mentioned in [147]. It has sometimes been overlooked by the building industry, which has traditionally prioritized energy efficiency and thermal comfort.

The use of data-driven ML models has also emerged as a solution to IAQ-related issues. A recent study discussed how to leverage IoT, big data, and ML models for air pollution monitoring [148] and research [149] discussed the opportunities and challenges of using IoT to achieve higher indoor air quality. For instance, research [150] shows a review of the use of ANN models to predict IAQ in schools. On the other hand, research [151] uses ANN to predict indoor environmental quality by predicting the PMV, the CO_2 level, and particulate matter. A similar study using ANN to predict indoor air pollutants was conducted for child daycare centers [152]. Furthermore, research [120] shows the leverage of deep learning in ML to optimize thermal comfort, IAQ, and energy saving in a faculty classroom. Research [153] shows the use of ANN for IAQ level prediction in an educational building. Research [154] shows the use of ML models to predict the change in CO_2 level in an office with multiple occupants during 1007 meeting sessions. A similar study with one year of indoor measurements in an office using four different ML models to predict future CO_2 levels is discussed in the research [155].These studies show that the use of ML for IAQ-related issues is focused more on predicting parameters like air pollutant levels than on predicting the IAQ-related comfort perceived by building occupants, which emphasizes the need for IAQ PCMs.

3.1.3 Visual personalized comfort models

Visual comfort presents the optimal combination of natural or artificial light, including glare control and access to outdoor views. It is one of the comfort aspects that impacts occupants' health [156], well-being [157], productivity [158], cognitive performance [159], work engagement [160] etc. Like other comfort aspects, measuring visual comfort is challenging as it comprises various dimensions, each of which presents a side of visual comfort.

Metrics for visual comfort can be dynamic or static [161]. Research often measures illuminance (lux), luminance (cd/m^2), and glare using HDR photographs and luminance meters. Non-visual effects, such as melanopic lux, lighting history, and outdoor views, also influence visual comfort. The best metric for assessing visual comfort remains debated. Some studies suggest vertical illuminance and luminance-based metrics [161], with DGP (Discomfort Glare Perception) being highly correlated with subjective feedback. However, measured metrics don't always align with occupants' perceptions [162]. Shafavi et al. [163] emphasize the lack of consensus but highlight the importance of understanding how these metrics interrelate.

Several survey-based field studies investigated the visual comfort of building occupants. For instance, Jakubiec et al. [164] investigated the visual comfort of 500 students in an educational building using surveys and simulations. Kong et al. [165] estimated visual comfort of 118 participants in a higher education building in China. Davoodi et al. [166], performed a post-occupancy evaluation of visual comfort. Research [167] provides a combination of surveys, room measurements, and simulations to elicit the impact of various metrics on visual comfort. They surveyed 192 students for 3 days from 09:00 – 13:00 in a school building in Tehran. They measured illuminance (lux) in the middle of the room and at table level, as well as the temperature in the middle of the room. Their findings show that visual comfort of students is significantly influenced by various factors, like perceived lighting level, view satisfaction, satisfaction with the lighting distribution in the room and glare perception.

Visual PCMs facilitate integrating users' visual preferences into the controller for personalized lighting and blind control. Some studies report the development of visual PCMs, although compared to thermal PCMs, these studies are very scarce. Ma et al. conducted an experiment in China by collecting on-site measurements and user preferences in the form of subjective feedback simultaneously and developed visual PCMs [34]. The experiment included six student participants. This low number was deemed sufficient for developing PCMs, as these individualized models do not require a large variety of subjects to achieve statistical significance. The experiment lasted six months, averaging 212 datapoints per participant. The ML models used were Random Forest, SVM, Gaussian Mixed Model, and Classification Tree. Random Forest and SVM were the best-performing models. They used several indices and evaluated their performance using a method called failure mode and effect analysis (FMEA) and a hierarchical technique for order of preference by similarity to the ideal solution (TOPSIS). Their evaluation showed that the best-performing indices for their models are unsatisfied vertical illuminance, daylight glare index, luminance ratio, and shadow position.

Another visual PCM development was reported by Jayathissa et al. [28], where 30 participants reported their perceived comfort for two weeks, 5 – 15 times per day, even when they changed rooms, collecting around 146 data points per participant. Despite visual PCM, this study also investigated thermal and aural comfort (satisfaction with the sound environment), making it one of the rare multi-comfort aspect studies dealing with PCM. The PCMs were developed using a Random Forest with 1 000 trees with the Gini criterion, where 60% of the collected data was used for training and 40% for testing. Xiong et al. [168] developed personalized satisfaction models using Bayesian inference to improve visual comfort and energy use, they collected visual preference data in single-use offices with dimmable lights and automated shading systems.

3.2 Methods

This section presents the methods for developing PCMs to predict occupants' comfort levels based on a combination of physical and subjective inputs. The methods involve two experimental exhibits and model prediction using ML. The experiments were used to collect data from indoor settings and user feedback on their perceived comfort. The first experiment was a laboratory experiment (hereinafter the lab) conducted in an office at the Faculty of Mechanical Engineering and Naval Architecture (FAMENA), University of Zagreb, Croatia. The experiment had four participants and lasted for three weeks. To test the findings of the lab experiment in more realistic and less controlled settings, another experiment was conducted in a classroom of a Technical School, Ruder Boskovic (RCK RB), in Zagreb, Croatia (hereinafter the field experiment). This field experiment had 24 high school students participating, lasting two weeks. Drawing from the two experiments, this section presents methods to effectively collect data for PCMs and to develop multi-comfort PCMs for multiple users with varying engagement levels in providing data. Different ML classification models were trained and tested to determine their effectiveness in predicting comfort across different comfort aspects for different users for the lab experiment. Then, the same was tested for the field experiment. Furthermore, this section also outlines the design of a smartphone application for data collection, the structure of the experiments, and the comparison of different developed models. Finally, this chapter also discusses how to deal with the lack of data from the users.

3.2.4 Design of personalized comfort models

In this research, PCMs are developed using physical indoor measurements and user-reported feedback on perceived comfort. The measurements are conducted for multiple comfort aspects, including air temperature, air humidity, air velocity, CO_2, and lighting level. Meanwhile, subjective feedback includes people's perceptions of indoor conditions, preferences, sensations, and satisfaction. Figure 3.2 shows the process of developing a PCM, which includes data collection and processing and ML model development. In the following sections, these processes are explained in more detail.

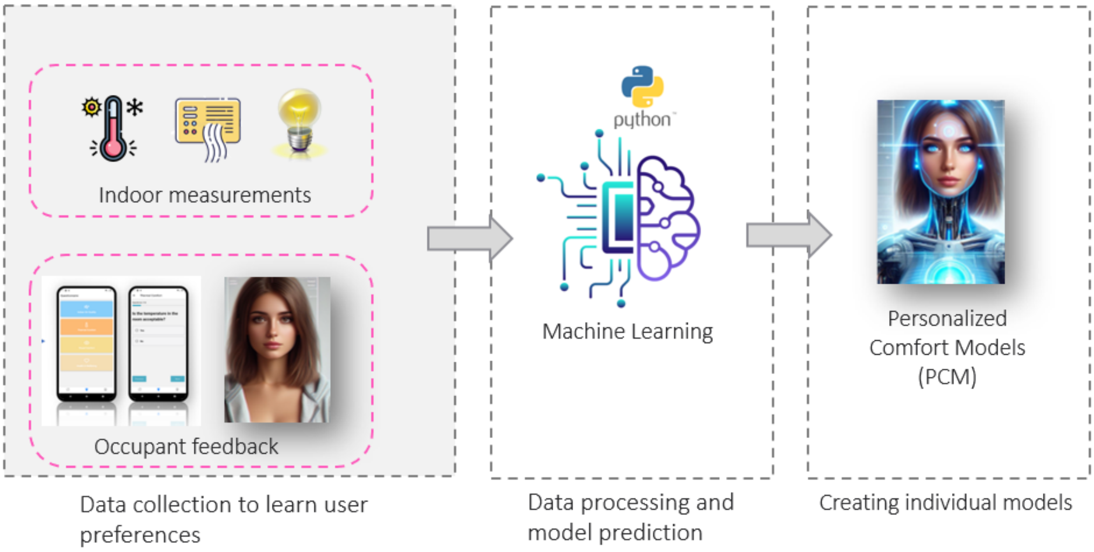

Figure 3.2 The process of developing a PCM, including data collection and ML model

3.2.5 Data collection for personalized comfort model development

Two experiments are conducted to collect data for PCMs. First, in the FAMENA faculty office, user preferences and indoor measurements were collected over three weeks from 21 November to 12 December 2023, involving four participants. Feedback was collected via a smartphone app, and indoor measurements were conducted simultaneously through static and portable sensors. The second experiment took place in RCK RB Technical High School, with 24 students in one classroom participating for two weeks, starting from 18 April up to 3 May

2024. The school experiment was conducted with the aim of integrating PCMs into the control system of the school building, which will be discussed in Chapter IV. The participants were thoroughly informed about the experiment through a prior lecture on how to report feedback and the rules (e.g., do not use blinds, open windows or table lamps, or manipulate the heating or A/C). Both experiments were approved by the Ethics Board Committee at the Faculty of Humanities and Social Sciences and the Ethics Board Committee at the FAMENA. Additionally, all participants or their legal guardians have signed a consent form for participation.

In the lab experiment, the user feedback was collected every 30 minutes, which is quite frequent, but this was set up to compensate for the times when one or some of the participants were not at the office. To create variability in the data and to test the comfort boundaries of users, different weeks of the experiment had different indoor conditions (e.g., some days had higher indoor temperatures, other days lower, more fresh air, less fresh air, etc.). The experiment layout is shown in Table 3.2 in more detail. To visualize the variability of indoor conditions, Figure 3.3 depicts how the indoor setpoints changed daily throughout the experiment. On average, 180 data points were collected for each participant throughout the three weeks. Each task of reporting feedback took the participants around 15 seconds per task.

Table 3.2 Experiment design for the lab experiment

Week of the experiment	Interventions
Week 1	Business as usual (no interventions)
Week 2	Various intervention days with diverse combinations, such as: – high temperature (heating on, A/C on heating) – low temperatures (heating OFF, A/C on cooling) – high lighting levels (natural lights, no blinds used, high glare) – low lighting levels (natural lights, blinds on, or half-way, no artificial light) – high CO_2 level (doors closed, natural increase of CO_2 levels from participants in the office)
Week 3	Three intervention days with additional variating CO_2 levels using additional CO_2 injection from a CO_2 bottle. On other days, business as usual.

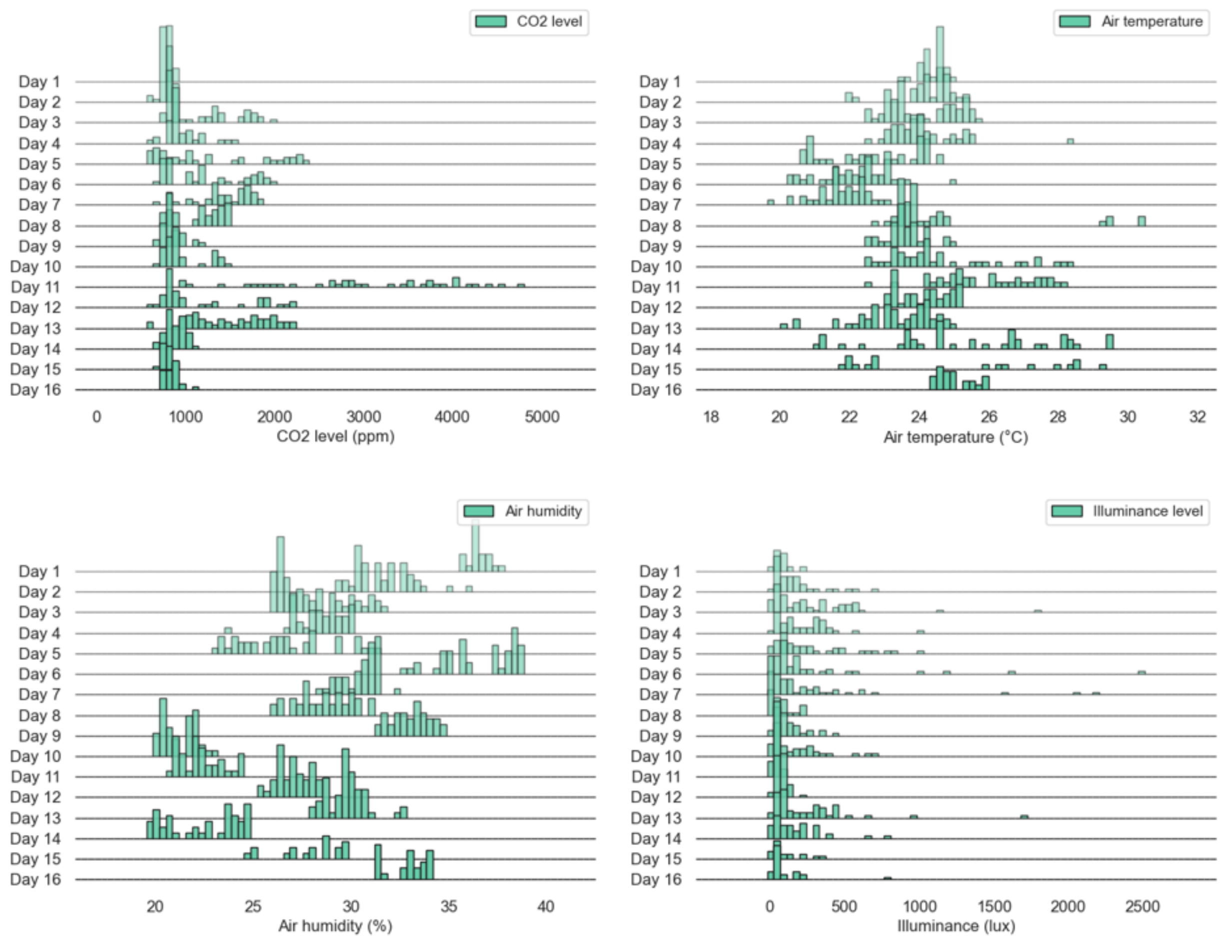

Figure 3.3 The indoor parameters variability throughout the days for the lab experiment

In the field experiment, the user feedback was collected once every hour at the end of each class. This frequency was selected to gather sufficient user feedback for a short time while still not interrupting regular class teaching. To create data variability, the experiment period was divided into standard operating days (with regular or standard indoor conditions) and intervention days (where the comfort boundaries were tested with setpoints outside the comfort zone, similar to the lab experiment). This is shown in Table 3.3 in more detail. The number of data points provided by the participants in the school building was lower, reaching 43 for some participants, but for some, even as low as 7 data points for two weeks. Each task of reporting feedback took the participants around 15 – 60 seconds per task. Figure 3.4 shows pictures taken during the field experiment while taking indoor measurements and feedback reporting using the smartphone app.

Two data sets are needed to develop personalized comfort models, including user preferences and indoor environment measurements. The indoor measurements collected through the experiments are presented in Table 3.4.

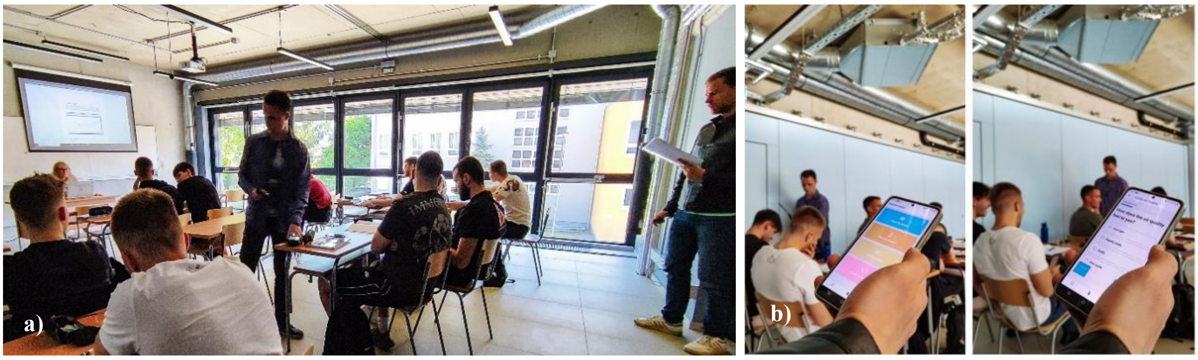

Figure 3.4 Pictures taken during the field experiment where a) the students are shown during manual measurements, b) students report their comfort feedback through the app interface

Table 3.3 The field experiment design

Day of the experiment	Interventions
Day 1	Free-floating (no HVAC)
Day 2	Business as usual (standard setpoints)
Day 3-7	Various intervention days with diverse combinations, such as: – high temperature (heating on) – low temperatures (cooling on) – high lighting levels (natural lights, no blinds, high glare) – low lighting levels (natural lights, blinds on, or half-way, no artificial light) – High CO_2 level (doors closed, natural increase of CO_2 levels from participants in the classroom)
Day 8	Business as usual (standard setpoints)
Day 9-11	Setpoints are regulated based on user responses and preferences.

Table 3.4 The measurements conducted at the lab and field experiments

The measurement	The instrument	Instrument position	Frequency
	The indoor measurements collected at the lab experiment		
Temperature (℃)	Static sensors (thermocouples)	MR*, T, A, W	5 s**
	Mobile sensors (Testo 401)	NB	30 min
CO_2 level (ppm)	Static sensors	MR, T, W	5 s
Air humidity (%), Air velocity (m/s)	Mobile sensors (Testo 401)	MR, T	30 min
Illuminance (lux)	Mobile sensors (Testo 401)	T (horizontal illuminance), Eye level (vertical illuminance), MR.	30 min
	Indoor measurements collected at the field experiment		
Temperature (℃)	Embedded sensors, thermostats	MR, WA, RD, OMR	5 min
	Mobile sensors (Testo 401)	NB	1 h
CO_2 level (ppm)	Embedded sensors	WA, MR	5 min
Air humidity (%), Air velocity (m/s)	Mobile sensors (Testo 401)	T, MR	1 h
Illuminance (lux)	Embedded sensors	MR, W, WA	5 min
	Mobile sensors (Testo 401)	T (horizontal illuminance), Eye level (vertical illuminance), MR.	1 h

**MR-Middle of the room (1.5m above ground); T-at table level for each participant; A-ankle level for each participant; W-at the windows, NB-near body, WA-at the wall, RD-return air duct, OMR-operative temperature in MR. **5s-frequency every 5 seconds; 30 min-frequency every 30 minutes.*

The user preferences include user perceptions on IAQ, thermal and visual comfort. (i.e., temperature, air quality, and lighting level). The feedback was collected using a smartphone application called HComfort, explicitly developed for this purpose and shown in Figure 3.5. The app was developed based on research findings in Chapter I, where 66% of nearly 1 000 respondents preferred using a smartphone app to report feedback. Ease of use and privacy security were identified as critical factors for data sharing. The user interface of the app is simple, featuring a welcome page, a home page with questionnaires, and a profile page, as shown in Figure 3.5. Developed using React Native and Amazon Web Services (AWS), the app leverages AWS for scalability and robust data protection. Data is stored in DynamoDB, a NoSQL database that facilitates easy scaling and information management. The architecture of the app development is shown in Figure 3.6. The decision to develop the app from scratch was driven by the lack of open-source options covering all three comfort aspects, allowing for greater flexibility and independence in managing users and questions. In the future, the app can be further developed to interact with building control systems, enabling bidirectional data flow to not only send data collected from users but also convey data from the system to users.

Each comfort aspect has its own set of questions to describe the comfort as much as possible; for instance, perceived thermal comfort is measured using thermal preference, thermal sensation, and perceived comfort. The questions used are: How do you prefer the room temperature? Options: Cooler, No change, Warmer [28], How do you currently feel? Options: Hot, Warm, Slightly warm, Neutral, Slightly cool, Cool, Cold. In terms of Thermal comfort, how would you describe your current comfort level? Options: Comfortable or uncomfortable. The other questions in the app to measure each specific comfort aspect are shown in Annex C for brevity reasons.

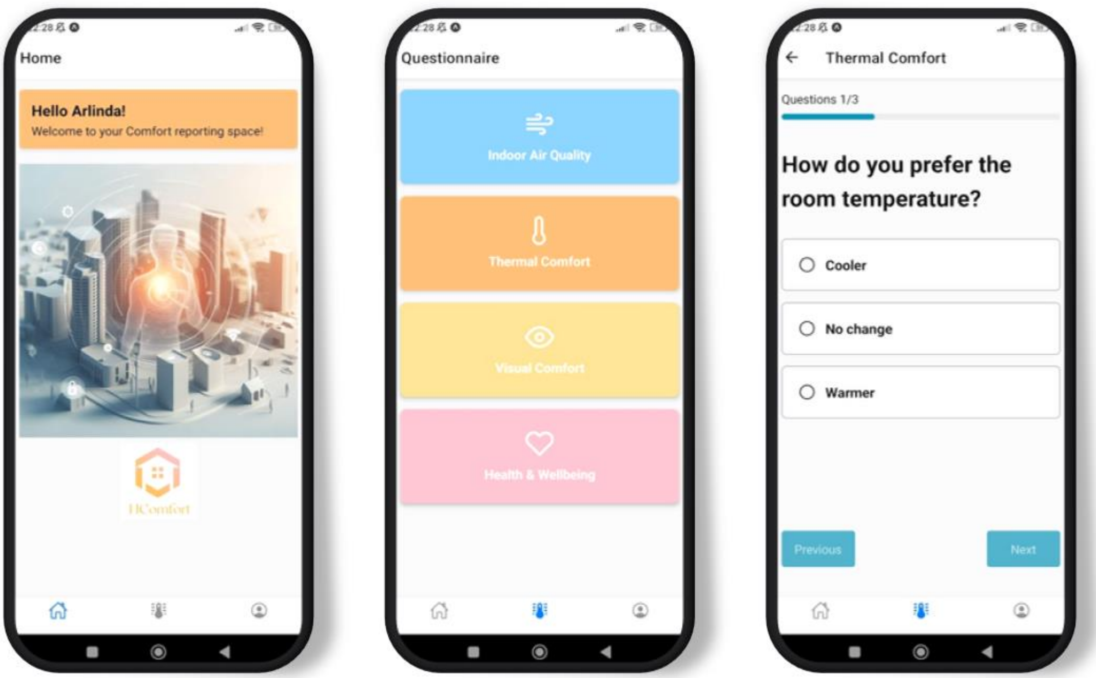

Figure 3.5 The smartphone application user interface is used to collect user feedback on their indoor environment perceptions

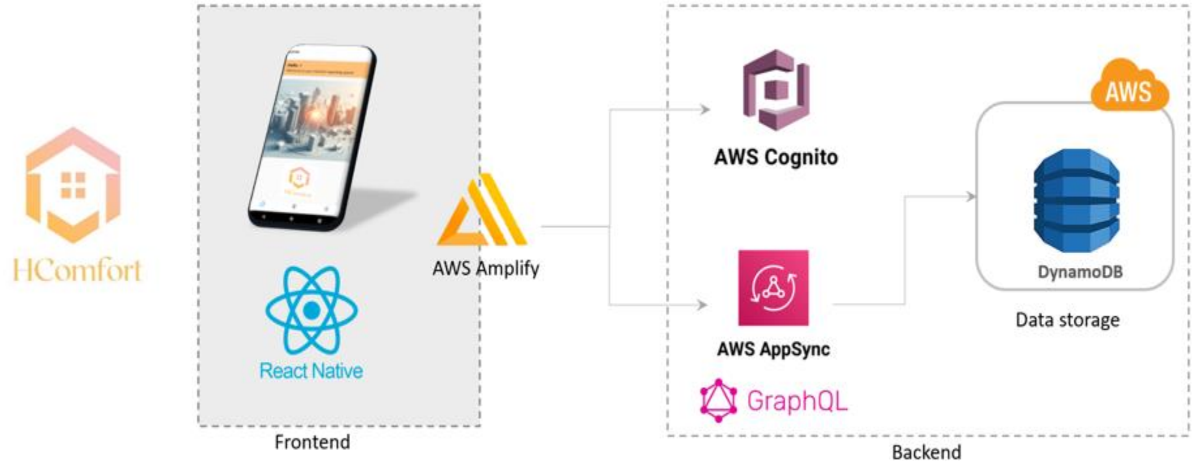

Figure 3.6 The HComfort React native application architecture

The data collected from the app is automatically stored in the DynamoDB database connected to the Python environments through an intermediator called Boto3. The user-reported data flows automatically from DynamoDB to the Jupyter lab notebook, where the PCMs are developed, as shown in Figure 3.7. This enables immediate updates of the PCMs, which are developed in a Python environment.

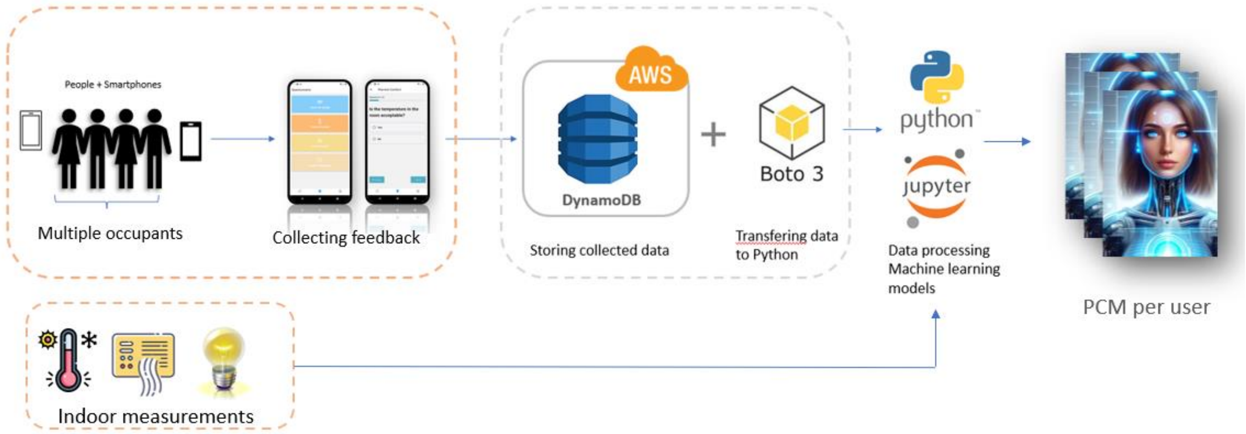

Figure 3.7 The data storage and flow process from users to the PCMs

3.2.6 Development of personalized comfort models using machine learning

ML models are powerful prediction tools and can be categorized into supervised and unsupervised learning. Supervised learning is used when the relationship between inputs and outputs is known, allowing models to be trained on labeled data. In contrast, unsupervised learning is used when the relationship between data points is unknown, requiring models to identify patterns independently. This research employs supervised learning to develop PCMs, as the collected data from the experiments include known inputs and outputs. The inputs are physical indoor measurements and subjective user feedback, while the outputs are the comfort levels (Comfortable or Uncomfortable) shown in Figure 3.8. This is a binary classification model. The dataset was divided into two parts: 70% for training the models and 30% for testing their performance. This ensures that the models are trained on a substantial portion of the data while retaining enough unseen data for the model to evaluate their predictive accuracy.

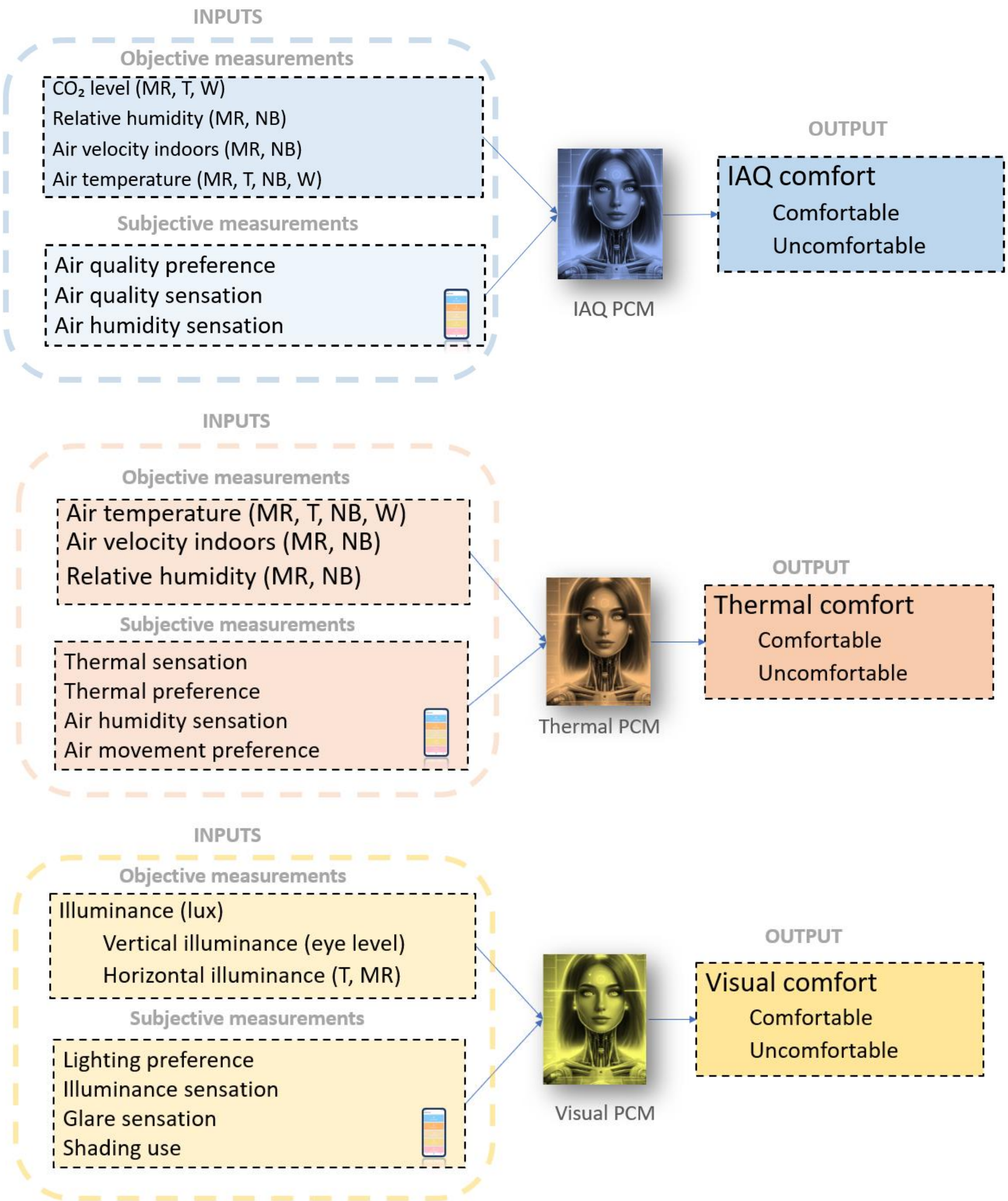

Figure 3.8 Inputs and outputs of the multi-comfort aspect PCMs, a) IAQ PCM, b) thermal PCM, and c) visual PCM. The measured inputs are as follows: MR – middle of the room, T – at the table, NB – near body, W – at the window

Nine different ML models are tested and compared to identify the best-performing model for the PCMs for the lab experiment and later for the field experiment. Each model has its strengths and weaknesses, and their predictive performance can vary. The reason for selecting different models is to get a variety of models from simpler ones (e.g., Naïve Bayes) to more complex models such as deep learning (LSTM). For the lab experiment, a simple prediction model was used as a baseline or reference model to compare the performance of the nine other models to it. This simple model is called a Dummy classifier that ignores inputs and makes simple predictions based on frequency of predicted responses. Artificial Neural Networks (ANNs) are robust ML models that mimic the human brain and are capable of modeling complex nonlinear relationships [169]. Decision Trees are versatile and robust models used in various applications [170]. When multiple decision trees are combined, they form a Random Forest, which overcomes the limitations of a single Decision Tree [171]. K-nearest neighbor (KNN) is a classification technique that approximates data point classifications by identifying the closest objects [172]. Logistic Regression is a statistical method that examines the relationship between influencing factors and a binary or categorical outcome [173]. Ada Boost [174] enhances accuracy by combining multiple weak learners into a strong learner and is effective for unbalanced datasets, often used with models like Logistic Regression. Recurrent Neural Networks with Long-Short Term Memory (RNN LSTM) [175] are deep learning models that predict time-series or sequential data. Naïve Bayes is a probabilistic classification model that uses evidence to find hypotheses [176]. Support Vector Machine (SVM) [177] is known for its simplicity and flexibility in various classification problems, providing balanced predictive performance even with limited sample sizes. These ML models were developed using Python programming, and Python packages were adopted for the ML models as shown in Table 3.5.

Table 3.5 Python packages used for ML model development

	Name of the ML model	Code snippet used
M1	Ada Boost Logistic Regression	Package: sklearn.linear model Imported: LogisticRegression & AdaBoostClassifier
M2	Artificial Neural Network (ANN)	Package: tensorflow.keras.models Imported: Sequential
M3	Decision Tree	Package: sklearn.tree Imported: DecisionTreeClassifier

**Continued table*

M4	K-nearest neighbor (KNN)	Package: sklearn.neighbors imported: KNeighborsClassifier
M5	Logistic Regression	Package: sklearn.linear_model Imported: LogisticRegression
M6	Recurrent Neural Network Long-short term memory (RNN LSTM)	Package: keras.layers Imported: LSTM, Dense, Dropout
M7	Naïve Bayes	Package: sklearn.naive_bayes Imported: GaussianNB
M8	Random Forest	Package: sklearn.ensemble Imported: RandomForestClassifier
M9	Support Vector Machine (SVM)	Package: sklearn.svm Imported: SVC

All ML classification models are trained and tested on the same dataset using a random seed set to 42 to ensure consistency. This means the models start on the same random index, ensuring they always yield the same results. Furthermore, the inputs have a significant impact on the prediction performance of the model. Therefore, a feature analysis is conducted to evaluate the impact of each input, and to assess which inputs can be removed without significantly affecting the model performance yet simplifying the model. In the context of PCM, this means using fewer data sources, i.e., fewer sensors, making PCMs viable even for buildings that do not have numerous and sophisticated sensors.

3.2.7 Model performance evaluation

Accuracy, precision, f1-score, and specificity are metrics used to compare the developed PCMs with various classifiers. These metrics present different ratios of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). A TP is when the model is supposed to predict the "Comfortable" state, and it accurately predicts comfortable, and a TN is when the model accurately predicts the "Uncomfortable" state. A FP or FN on the other hand are when the model wrongly predicts either "Comfortable" (FP), or "Uncomfortable (FN), respectively. To visually depict the prediction potential of each individual classifier, the Confusion Matrix method is used to show how many times the model predicted what it was supposed to predict. The example of the Confusion Matrix is presented in Figure 3.9. The higher the True predictions (shown in green) the better the performance of the model. And contrarily, the higher the False predictions (shown in red color), the worse the performance of the model is.

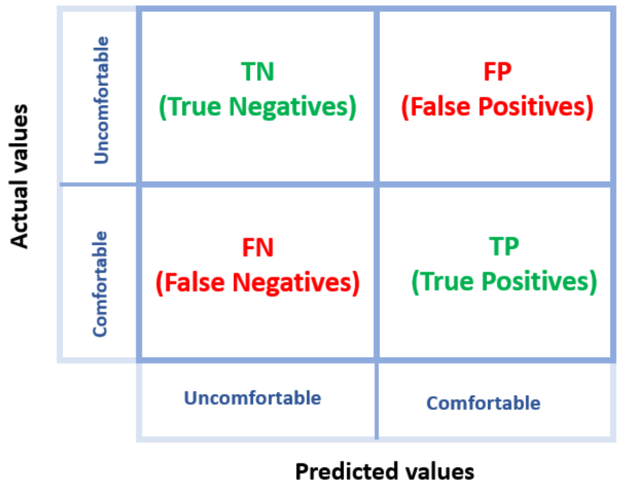

Figure 3.9 The Confusion Matrix concept depicting the number of occurrences the model predicted True or False predictions

Accuracy shows the ratio of TP and TN predicted, compared to all other predictions. It is calculated as:

$$ACC = \frac{TP + TN}{FP + FN + TP + TN} \tag{1}$$

Precision is a metric that shows the ratio of predicted TPs and is calculated as follows:

$$PRE = \frac{TP}{TP + FP} \tag{2}$$

For imbalanced datasets, such as those collected in buildings with more “Comfortable” than “Uncomfortable” responses, it’s crucial to use metrics that account for this imbalance. The model may be biased towards predicting the majority class (“Comfortable”), leading to high precision but poor performance for the minority class (“Uncomfortable”). Hence, the F1-score is a more appropriate metric for evaluating models trained on imbalanced data. It considers both True Positives (TP) and True Negatives (TN), providing a balanced measure of how well the models predict both “Comfortable” and “Uncomfortable” states. The F1-score is calculated as:

$$F_1 = 2\ \times \frac{PRE \times REC}{PRE + REC} \tag{3}$$

where REC is the recall metric that is calculated as:

$$REC = \frac{TP}{TP + FN} \tag{4}$$

In the context of PCMs integrated into building control systems, it is crucial to accurately predict when a user is “Uncomfortable”. The reason is that the system only triggers changes to the indoor environment when the PCM predicts discomfort. Therefore, the best PCM models are those that effectively predict the “Uncomfortable” state (TN). High FN (predicting discomfort when users are comfortable) leads to unnecessary changes and higher energy consumption. High FP (predicting comfort when users are uncomfortable) results in user dissatisfaction and prolonged discomfort. Thus, models with the fewest False predictions are preferred, with an emphasis on maximizing TN. To highlight models that best predict TN (“Uncomfortable”), the Specificity metric is used, defined as:

$$Specificity = \frac{TN}{TP + TN} \tag{5}$$

3.3 Results

After analyzing the data collected from the lab and field experiment and developing PCMs for laboratory settings and for the field experiment with less control over user engagement levels, this section shows the yielded results and corresponding findings. Some of the research questions answered in this section include: how to develop multi-comfort PCMs for multiple occupants using ML models? How to effectively collect data to develop data-driven PCMs? Which is the most reliable ML model for PCM? How many data points are needed for an optimal PCM? How to overcome the lack of data for people with different engagement levels on reporting data?

3.3.8 Findings from the lab experiment: user preferences and personalized comfort models

Throughout the three weeks of the lab experiment in a faculty office, a total of 623 datapoints were collected for four participants. The distribution of data across participants is shown in Figure 3.10. The participants in the lab experiment were more dedicated to regularly reporting their feedback and more intentional in the sincerity of their responses compared to the field experiment. For that reason, the lab experiment is used as a reference scenario to develop and test the models, that are later used in the field experiment. The lab experiment results encompass user preferences and comfort levels over three weeks, focusing on IAQ, thermal comfort, and visual comfort. These findings are compared with the standard setpoints typically used in buildings. On the other side, the results also show the PCMs developed for the four participants which is elaborated in more detail in the subsequent sections.

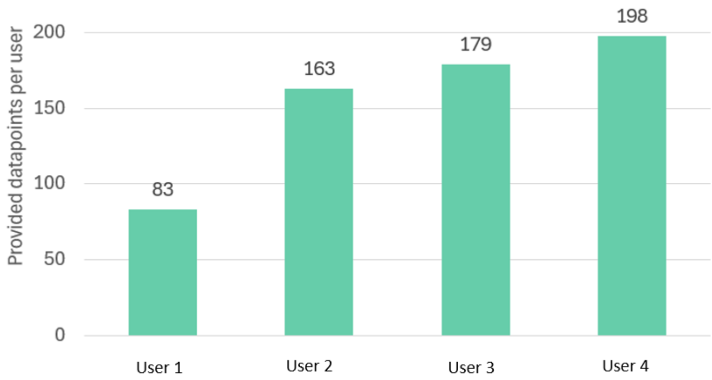

Figure 3.10 Distribution of collected datapoints for all participants in the lab experiment

User preferences. The perceived comfort during the lab experiment varied significantly, as shown in Figure 3.11. The high discomfort rate was caused purposefully to create more variability in the user responses and to test the comfort boundaries of the participants. Figure 3.11 shows that the IAQ comfort was the one affecting participant the most and where they felt the most discomfort. The changes in perceived comfort throughout different days of the experiment, especially during the intervention days, are presented in Annex D due to brevity reasons.

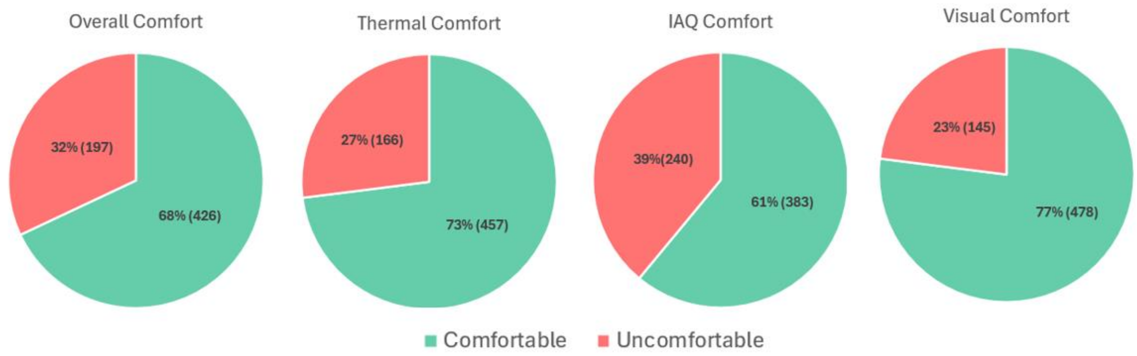

Figure 3.11 The perceived comfort for all participants in the lab experiment for different comfort aspects

Considering that various comfort aspects were evaluated simultaneously during the experiment, it is important to show how each individual perceived each comfort aspect and to compare their comfort profiles. The participants, although being in the same office under the same conditions, reported different comfort perceptions. Figure 3.12 shows how different users experience thermal comfort differently for varying indoor air temperatures. The findings from this analysis show that:

- Thermal comfort is perceived differently for different users across the same temperature ranges.
- The range of temperature yielding the peak comfort for all users can be narrowed down to $22.5 - 25$°C. This outcome challenges the standard recommended setpoints for office environments such as CIBSE recommending 20°C for offices in the United Kingdom [178], but in other cases it overlaps with the upper boundaries of the recommendations such as OSHA $20 - 24$°C in the United States [179], and ASHRAE 55 for winter when the relative humidity is 30% then the recommended temperature is $20.5 - 25.5$°C. The comfort temperature ranges go in line with findings of other studies in office buildings such as in research [133] by Wang et al., where by using the ASHRAE Global Thermal Comfort Database for office buildings in the US, they retrieved that for heating season (same as in our experiment), the comfort operative temperature varies between $20.5 - 24.9$°C.
- There are outliers in the reported comfort or discomfort for temperatures outside the normal comfort zone. This shows that it is impossible to always predict the thermal comfort of occupants correctly, due to the subjective nature of occupant preferences where for the same temperature individuals can feel comfortable sometimes, and uncomfortable other times depending on other factors.

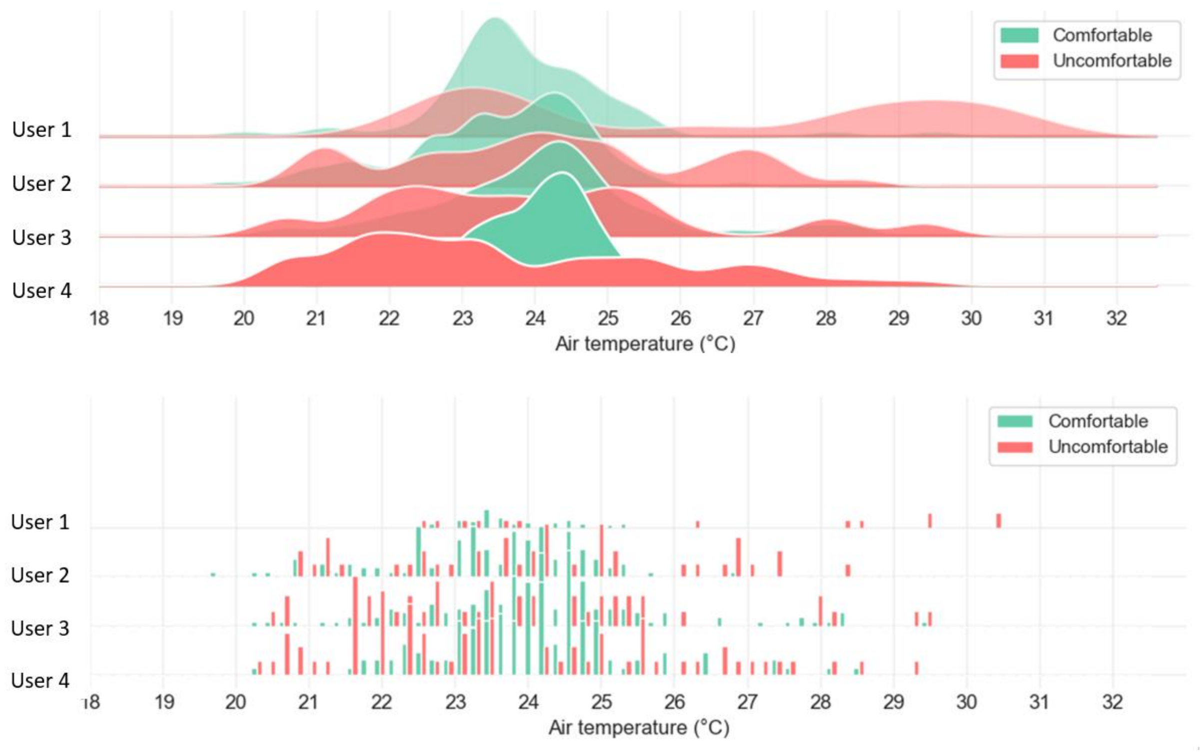

Figure 3.12 The difference in perceived thermal comfort under the same indoor conditions for the lab experiment participants. Upper part: the KDE plot showing the density of distribution, and the lower part: showing the bar plot for clearer depiction of the data distribution and outliers

People find it difficult to notice the change in air quality when remaining in a room. The poor IAQ is often noticed only when one changes the room, or the conditions are getting unbearably worse. The imperceptible nature of CO_2 in the air makes it even more harmful to people if the concentration gets higher. This was also noticed in the outcomes of the office experiment as shown in Figure 3.13. Results show that:

– IAQ comfort is perceived differently from different occupants.
– The comfort peak in terms of IAQ is around 800 ppm, which goes in line with ASHRAE standard value of comfortable indoor air quality limit of 1 000 ppm.
– However, even at standard values of CO_2 (less than 1 000 ppm) participants reported feeling uncomfortable, showing the impact of other factors on IAQ comfort perceptions.

– The inability to perceive high concentrations of CO2 was highlighted during the intervention days. Despite extremely high CO2 levels (above 3 500 ppm), participants occasionally reported feeling “comfortable” for IAQ, indicating a clear failure to sense the elevated CO2 levels. These high CO_2 concentrations were induced purposefully and closely monitored not to exceed the allowed threshold according to ASHRAE, yet sometimes, even without artificially induced CO_2, on some days the natural CO_2 levels increased to high concentrations when doors and windows were closed. This is important as it shows that IAQ needs more attention and even nudges to warn occupants when poor IAQ is present.

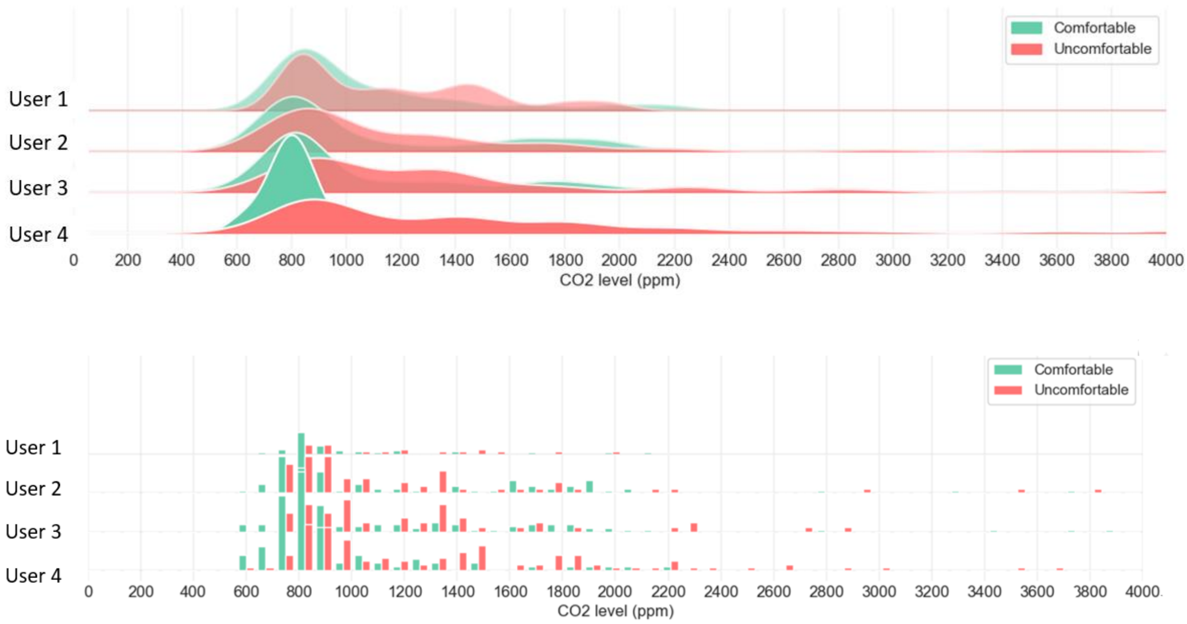

Figure 3.13 The difference in perceived IAQ comfort under the same indoor conditions for the lab experiment participants. Upper part: the KDE plot shows the density of distribution, and the lower part: shows the bar plot for a clearer depiction of the data distribution and outliers

Visual comfort in terms of lighting level is highly dependent on the spatial position of the occupants in the room compared to the lighting source. The visual comfort perception of the participants in the lab experiment is presented in Figure 3.14. The findings show that:

- Like other comfort aspects, visual comfort is highly individual but also deeply dependent on the sitting position of the participants in the room compared to the artificial or natural lighting sources in the room, i.e., windows.
- The lighting levels in the office were, in the majority of cases below the standard recommended values of 500 – 1 000 lux according to EN 12464, and 300 lux for office spaces according to CIBSE [180]. However, even in below-optimal conditions, the participants were not always dissatisfied with the illuminance level. This shows that the preferences vary significantly, and the often-used 500 lux lighting level setpoints in the offices can also be lower. This finding goes in line with research [181] which shows that optimal visual performance can be achieved even with lower lighting levels than 500 lux. The survey-based research of Mui et al., in Hong Kong offices with 293 surveyed occupants, shows that a horizontal illuminance of 518 lux reaches 86% satisfaction in terms of visual comfort [182]. However, the small group of participants in the lab office cannot be used to generalize the findings that less than 500 lux is also acceptable.

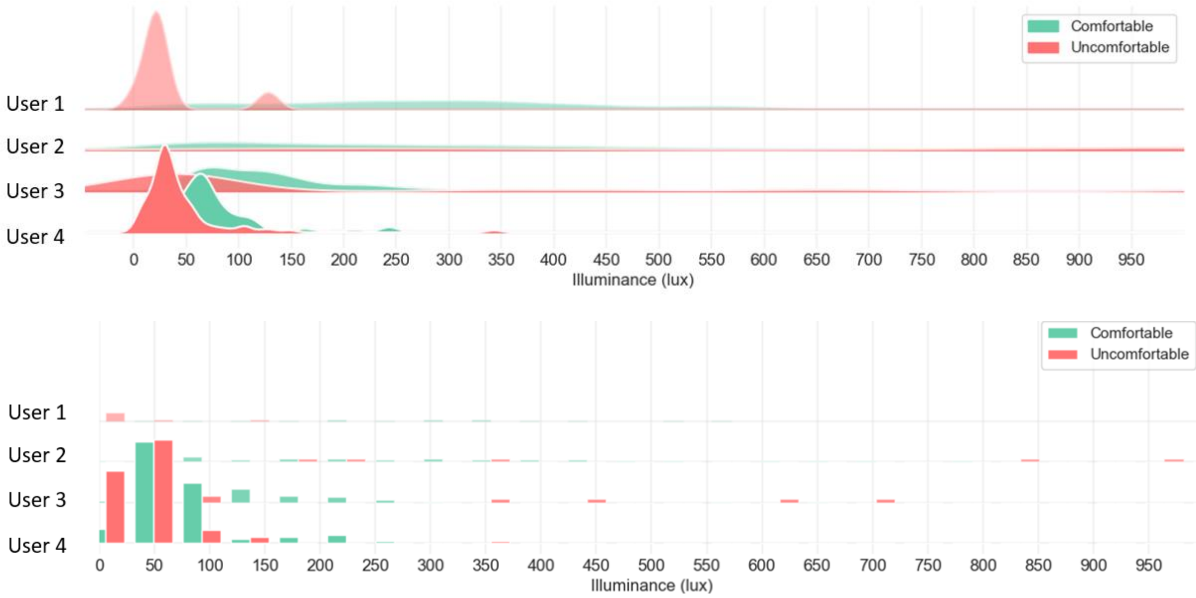

Figure 3.14 The difference in perceived Visual comfort under the same indoor conditions for the lab experiment participants. Upper part: the KDE plot showing the density of distribution, and the lower part: shows the bar plot for clearer depiction of the data distribution and outliers

While it is important to know when the participants feel comfortable and uncomfortable, knowing their preferences regarding the indoor conditions is also beneficial.

For instance, someone may be more inclined to prefer lower temperatures over higher temperatures. User preferences regarding the three comfort aspects are presented in Figure 3.15, to show the nuanced preferences of different users, emphasizing the fact that the "one-fits-for-all" approach is difficult to reach, but there are temperature ranges that can satisfy most of the participants.

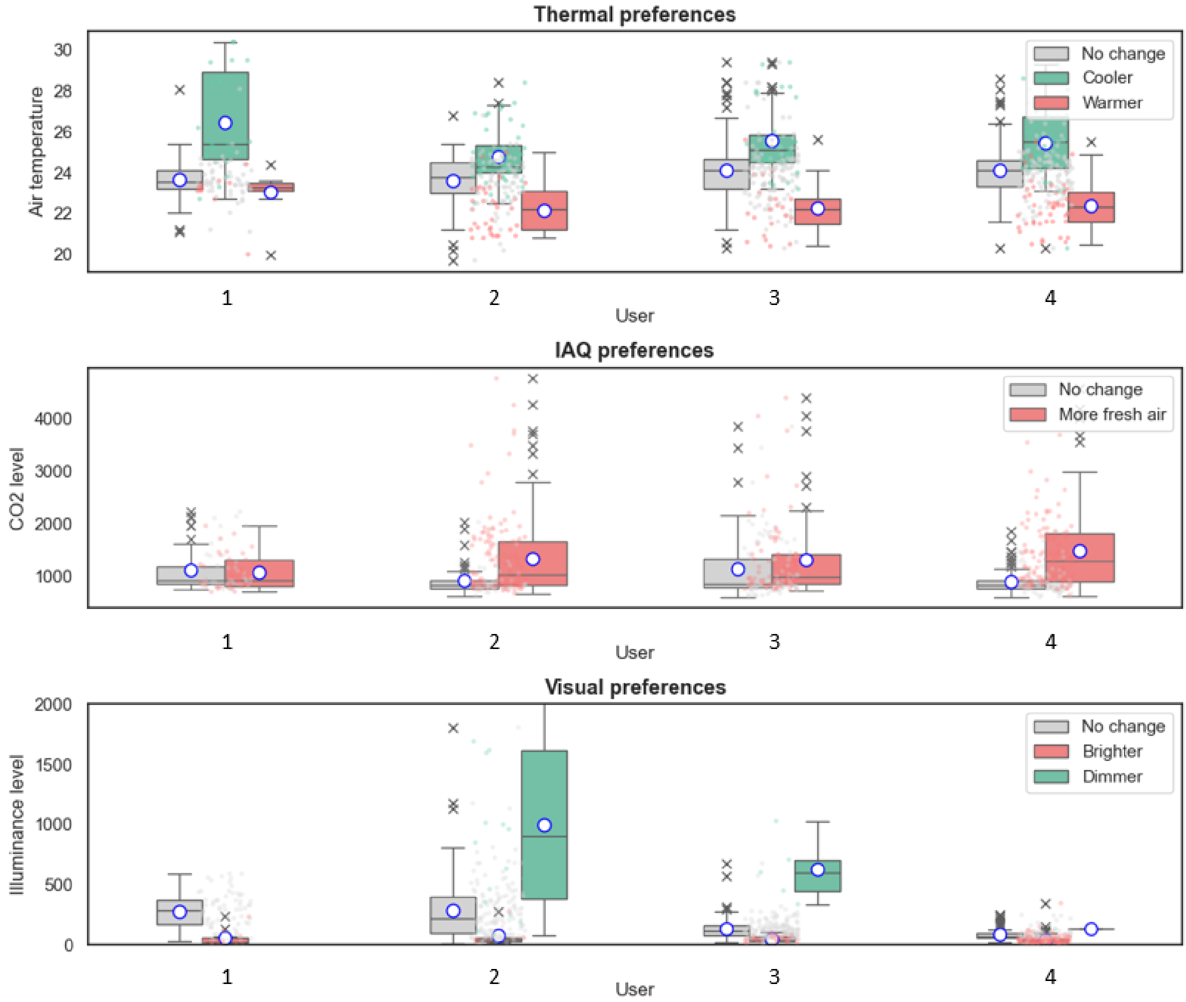

Figure 3.15 The correlation between thermal comfort and thermal preferences for the lab experiment

Since this chapter focuses on PCMs, other important findings are presented in Annex D for brevity. This Annex provides detailed analyses of various comfort perceptions and correlations, user preferences, and the relationships between comfort, productivity, mood, and participant states. For example, it explores how perceived thermal comfort and IAQ correlate with temperature and CO_2 levels, and how users react to higher temperatures with lower IAQ perceived comfort. Additionally, it examines the correlation between occupant satisfaction with indoor conditions and perceived comfort, as well as the relationship between comfort, productivity, and mood, although the causal effect was not confirmed.

Personalized comfort models. Several ML models were trained and tested for different users in the lab experiment. These results present the reference models which are later used and tested in the school field experiment. The results show that not all ML models have the same prediction performance, and that the predictability also depends on the comfort aspect being predicted, the tolerance level of users, their acceptance on the indoor conditions (individuality of the users), and of course, on the number of collected datapoints.

To show the performance of the models, a confusion matrix is used for a clearer depiction on how many times the model predicted the true values (what it was supposed to predict, either Comfortable or Uncomfortable), and how many times it predicted falsely. To avoid redundancy, only the confusion matrices of Random Forest are shown below in Figure 3.16 for user 4. Figure 3.17 shows the confusion matrices for thermal PCMs for all users that were developed with Random Forest. The comparison of the performance of nine different ML models for all four participants compared to a baseline model (the simplest prediction model called the Dummy classifier) is shown as a heatmap in Figure 3.18. The prediction performance was measured with F1 score, as an appropriate metric for imbalanced datasets that shows if a model is a good predictor of both "Comfortable" and "Uncomfortable" instances and with Specificity, which shows how many times "Uncomfortable" was predicted correctly.

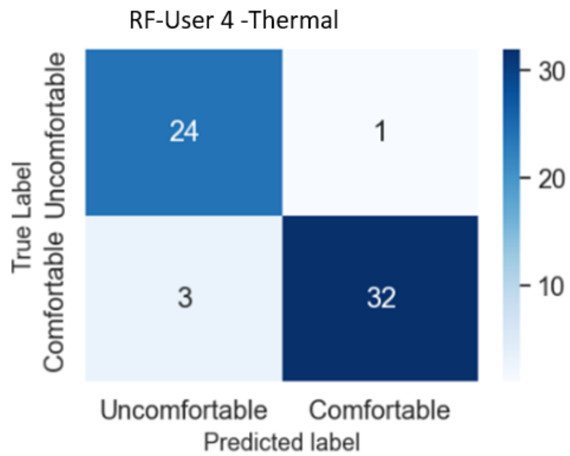

Figure 3.16 The confusion matrix shows the performance of the Random Forest model for User 4 Thermal PCM. It indicates that "Comfortable" was correctly predicted 32 times and "Uncomfortable" 24 times. The model made 1 false prediction for "Uncomfortable" and 3 false predictions for "Comfortable"

To compare which model from the nine ML models has the best prediction potential across all classes (users and comfort aspects) compared to the baseline model, the F1 scores (prediction potential) are shown in Figure 3.18 and Figure 3.19. The findings show that:

- There is a variety of prediction performance of different ML models for the same user and same comfort aspect. However, the best performing model on average for all users and all comfort aspects is Random Forest, followed very closely by Decision Trees. Comparison of average F1 scores and Specificities for all participants and all comfort aspects is shown in Figure 3.19.
- As the models are used to predict comfort, which in its nature is a subjective and complex concept to predict, in this research, if a model yields a prediction performance of F1 score above 0.7, the model is considered appropriate and the higher the F1 score, the better the prediction performance. Yet, the best performing models such as Random forest and Decision tree, yielded an average F1 score value of 0.87 and 0.86, respectively, across all users and all comfort aspects.
- When selecting the best model, factors beyond prediction performance should be considered, such as training duration and computational effort. ANN and LSTM had the longest training times and required higher computational effort, yet produced similar results to Random Forest, Decision Trees, KNN, and Naive Bayes. The optimal model should deliver satisfactory results across many users and comfort aspects, covering a wide range of scenarios. In this case, Random Forest and Decision Trees proved to be the most effective.
- User 1 models performed the least effectively, likely because they had the smallest dataset with little variation (mostly reporting comfortable). This led to overfitting, where the models fit the available data too perfectly but perform poorly on new data. This was particularly evident in visual comfort, where model predictions were 100% accurate which is a sign of overfitting rather than perfect prediction in ML.
- User 4 had the best-performing models as they had the largest dataset (198 data points). However, the models performed slightly worse for thermal and visual aspects than the IAQ model because of the users’ varying preferences for temperature and lighting levels.
- Thermal comfort PCM has lower F1-scores than the IAQ and visual comfort PCMs. This can be attributed to participants feeling comfortable across a wide range of temperatures. For example, a participant might feel comfortable at 21℃ one day and cold and uncomfortable at the same temperature on another day. This highlights that thermal comfort

is highly conditional and influenced by various factors, including historical thermal comfort and the interaction of different comfort aspects, not just indoor temperature.

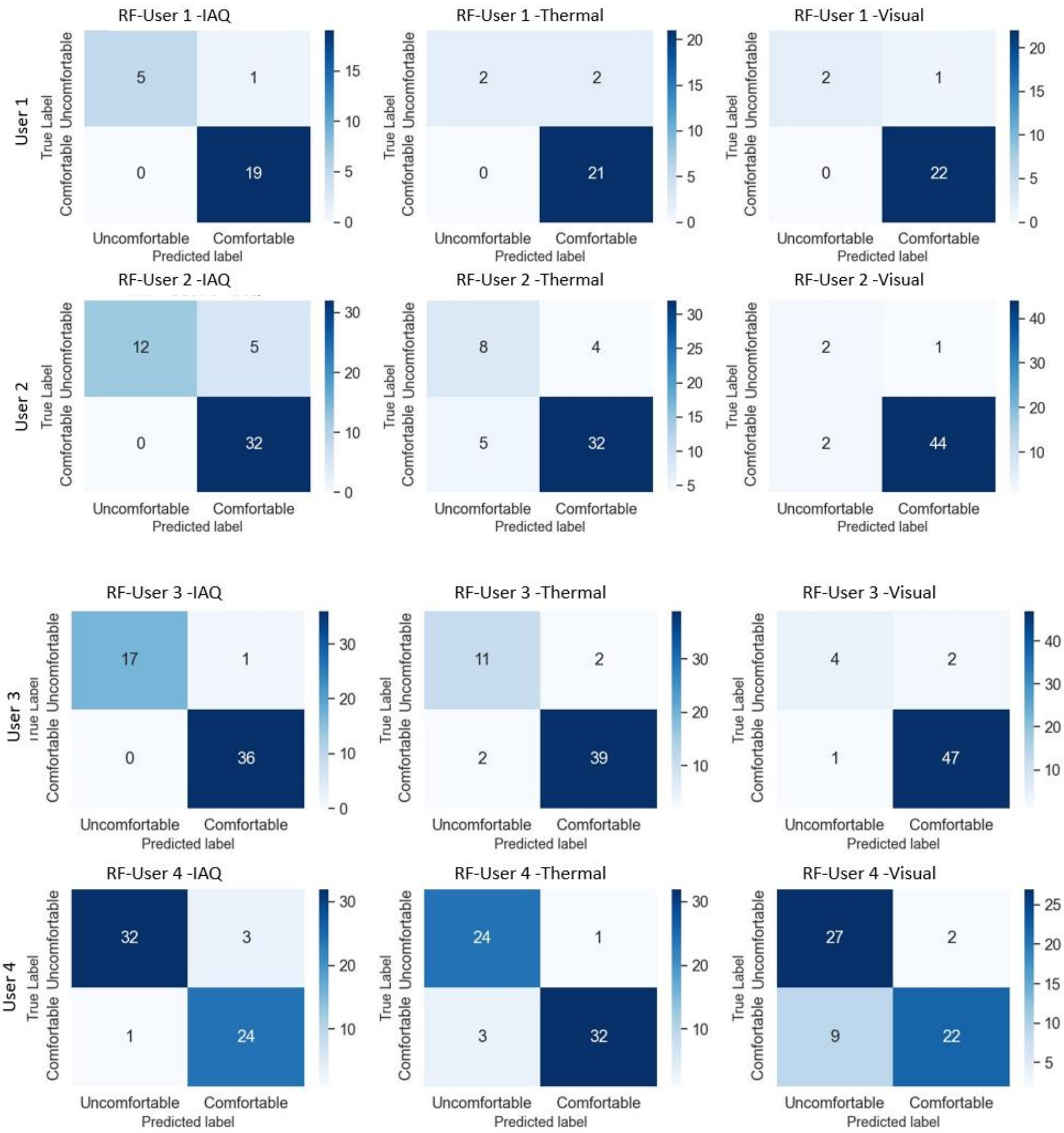

Figure 3.17 Confusion matrices for each individual user and each comfort aspect – an overview of the prediction performance of the Random Forest model in predicting True Positives and Negatives, and False Positives and Negatives

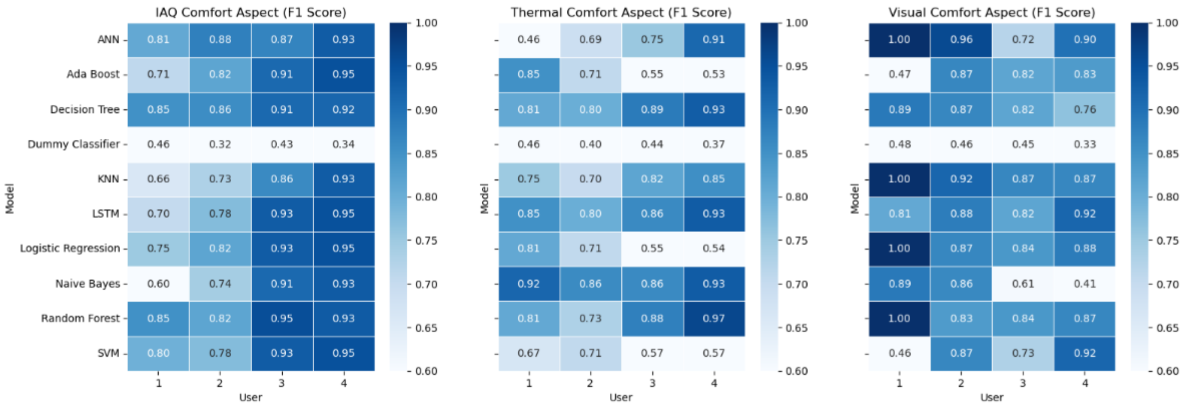

Figure 3.18 The comparison of model performance measured with F1 score for each individual user. Results are shown for IAQ PCMs (left), thermal PCMs (middle) and visual PCMs (right)

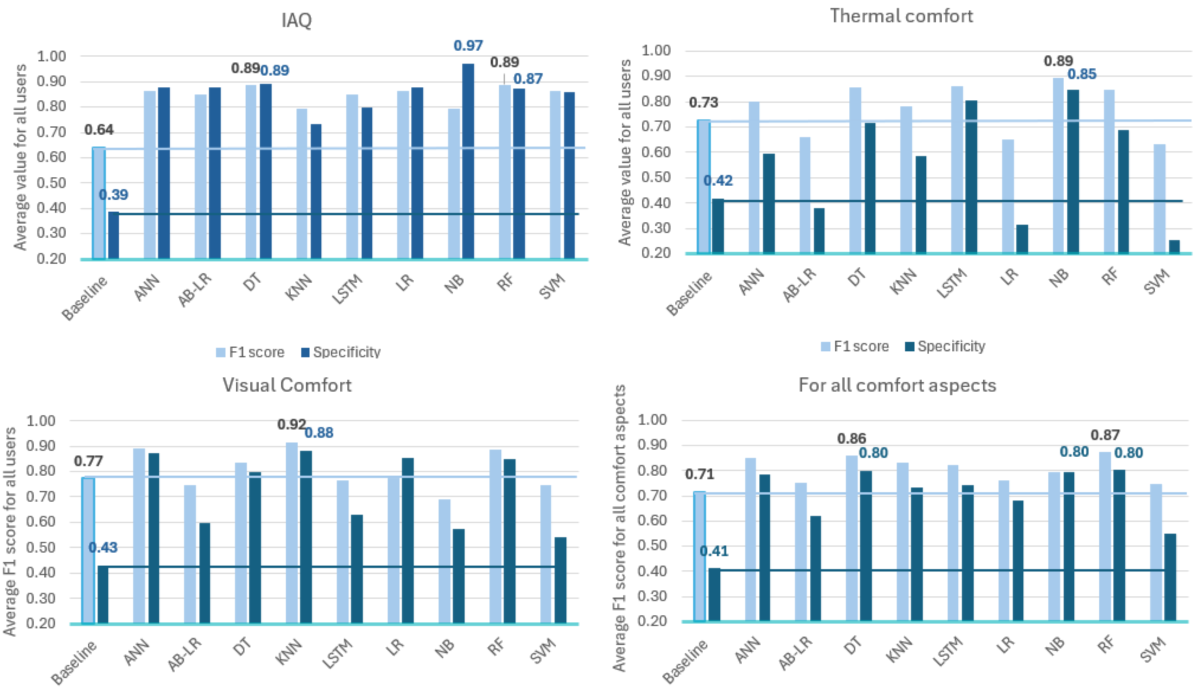

Figure 3.19 The comparison of model performance measured with average F1 score and specificity for all users. Results are shown for IAQ PCMs (top left), thermal PCMs (top right), visual PCMs (bottom left) and all comfort aspects (bottom right)

3.3.9 Feature analysis for input selection in personalized comfort models

The models developed for the participants in the lab experiment include a lot of inputs and are used to predict comfort. To test the importance that each input feature has on the performance of the model, a feature analysis was performed for the selected best performing model, which is Random Forest. The feature performance analysis is conducted for all users and all three comfort aspects and the results are presented in Figure 3.20 (IAQ comfort), Figure 3.21 (thermal comfort), and Figure 3.22 (visual comfort).

The most important features identified from the input feature analysis for IAQ comfort PCMs are the perceived air quality sensations of the users (very stuffy to very fresh, etc.), the perceived air humidity sensation (very dry to very humid), the air quality preference (want more fresh air or no change), air temperature (measured at different points in the room), CO_2 levels, and the air humidity. Results suggest that air temperature impacts the IAQ PCM more than the CO_2 levels, emphasizing the correlation between comfort aspects (in this case, IAQ and thermal comfort). The least important input feature for IAQ PCM is air velocity. (Figure 3.20)

The feature analysis of the thermal PCM with Random forest (Figure 3.21) shows that thermal preference, air temperature (measured at different points), air humidity, and thermal sensation highly impact thermal PCM performance. However, it should be noted that these vary from person to person, depending on their expressed responses. The least important input features are the measured air velocity, air humidity sensation, and air velocity preference.

As per the visual PCMs (Figure 3.22), results show that the least important input features are blind usage and glare perception, meaning that these features did not contribute much to the prediction potential of these models. The most important ones are illuminance measured in the middle of the room, vertical and horizontal illuminance measured at table level and eye level in lux, lighting preference (want brighter or dimmer), and illuminance sensation (too dark, too bright, neutral).

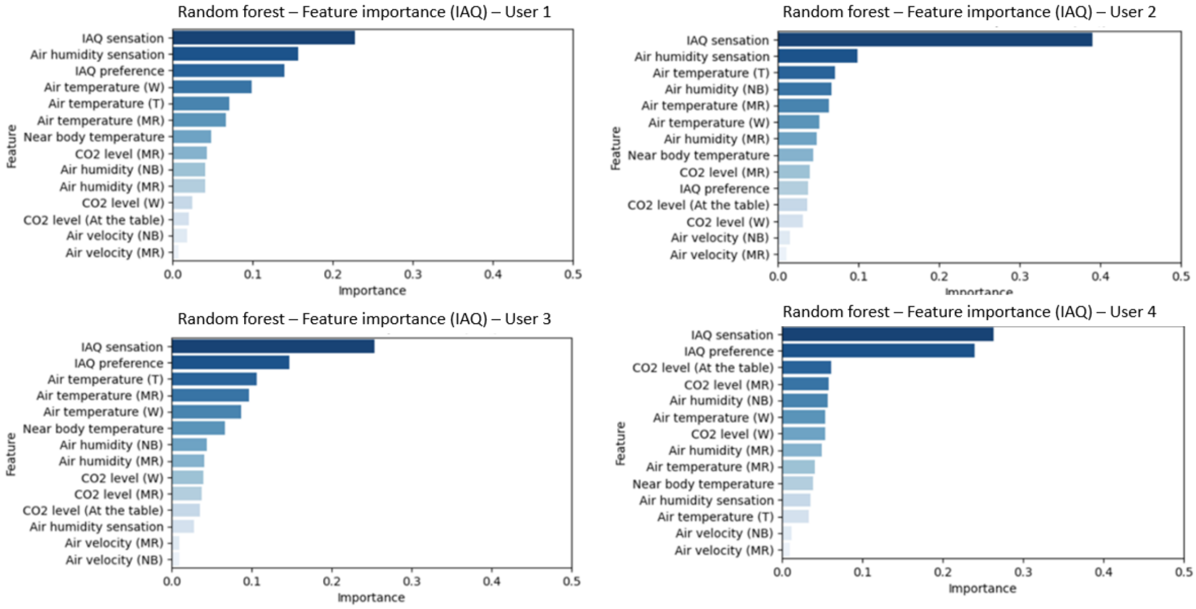

Figure 3.20 Feature importance analysis for Random Forest for IAQ comfort aspect. Data are presented for each user.

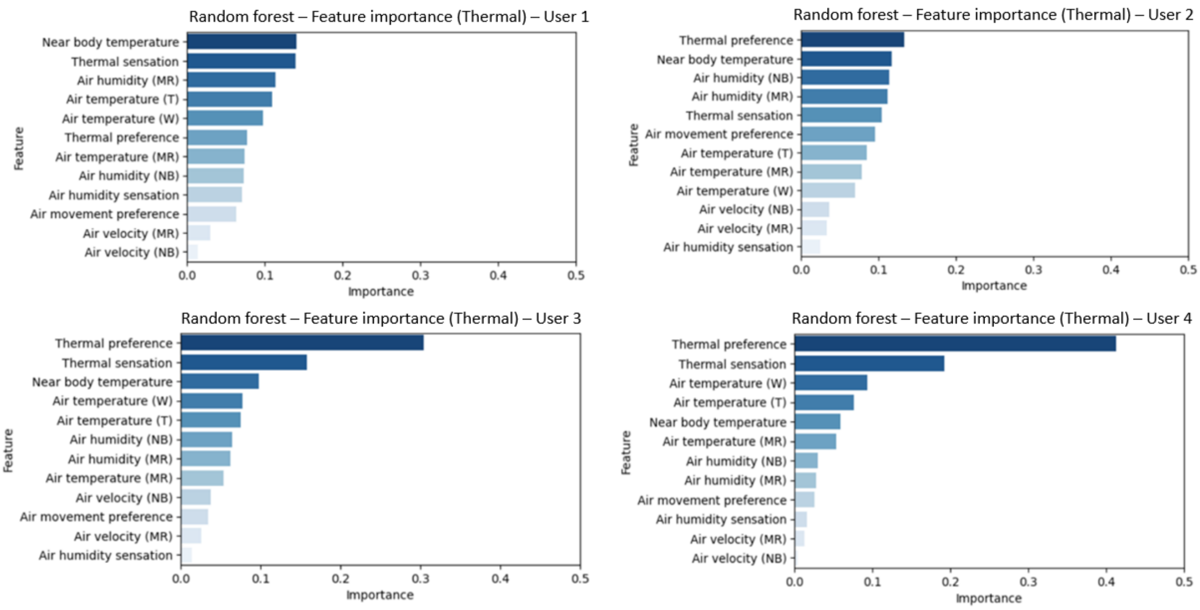

Figure 3.21 Feature importance analysis for Random Forest for thermal comfort aspect. Data are presented for each user

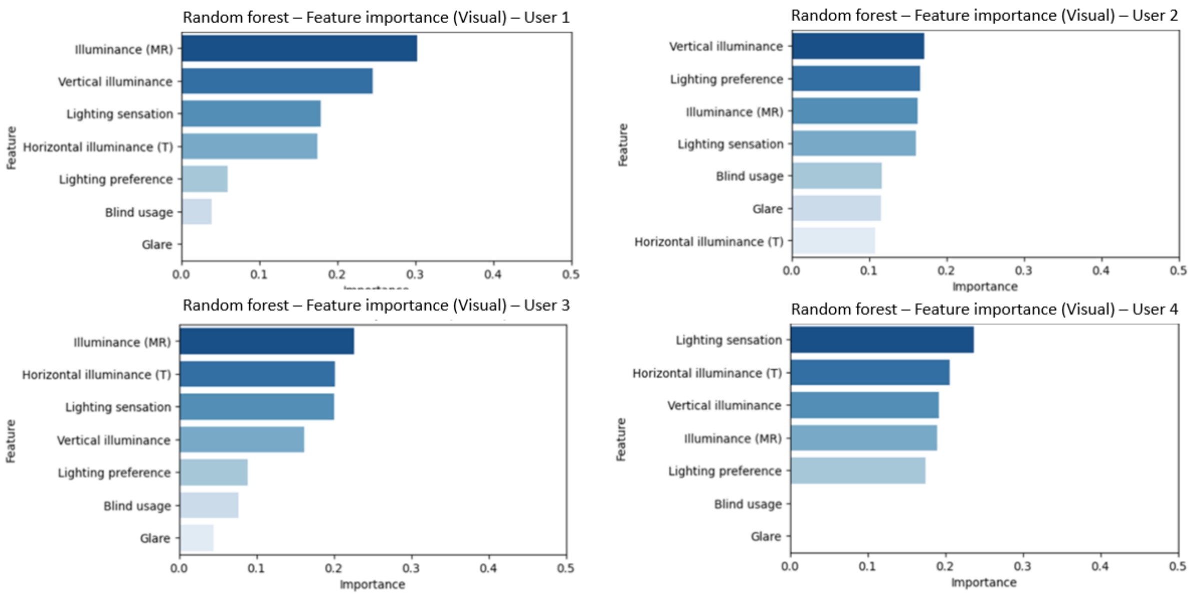

Figure 3.22 Feature importance analysis for Random Forest for visual comfort aspect. Data are presented for each user

Considering the feature importance, some features with little impact were removed e.g., air velocity. The models were simplified by using only one data source for each parameter, such as using air temperature from a single sensor in the middle of the room, instead of multiple sensors from different locations. The feature reduction enables one to evaluate the potential of developing PCMs with less measured sources or reported variables. The reason behind this is to make the models easily reproducible since most buildings usually have, e.g., one thermostat that measures the room temperature in only one location. Figure 3.23 shows the comparison of variables between the model with all initial inputs and the reduced model, while Figure 3.24 shows the differences in the prediction potential between those two models.

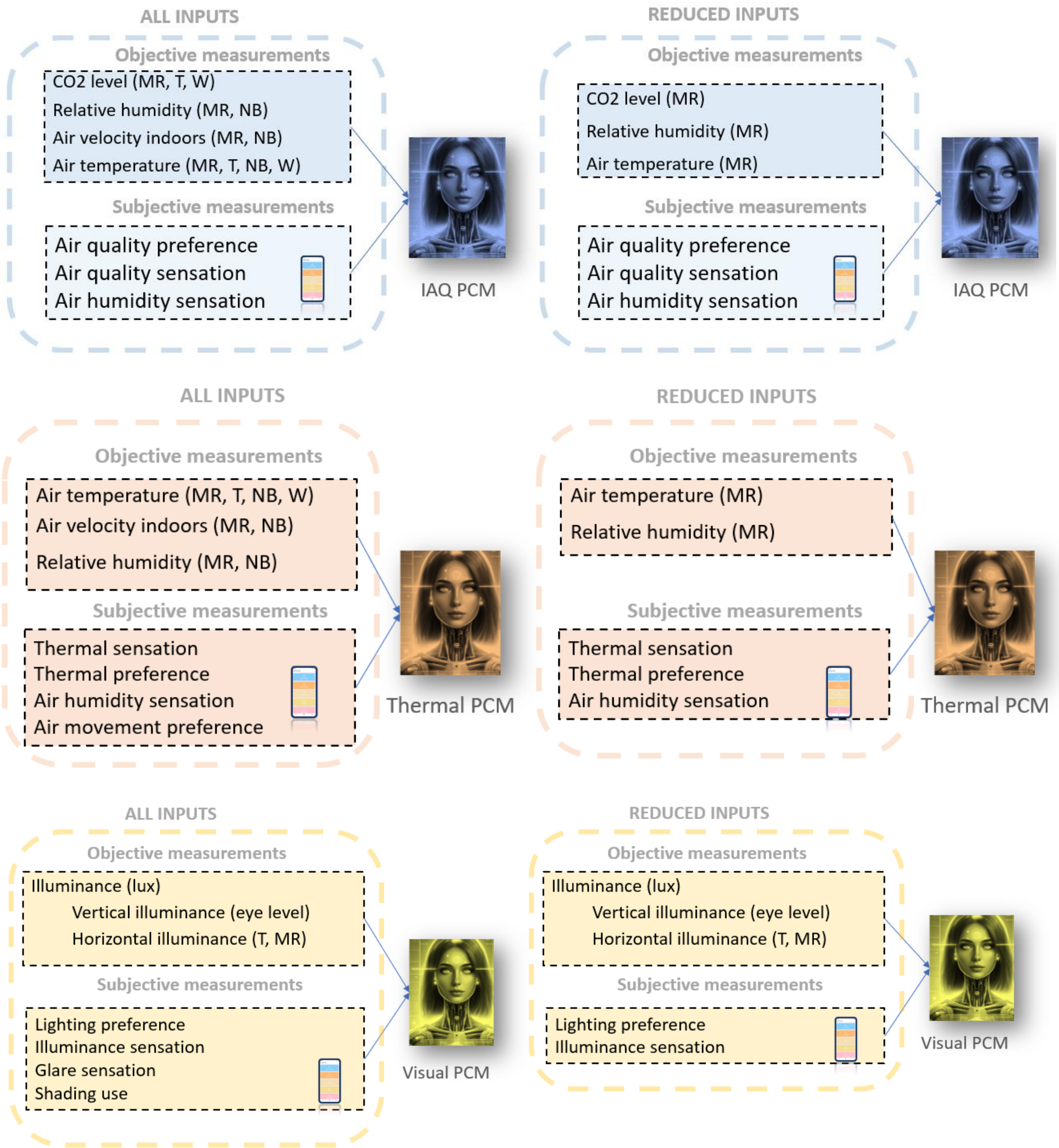

Figure 3.23 The comparison of the full PCMs (all input features) and the reduced PCMs (reduced input features)

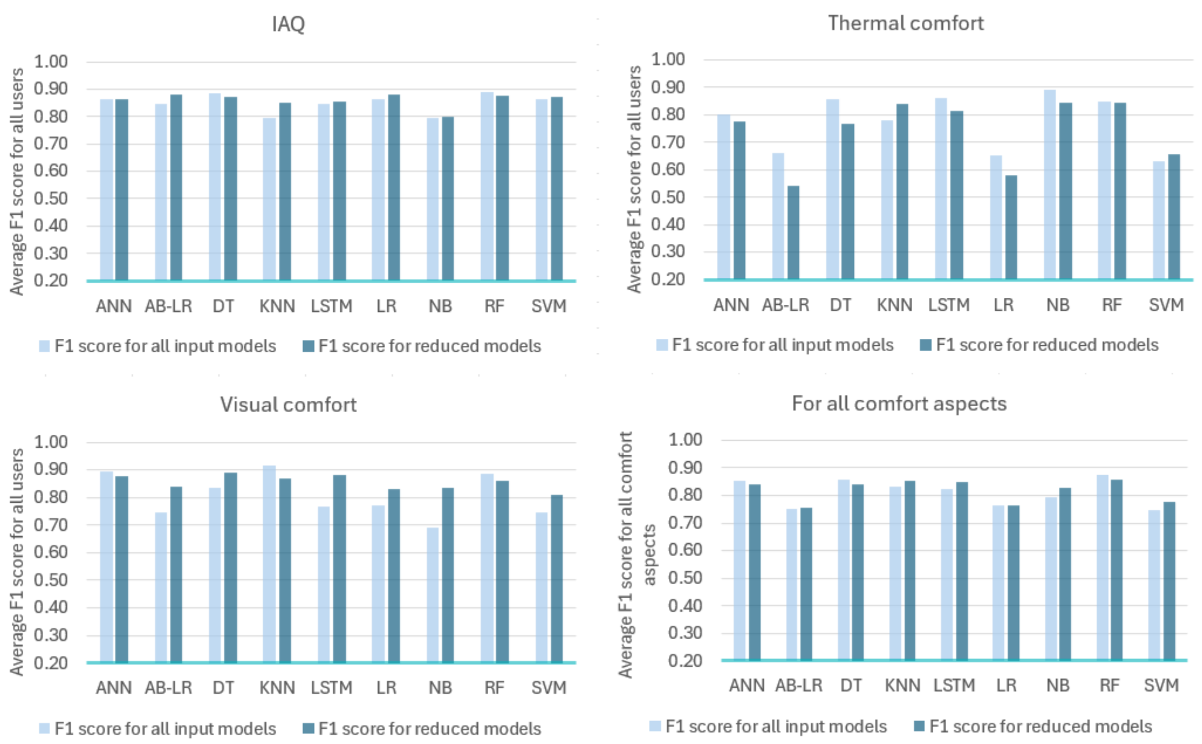

Figure 3.24 The difference between the F1 scores for the PCMs with all initial inputs and the reduced PCMs. Results are shown as average values between all users

For a more explicit depiction of how the feature reduction impacts the PCMs for different comfort aspects, Figure 3.25 shows the difference between the F1 score for reduced models and F1 scores for all inputs, or more precisely: $\Delta\mathrm{F1\ score} = F1\ score_{(reduced)} - F1\ score_{(all\ inputs)}$. The results indicate that for thermal PCMs, the F1 score decreases for some ML models. However, IAQ and visual PCMs show improved performance with fewer inputs. Notably, feature reduction did not significantly impact performance for the Random Forest model, which is the best-performing model. The baseline model (Dummy classification) is not included here as it ignores the input features and will not be used for comparison in following sections, leaving only the nine other ML models for comparison.

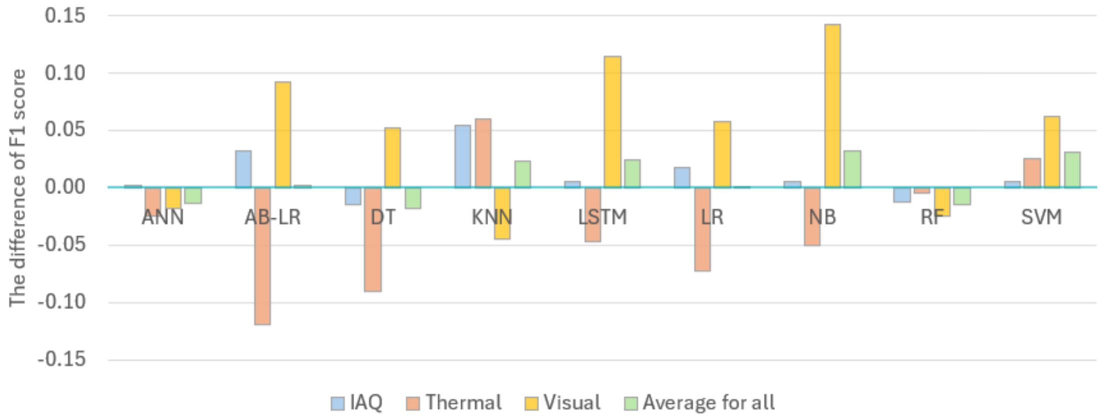

Figure 3.25 The difference between the F1 scores of the PCMs with all inputs and the PCMs with the reduced inputs for IAQ, thermal comfort, visual comfort, and the average for all three comfort aspects

3.3.10 Comparison between comfort-based and preference-based models

To determine the comfort of occupants using PCMs, some researchers use preference-based models by predicting, for instance, thermal preference (e.g., want cooler, no change, want warmer) or thermal sensation (feeling hot, warm, neutral, cool, cold). This study has applied a simplified approach using a binary classification model that categorizes comfort as Comfortable or Uncomfortable. The main benefit of such comfort-based models is the reduced number of data points needed as input to achieve satisfactory predictions compared to multiclass models. Figure 3.26 compares the performance of comfort-based and preference-based models using data from four participants in the lab experiment. Overall, the average F1 scores across all users and comfort aspects reveal that both comfort-based and preference-based models have similar prediction capabilities, particularly when using tree-based models for the PCMs.

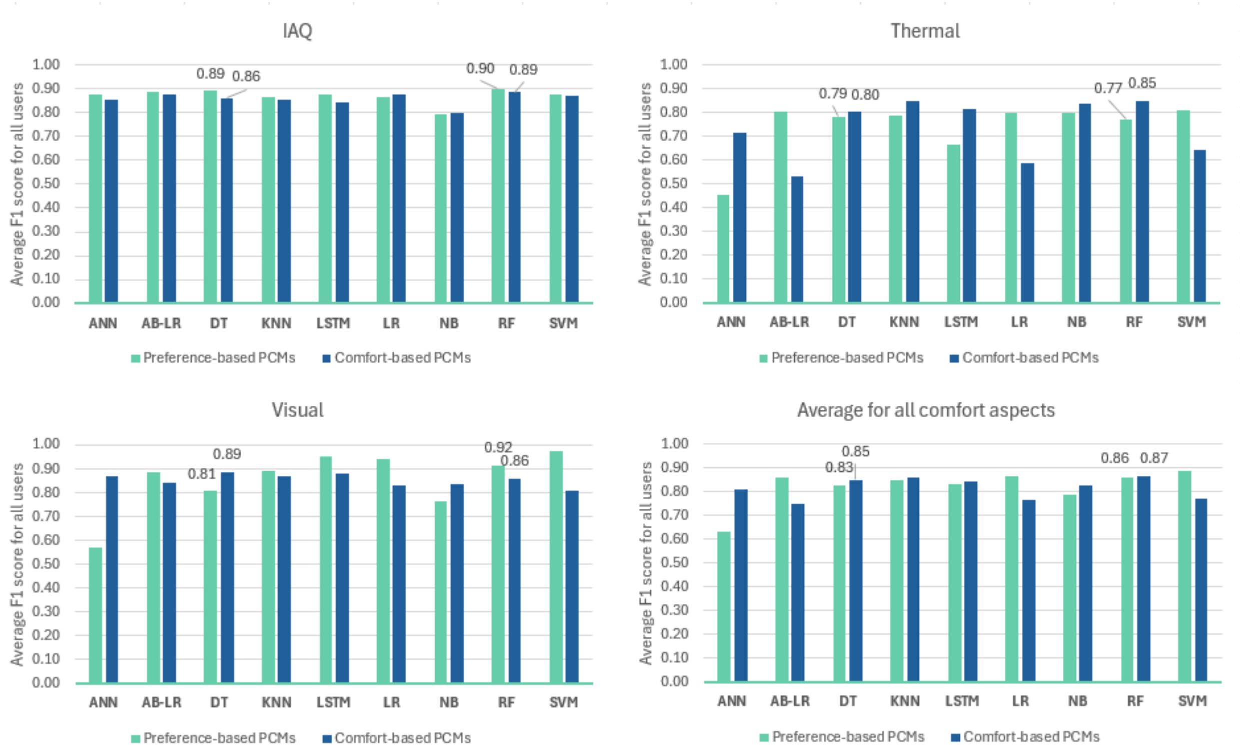

Figure 3.26. Comparison of comfort-based and preference-based PCMs for different comfort aspects

3.3.11 Analysis on the amount of datapoints needed for PCM development

This section presents the results of an analysis to determine the minimum amount of data required to develop well-performing PCMs. The analysis involved testing models with varying numbers of data points by partitioning the user dataset into 10-point slices. These slices were incrementally added to the model to observe when the prediction performance improved and stabilized. The models were initially trained with 20 data points per user, then increased to 30, 40, and so on. This process was applied to all three comfort aspects and the models with all initial inputs (Figure 3.27) for two users with the highest number of data points. For brevity reasons, additional results (results for the reduced models and the results on the specificity) are shown in Annex D. Figure 3.27 shows that:

- Some models converge their accuracy or stabilize their performance after 50 – 60 collected data points. This goes in line with research [27] and [20].
- Random Forest, Decision tree, KNN, ANN, and LSTM significantly improved their performance after around 50 – 60 data points.

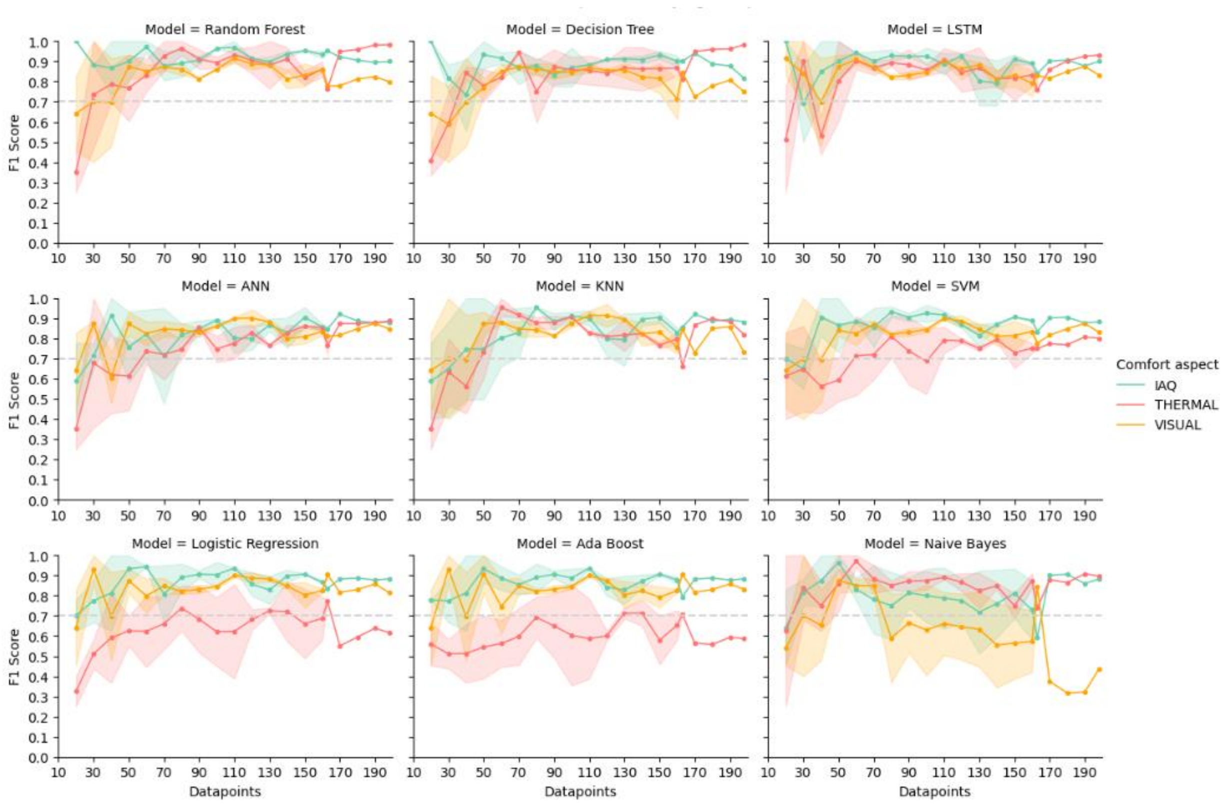

Figure 3.27 Comparison of prediction accuracy (F1 score) of PCMs depending on the number of data points for all comfort aspects. Data are shown for the models with all initial inputs

3.3.12 Findings from the field experiment: user preferences and personalized comfort models

To test the PCMs developed in the lab experiment, a field study was conducted in a school building with 24 participants with limited knowledge of control systems. These participants were typical building occupants whose feedback reporting habits and engagement levels with the building controller were naturally varied and uncontrolled. Although reminders were used to nudge them to report, compliance was sometimes inconsistent. Throughout the two weeks of the experiment, a total of 702 data points were collected from 24 participants in one classroom. The participants reported feedback 3 to 7 times per day; due to varying class schedules, they were not always available to report. The distribution of data across participants is shown in Figure 3.28. The results of the field experiment include user preferences and comfort levels related to IAQ, thermal comfort, and visual comfort over two weeks. These results are compared to the standard setpoints typically used in buildings. Additionally, the results entail PCMs developed for the participants, which are discussed further in the subsequent sections.

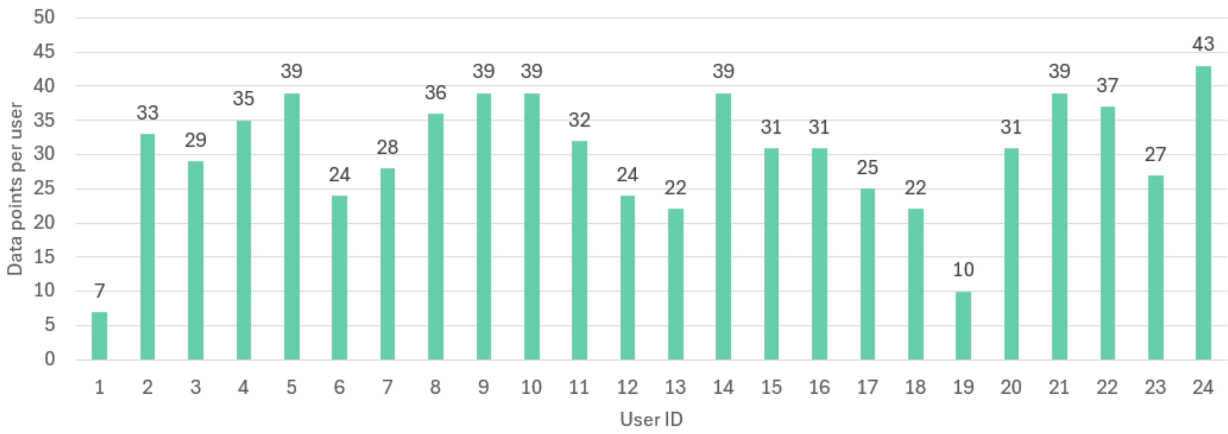

Figure 3.28 The number of data points provided by each user during the field experiment

<u>Findings on user preferences and perceived comfort during the field experiment.</u> The perceived comfort during the field experiment varied significantly as shown in Figure 3.29. Although a higher discomfort rate was expected, especially during the intervention days of the experiment when their comfort boundaries were tested, the participants were mostly comfortable throughout the experiment. Figure 3.29 also indicates that IAQ was the primary factor affecting the comfort of participants, causing the most discomfort. This observation aligns with the findings from the lab experiment.

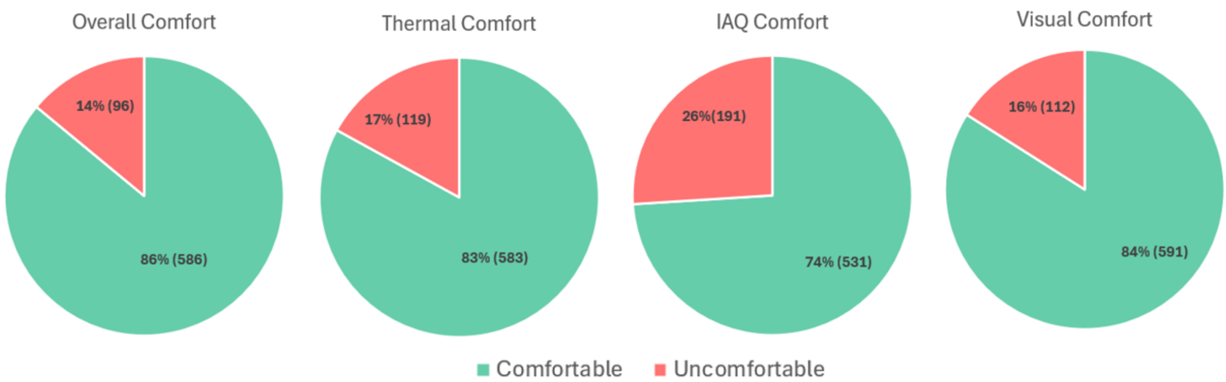

Figure 3.29 Distribution of the perceived comfort for different comfort aspects (IAQ, thermal and visual comfort) and the overall comfort for all participants

Figure 3.30 shows the perceived thermal comfort for the field participants. The distribution of thermal comfort responses is presented for different indoor temperatures and for different participants. The other data distributions for IAQ and visual were similar to the lab findings and will, therefore, not be presented to avoid redundancy.

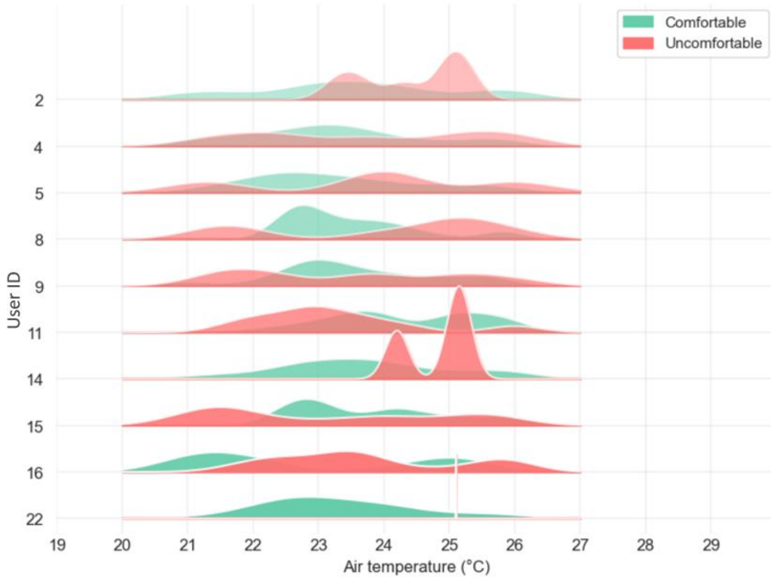

Figure 3.30 Distribution of perceived thermal comfort votes for different users across different air temperatures during the field experiment

The comfort ranges or boundaries for air temperature and CO_2 levels, representing the upper and lower limits of comfort for each participant (calculated excluding outliers), are shown in Figure 3.31. The findings show that the temperature range in which most participants feel satisfied is 21.8°C – 24.8°C. Based on these findings, if the classroom was controlled according to standard temperatures ranges of 21 – 22°C, oftentimes the students would be outside their comfort range. This highlights the importance of considering user preferences when defining indoor setpoints. The acceptable CO_2 levels are shown to be consistent with the standard setpoints of less than 1 000 ppm according to ASHRAE. The visual comfort ranges are not presented as they largely depend on the position of the user (where they sit in the classroom), and there is too much variability to draw any significant conclusions.

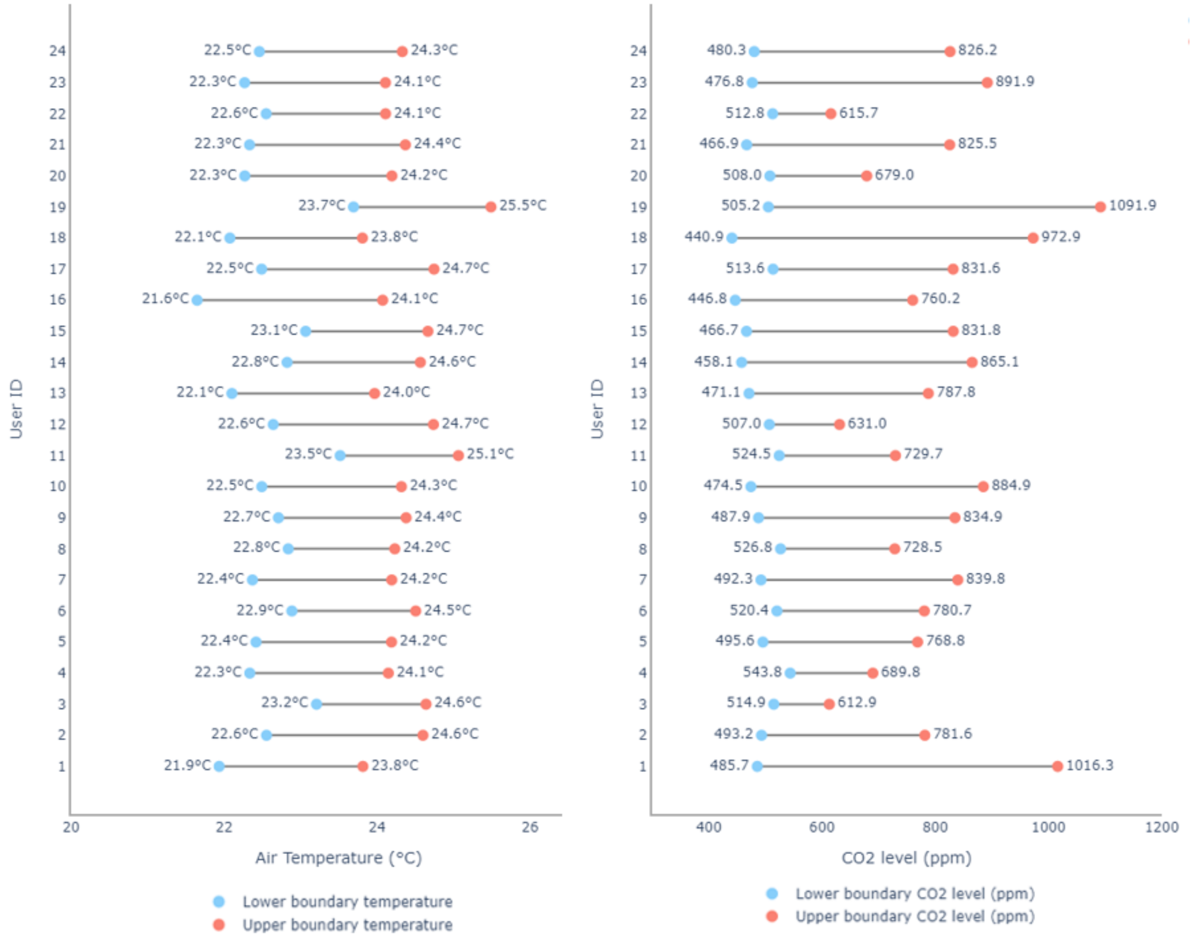

Figure 3.31 The comfort ranges for each participant. Left: Temperature comfort boundaries and right: CO_2 level comfort boundaries

Personalized comfort models from the field experiment. After developing PCMs in the lab conditions, the same ML models were applied in a field experiment at a school building. User engagement in reporting data varied significantly, with some participants providing up to 43 data points, while others provided fewer than 10. Although the literature suggests a minimum of 50 data points for PCM development [20] and 50-60 datapoints according to the lab experiment, the PCMs in the field experiment were developed with data less than the recommended threshold. The reason behind this is the high variability in indoor conditions during the intervention days of the experiment, leading to varying data and using comfort-based models (with binary classification) that perform well even with fewer data points. To address these challenges and provide a solution on how to develop PCMs for different types of user engagement in providing data, participants in the field experiment were categorized into four groups based on their reporting behavior:

1. Group I – High engagement: these users actively reported comfort responses sincerely, providing sufficient and variable data. For them, PCMs can be developed directly by training the model on the provided data.
2. Group II – Always comfortable: these individuals consistently report being comfortable and having a wide tolerance range, even when indoor conditions change. Hence, their responses lack variability. For this group, peer data (data from other occupants) can be added to their own data and form a "Peer-based PCM", allowing the model to be updated as more personal data becomes available.
3. Group III – Comfortable but want change: these users reported feeling comfortable but still desired changes (e.g., cooler or warmer conditions). Hence, a binary classification model (comfortable/uncomfortable) is unsuitable for them. For this group, a preference-based PCM (e.g., want cooler, no change, want warmer) is needed to capture their nuanced preferences. The preference-based approach is not proposed for all groups because the goal was to test if the simpler binary classification PCM (comfortable/uncomfortable) could be effective, as it is easier to develop.
4. Group IV – Low engagement: this group includes individuals who either do not share data, have been absent, or are new occupants, resulting in a lack of data. For them, standard setpoints or peer-based PCMs can be used, and they can be updated as new data becomes available.

This categorization and the proposed solutions for PCM development are illustrated in Figure 3.32. It should be noted that the naming of the groups was based on convenience, according to observations during the experiment. These names (e.g., "high engagement participants") are not standardized terms. Since the number of participants was relatively small in the experiment, the categorization was proposed based on close observations of the data during and after the experiments. For larger groups of people, research studies use clustering methods to group people based on similar characteristics, such as cohort-based models in [90].

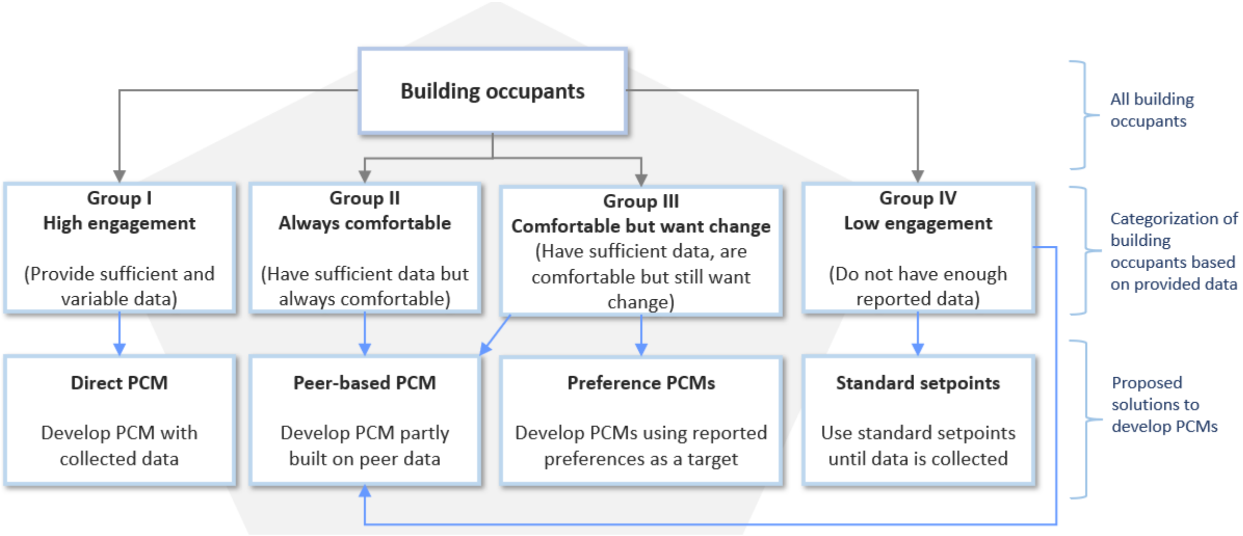

Figure 3.32 The proposed categorization of users based on the provided data

The results for the PCMs for the Group I – "High engagement" occupants, built directly with user-provided data, are shown in heatmaps in Figure 3.33. The heatmaps provide a detailed view of the performance (F1 scores) of various ML models across different users for three comfort aspects: IAQ, thermal, and visual comfort. Each heatmap represents the F1 scores for each model and user combination, with darker shades indicating higher scores. The results show significant model performance variability across users and comfort aspects. Due to the relatively low number of data points provided by users (around 40 data points) and the lack of variability, the model performance is lower compared to the lab experiment models.

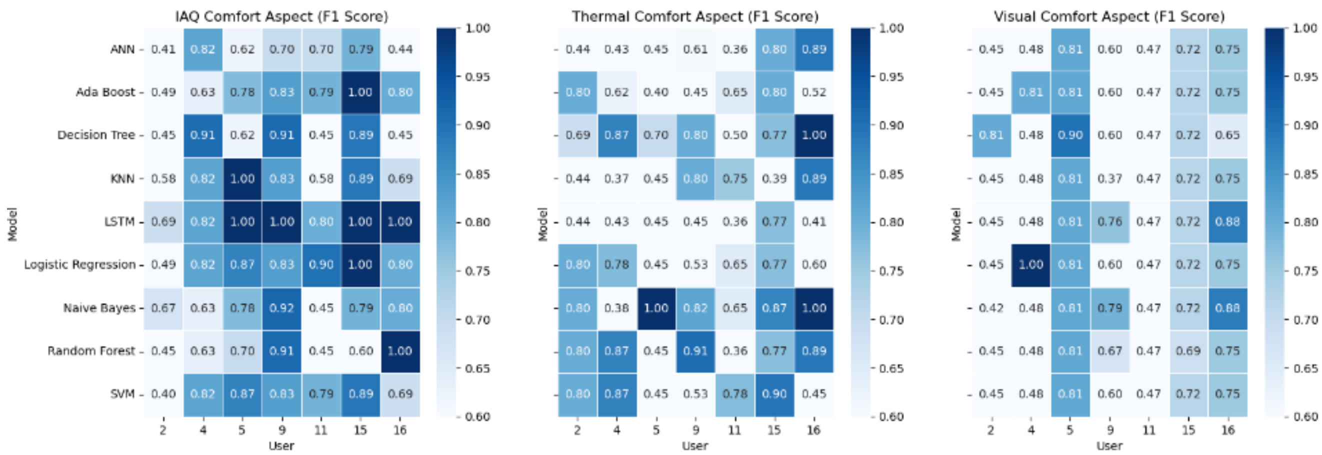

Figure 3.33 The comparison of model performance measured with F1 score for each user for Group I – "High engagement" occupants. Results are shown for IAQ PCMs (left), thermal PCMs (middle), and visual PCMs (right)

To better visualize which ML model is more robust for different people and different comfort aspects, for all seven occupants from Group I – “High engagement”, the average F1 score values are shown in Figure 3.34. For IAQ models, LSTM and Logistic regression are the best-performing ones, although with LSTM, it can be because of overfitting as this model requires more data to perform better. For thermal comfort, Naive Bayes, followed closely by Decision Tree, performs the best, and lastly, for Visual comfort, Logistic regression, followed by Decision Tree, performs the best. If the average value across all users and all comfort aspects is taken, then the Logistic regression and Naive Bayes show the highest prediction potential for Group I. This aligns with the characteristics of the ML models as they perform better when small datasets are available.

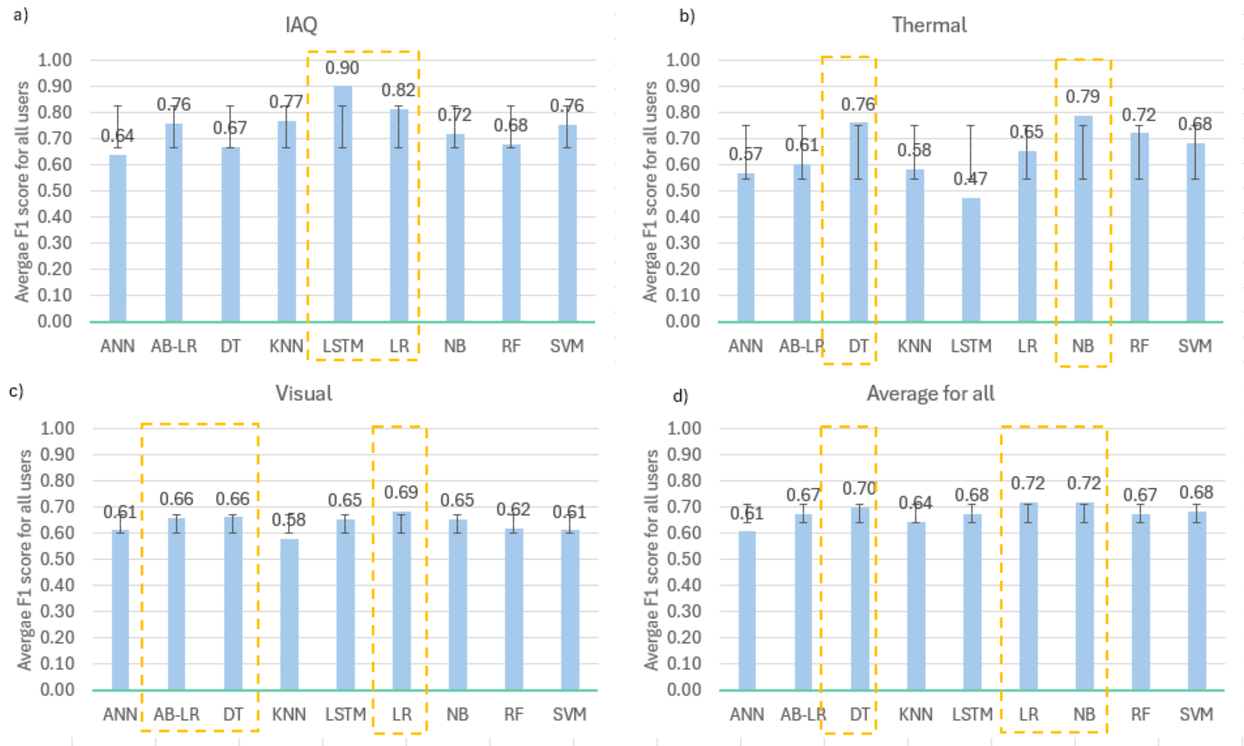

Figure 3.34 The comparison of model performance measured with average F1 score for all users for Group I – “High engagement”. Results are shown for IAQ PCMs (top left), thermal PCMs (top right), visual PCMs (bottom left) and all comfort aspects (bottom right)

For Group II – “Always comfortable”, who are always satisfied, the PCMs were developed using data augmentation by adding data from peers. For example, if a participant from the field experiment had their own 40 data points but with no variability, then an additional 30 data points were added to the mix to increase variability. These additional data were from the lab experiment participant who had the best-performing PCM. Figure 3.35 shows the results of the peer-based model built by mixing personal data with peer data from the lab experiment. The results show good prediction potential with high F1 scores. Given that this group consistently reports being satisfied and comfortable, even if the model is initially based on peer data, it can effectively serve these individuals due to their high tolerance for varied indoor conditions. Using peer data provides a robust starting point, ensuring their comfort is maintained while allowing the model to adapt and become more personalized as additional individual data is collected.

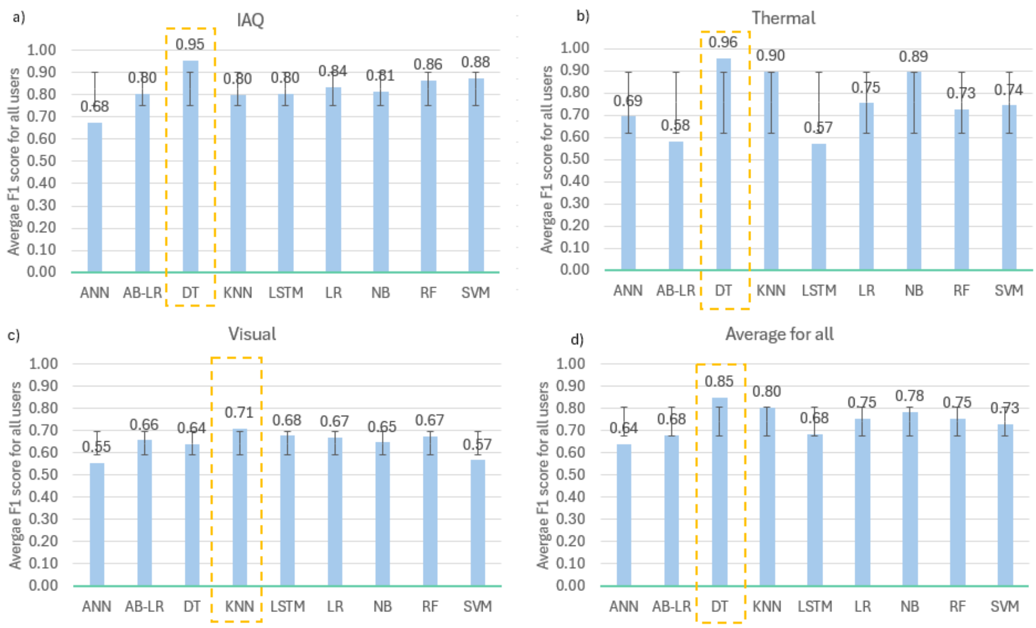

Figure 3.35 The comparison of model performance measured with average F1 score for all users for Group II – "Always comfortable" by adding an additional 30 peer data points on top of their own data. Results are shown for IAQ PCMs (top left), thermal PCMs (top right), visual PCMs (bottom left) and all comfort aspects (bottom right)

For Group III – "Comfortable but want change" that feels comfortable but wants change, the preference-based approach was proposed to predict the need to change conditions (e.g., cooler, no change, or warmer). Figure 3.36 shows the yielded results for the preference-based model. However, the results highly depend on the user, showing that the PCMs do not perform very well for IAQ (when the options were "no change" or "want more fresh air"). For thermal comfort, machine learning models designed for imbalanced datasets, such as Logistic Regression, AdaBoost, and SVM, demonstrated better performance. The models for visual comfort predicted quite well, apart from one user. The comparison of the model performance is shown in Figure 3.37. Whereas to illustrate how the performance of Group I models would change if preference-based models are used instead of comfort-based models, the comparison results are shown in Annex E.

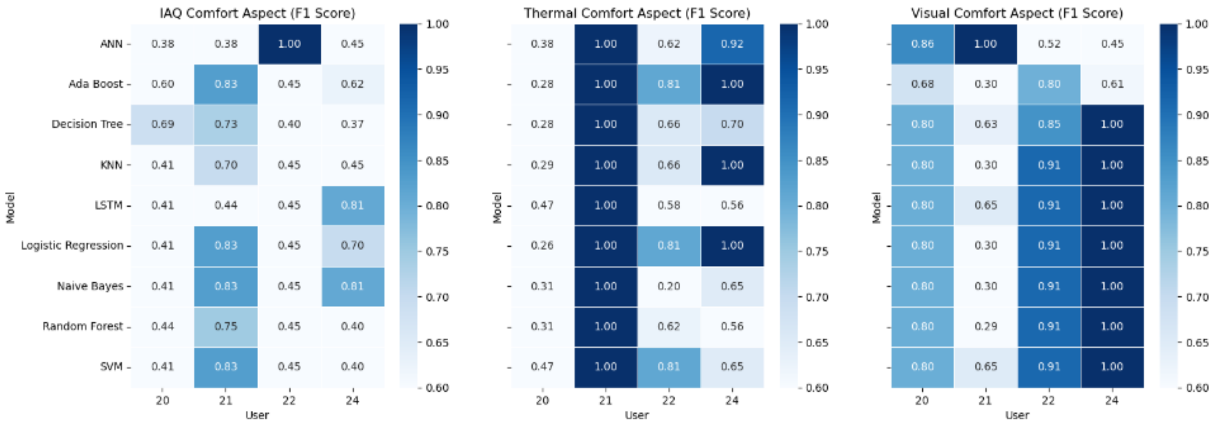

Figure 3.36 The comparison of model performance measured with F1 score for each individual user for Group III – "Comfortable but want change" using preference-based PCMs. Results are shown for IAQ PCMs (left), thermal PCMs (middle) and visual PCMs (right)

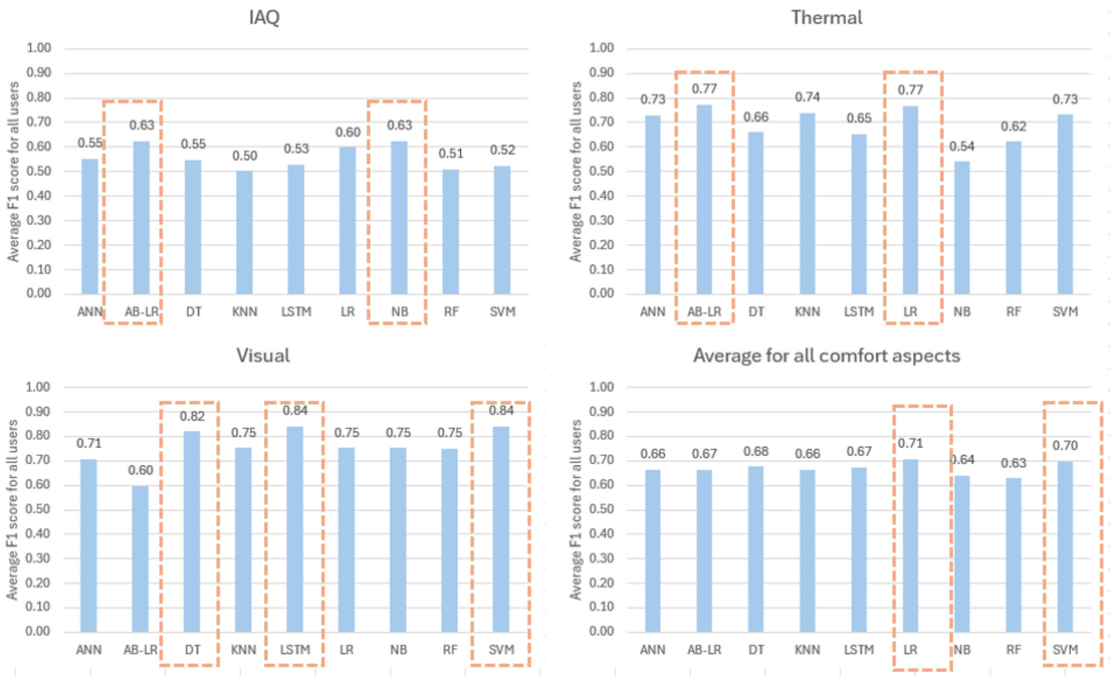

Figure 3.37 The comparison of model performance measured with average F1 score for all users for Group III – "Comfortable but want change" by using preference-based PCMs. Results are shown for IAQ PCMs (top left), thermal PCMs (top right), visual PCMs (bottom left) and all comfort aspects (bottom right)

The findings show that for all three groups of participants, namely Group I – "High engagement," Group II – "Always comfortable" and Group III – "Comfortable but want change," Decision Tree is the ML model that has the optimal performance across different user groups and different comfort aspects. With an average F1 score of 0.74 for Decision Tree.

Followed by Logistic regression (0.73) and Naïve Bayes. This goes in line with the findings from the lab experiment, where Decision Trees was the 2nd best performing model, closely after Random Forest. With this, it can be concluded that Tree-based ML models are the best models to be used to develop PCMs.

3.3.13 Comparing the findings from the lab and field experiment

Table 3.6 provides a summary of the two experiments, namely the lab and field experiment. The findings show that Tree-based ML models can be used to develop PCMs despite variations in user engagement levels or comfort aspects.

Table 3.6 Comparison between the lab and field experiment setting and results

	Lab experiment	Field experiment
Experiment venue	Faculty office	School classroom
Duration	Three weeks	Two weeks
Participants	4	24
Number of reported data	83 –198 data points per user	7 – 43 data points per user
User engagement	Continuous feedback	Diverse feedback habits. Data insufficiency. Four groups of participants were identified: – Group I – “High engagement occupants”, – Group II – “Always comfortable”, – Group III – “Comfortable but want change”, – Group IV – “Low engagement”.
PCM development	Direct PCMs (comfort-based PCMs)	For the groups mentioned above, different PCM development methods were tested: – Group I (Direct PCMs) – Group II (Peer-based PCM & Preference-based PCM) – Group III (Peer-based PCM & Preference-based PCM)
Highest PCM prediction performance	Average F1 score of 0.87 with Random forest and Decision tree (0.86) (calculated across all users and all comfort aspects)	Average F1 score of 0.74 for Decision tree and Logistic regression (0.73) (calculated across all groups and all comfort aspects).
Optimal ML model	Random Forest and Decision Tree	Decision Tree and Logistic regression

3.4 Discussion and conclusions

This chapter presents the development of data-driven PCMs to predict the comfort level of building occupants. This is achieved by collecting user feedback on their perceived comfort regarding IAQ and thermal and visual factors while conducting indoor measurements to understand the conditions under which individuals feel comfortable or uncomfortable. This is important to tailor indoor conditions based on user preferences, reducing the need for continuous input from users as the models learn and represent user preferences. The PCMs are developed using supervised ML models with known inputs and outputs. Inputs include subjective feedback and indoor measurements, while outputs classify the user's comfort state as either Comfortable or Uncomfortable, making the PCMs a binary classification model.

Developing data-driven PCMs requires extensive data, involving both subjective data provided as feedback from occupants and environmental measurements indoors. Subjective inputs collected from the users included their comfort perception and preferences. Some measured subjective parameters include thermal sensation and preference, IAQ sensation and preference, visual or lighting sensation and preference, etc. Feedback was gathered using a self-developed smartphone app called HComfort, chosen based on the findings from the conducted survey in which 66% of users preferred this method (details are in Chapter II). The app ensured data privacy security via Amazon Web Services (AWS). It enabled seamless data flow from the app to the DynamoDB database and then to Jupyter Labs in Python for PCM development. This setup allows continuous updates of the PCMs as more data becomes available, presenting a practical method for developing PCMs. Indoor measurements were collected through various sensors that measured air temperature, CO_2 level, lighting level, air humidity, and air velocity at multiple measurement points.

Two experiments were performed: a faculty office for three weeks with 4 participants (called the lab experiment) and a classroom in a school building for two weeks with 24 participants (the field experiment). The experiments were designed to create variability in indoor conditions for different days, also called the intervention days, that were planned to test the comfort boundaries of the users.

The findings show that data-driven PCMs using ML models can be developed for multiple occupants and multiple comfort aspects, yielding variable prediction performance across users and comfort aspects. Model performance depends on the number of available data points per user, selected inputs and outputs, data variability, and the type of ML model used. This indicates that it is challenging to have one “universal key” method to develop models that can be utilized for different types of occupants to lead to the best-performing PCM for all users or different comfort aspects. Still, there is an optimal approach that can handle the variations. For that reason, the development of PCM for multiple occupants and different aspects of comfort (IAQ, thermal, visual) is explored in this research, using nine different ML classification models. The tested models include ANN, Ada boost with logistic regression, Decision trees, KNN, LSTM, Logistic regression, Naïve Bayes, Random Forest, and SVM. The models were developed and tested under controlled conditions (the lab experiment) and in a field experiment with less control over user engagement in reporting feedback.

The lab experiment results indicate that Random Forest is the best-performing ML model, based on an average F1 score (0.87) for predicting Comfortable and Uncomfortable responses across all users and comfort aspects and specificity (0.80) for predicting specifically Uncomfortable responses. Accurate prediction of Uncomfortable responses is crucial for building control systems, as it informs the controller to initiate actions to regulate indoor conditions. Decision Tree models closely follow with an F1 score of 0.86 and a specificity of 0.80. This finding aligns with other research on PCMs, such as an F1 score of 0.72 for thermal comfort, 0.79 for visual comfort using Random forest [28].

A feature analysis for the Random Forest model was conducted to identify inputs with minimal impact on performance, simplifying the model by retaining only essential inputs. For example, while air temperature sensors were placed at various locations in the room (middle, windows, table, near body), only the air temperature measurement from the middle of the room was retained for the reduced model. This approach ensures that PCMs can be developed for various buildings with a standard number of sensors. Comparing PCMs with all inputs to those with reduced inputs shows that effective PCMs can still be developed with fewer features. This analysis was performed for different ML models and comfort aspects, with varying results. For some models, reducing inputs decreased accuracy; for others, it increased it. For instance, in IAQ, simplifying inputs increased the F1 score by 0.06. For thermal comfort, the F1 score increased by up to 0.06 for KNN, LSTM, and Random Forest models but decreased by up to 0.15 for ANN, AdaBoost, and Decision Tree models. This indicates a trade-off between simplicity and performance, as removing some inputs can result in a loss of valuable information. Despite simplification, Random Forest and Decision Trees maintained high performance, demonstrating robustness even with fewer inputs.

A comparison was conducted to evaluate the effectiveness of comfort-based models (predicting if a user is comfortable or uncomfortable) versus preference-based models (predicting if a user wants warmer, no change, cooler, brighter, no change, or dimmer) for PCMs in building control systems. The lab experiment results showed minimal differences in prediction accuracy between the two approaches across various ML models and comfort aspects. Tree-based models, such as Random Forest and Decision Trees, performed well in both cases, corroborating with research [28] which used preference-based models with Random forest. This indicates that both methods are viable for developing PCMs. However, from a user perspective, preference-based models may be more intuitive, as occupants can more readily specify if they want conditions to be warmer, cooler, brighter, or dimmer, compared to simply stating their comfort level. Therefore, for building control integration, preference-based PCMs might offer a more straightforward and user-friendly approach for collecting occupant feedback, as proposed in other studies such as [28].

Since data-driven PCMs depend on user-provided data, which is a challenging and time-consuming task, it is important to determine the minimum number of data points needed for effective model development. To estimate this, PCMs from the lab experiment were tested for the participants using varying numbers of data points. Data from two users with the most data points were incrementally added to the PCMs in sets of 10 until performance stabilized. Results suggest that 50 – 60 data points are needed for optimal PCM performance, aligning with findings from other studies, such as 50 data points in [20], 60 datapoints by Kim et al. [27]. Although there are other studies suggesting more, like 90 [137] and 250 – 300 data points in [136]. Yet, while sometimes there might be sufficient data available, the models can perform poorly due to the lack of variability. Hence, it is important for the data to have variability in the provided user feedback for a balanced dataset to train the ML models effectively. In actual buildings, it is practically impossible to expect perfectly balanced datasets (same amount of provided Comfortable and Uncomfortable votes), as it would mean that the building is managed very poorly [134]. One solution could be to use intervention days, where indoor settings are purposely altered (e.g., regular days, cold days, hot days, more fresh air, less fresh air, increased lighting, reduced lighting) to test occupants' comfort boundaries through planned disturbances. However, of course, this would cause inconvenience to the users, and it is not a feasible solution in actual buildings. This was tested in the school field experiment with typical school occupants, and unsurprisingly, on the intervention days, they were not satisfied with the indoor conditions.

The school field experiment results showed that the number of data points per user was significantly lower than in the lab experiment, ranging from 7 to 43. Due to variability in indoor conditions, some datasets were still sufficient to develop PCMs, while others were not. Based on the observation of the feedback engagement during the experiment, occupants were categorized into four groups. Group I – “High engagement” occupants who provide sufficient and variable data to develop their own PCMs. Group II – “Always comfortable” occupants are always comfortable; hence, the reported data lack variability. For them, data augmentation with pre-collected peer data can be used to develop hybrid peer-based PCMs, which can be updated as more data becomes available. Group III – “Comfortable but want change” are the ones that express being comfortable but want change (e.g., warmer or colder). For this group, preference-based models (or models that predict preferences, e.g., if one wants cooler or warmer) or peer-based models can be used. Lastly, Group IV – “Low engagement” occupants (not reporting feedback), have insufficient data for PCM development. For them, standard setpoints or peer-based models can be used. Different PCM development approaches were tested for the first three groups using the nine different ML models (the same as for the lab experiment). Decision Tree achieved the highest prediction accuracy with an F1 score of 0.74, followed closely by Logistic regression (0.73). These values are averages across all groups and all comfort aspects. Again, the findings align with values achieved in existing literature (F1 score of 0.72 and 0.79 for different comfort aspects)[28]. The prediction accuracy is slightly lower than that of the models for the lab experiment, as less data was available to train the models.

The lab and the field experiments provided important insights into the perceived comfort of the participants. Participants in both groups reported being comfortable at higher indoor temperatures than standard setpoints. In the lab experiment, the most comfortable temperature range was 22.5 – 25°C, which is higher than the 20°C standard for offices by CIBSE [178], but within the setpoints of 20 – 24°C according to OSHA in the US [179] and 20.5 – 25.5°C according to ASHRAE 55. This finding also complies with the findings from Wang et al., in [133], in which they identified that the comfort temperature range was 20.5 – 24.9ºC for office buildings in the US. The field experiment in the school building supported these findings, with a thermal comfort range of 21.8 – 24.8°C after removing outliers. Despite being conducted in different seasons (winter for the lab and spring for the field experiment), both experiments indicate a desired air temperature slightly higher than the regular setpoints of 20 – 22°C.

The comfort analysis was also conducted for IAQ and visual comfort. For IAQ, peak comfort was reported at CO_2 levels around 800 ppm, aligning with the under 1 000 ppm guideline from ASHRAE. However, there were instances during the lab experiment in which the CO_2 levels were purposely elevated during the intervention days, reaching 3500 ppm for the lab experiment. This was closely monitored not to get dangerously high CO_2 levels (values up to 5000 ppm are considered non-toxic for short periods according to ASHRAE [183]). Nevertheless, the occupants still often reported feeling comfortable, indicating a lack of awareness of poor IAQ. This highlights the need for nudges or warnings about poor air quality, especially for buildings that rely on natural ventilation, such as when occupants manually open the windows. Similar results were observed in the field experiment, where high CO_2 levels naturally increased when turning off the ventilation system. For visual comfort, user perceptions varied based on their positions in the room, mainly whether they were near windows. The lab experiment showed that indoor lighting levels were usually below the recommended 300 lux according to CIBSE [180], or 500 –1 000 lux according to EN 12464. Yet, the users reported feeling comfortable most of the time, suggesting a high adaptability to the lighting level. Similar findings were observed in the field experiment in the school building.

3.4.14 Practical implications and recommendations

Developing multi-occupant and multi-comfort aspect PCMs demonstrates significant potential for improving building control systems. Insights gained from the lab experiment and the field study provide valuable information for designers, practitioners, and other stakeholders who aim to apply HCC by prioritizing occupant comfort in buildings. These insights highlight the importance of integrating PCMs into control systems to establish a better user-building interaction. Key takeaways, practical implications, and guidelines include:

– Tailored indoor conditions: by implementing data-driven PCMs, building control systems can dynamically adjust indoor conditions to match occupants' preferences, thus enhancing comfort and satisfaction without requiring continuous user input. The ability to predict and adapt individual comfort needs based on real-time data allows for a more personalized indoor environment.

- Efficient resource utilization: the implementation of PCMs can significantly improve the control of HVAC systems by adjusting to actual comfort requirements rather than relying on static setpoints.
- Scalability: the use of robust ML models such as Random Forest and Decision Trees, which perform well even with reduced input features, demonstrate the feasibility of deploying PCMs across various building types with different sensor setups and data availability.
- Increasing awareness: the findings on IAQ and visual comfort highlight the need for occupant awareness regarding indoor environmental quality. Integrating informative nudges or alerts into building control systems can improve occupants' understanding and engagement with their indoor environment.
- User-friendly data collection: it is encouraged to use intuitive and secure smartphone applications to gather user feedback. The app must be easy to use, have clearly stated questions, and address privacy concerns to encourage widespread adoption and consistent data input from occupants.
- Sensor data collection: for effective PCM development, it is essential to have environmental measurements. One measurement per parameter is sufficient (e.g. one temperature sensor in the middle of the room, one CO_2 sensor), and using standard sensors simplifies the data collection process.
- The needed number of data points: a minimum data requirement needs to be established (e.g., 50 – 60 data points per user) to ensure the reliability of the models. Data can be added to update the model continuously.
- Target of the PCM: using comfort-based or preference-based PCMs does not significantly impact the model performance when employing tree-based ML models. Hence, it is better to use inputs that are more intuitive to the users (e.g., it is easier for the user to report if they want warmer or cooler conditions than to state if they are comfortable or uncomfortable).
- Diverse PCM approaches: at times, different PCM strategies need to be implemented for various occupant groups (high engagement occupants, occupants who are always comfortable, occupants who are comfortable but still desire change, low engagement occupants). Peer data can be used to develop peer-based models when necessary to compensate for the lack of individual data.

- Intervention days: although not always practical, if possible, scheduling intervention days in controlled environments can be beneficial. This expands the data variability and tests the robustness of the PCM. However, intervention days should be thoroughly planned and balanced against potential occupant inconvenience.

For future research, it would be beneficial to extend the duration of data collection from occupants to observe changes in their feedback engagement over longer periods. Additionally, expanding the research to include other comfort aspects, such as acoustic comfort, and testing these models in various field studies would provide a more comprehensive understanding. Chapter IV of this thesis introduces a framework for the integration of PCMs into building control systems. This framework offers a practical approach for developing HCC in buildings.

Chapter IV.

4. Integration of user preferences into building control systems

"First life, then spaces, then buildings,
the other way around never works."
J. Gehl

When regulating indoor environments, it is essential to remember that buildings are built for users. Human-centric control (HCC) prioritizes occupant needs and preferences by following an occupant-in-the-center tenet. This is important to increase user comfort, satisfaction, and well-being by tailoring indoor spaces to their needs. Hahn et al.,[184], emphasized that the best way to consider occupant preferences is by directly asking them rather than solely relying on building control systems. This research examines the impact of integrating user preferences into building control systems through multi-occupant and multi-comfort aspect personalized comfort models (PCMs). A proposed framework incorporates these preferences, improving user comfort and satisfaction. This was achieved by conducting a field experiment in the RCK Ruder Boskovic high school building, with 24 participants over two weeks. The study evaluated user satisfaction when indoor settings were controlled by standard setpoints versus user preferences. Additionally, user insights were gathered through semi-structured interviews to understand their experience with HCC, comfort and satisfaction during the experiment, practical recommendations, and future intentions to use such systems.

4.1 Literature review

Building control systems have significantly evolved to improve energy performance and comfort by automating the operation of energy-consuming service systems such as HVAC and lighting [40]. According to research [185], employing intelligent technologies and analytics in building control systems can achieve an average of up to 18% energy savings. Several control strategies are used in buildings, from more conventional ones such as rule-based, PI, and PID to more advanced methods like fuzzy logic, Model Predictive Control (MPC), and ML-based control strategies. The latter is increasingly being used with the development of ICT and IoT in buildings that provide easier access to data. For instance, [186] provided a framework for demand-driven cooling controls where 7 – 52% of energy savings were achieved in offices used as case studies compared to scheduled cooling operations. Another study used MPC integrated with ML techniques where 58.5% cooling energy savings were achieved in an office compared to conventional control [187]. While control systems greatly improve building performance, occupant behaviour significantly increases energy consumption [188], sometimes up to 33%, according to [189]. Hence, integrating control systems with a human touch enables more significant potential for improving building energy performance and occupant comfort and well-being.

However, the increased level of automation impedes occupants' adaptive comfort by disabling them from regulating the indoor environment, such as changing the indoor temperature or airflow and adjusting the lights or blinds. This lack of consideration of user preferences and needs regarding the indoor environment has decreased occupant satisfaction with indoor conditions. Studies show that occupant satisfaction increases when they can control and adapt the indoor environment to their needs, enhancing both comfort and a psychological effect from a sense of empowerment [190]. A research study in 5 office buildings in the Netherlands shows that higher controllability led to higher user satisfaction with thermal and visual comfort. Furthermore, the possibility of having control access showed a positive psychological effect impacting overall user satisfaction [191]. Hence, enabling control access for users or integrating user preferences into automated control systems is crucial.

Modern buildings have enabled mutual interaction between buildings and occupants through improved sensing, communications, and controls [192]. HCC in buildings empowers occupants by integrating their behaviour, preferences, and needs into building control systems for HVAC and lighting, thereby enhancing both occupant comfort and building performance [193]. This can be done by either enabling manual access to control or using automated systems that learn user preferences and adjust accordingly [193]. The latter can be implemented using PCMs. The application of AI techniques and PCMs in a review of studies until the year 2020 showed that energy savings of 21.8 – 44.4% can be reached and an increase in comfort levels of 21.6 – 85.7%, according to [194].

The field implementation of HCC is scarce, as mentioned in [195]. Research [193] shows a collection of 58 case studies with field-implemented HCC systems. These studies are categorized into observation and intervention field studies. Observation studies involve data collection of occupant interaction, while intervention studies compare conditions before and after HCC implementation, emphasizing its impact. Several studies have integrated user preferences into control systems using AI-driven comfort predictions. For instance, Lu et al. [196] used readily available data from the ASHRAE RP884 dataset to develop thermal comfort models and integrate them into building control systems by simulation. They used KNN, Random Forest, and SVM to develop the comfort models. Their models achieved a recall of 49.3% with thermal sensation as an output. Another simulation using a deep neural network with Bayesian regularization and Deep Deterministic Policy Gradients (DDPG) tested control policies with TRNSYS software [197]. Murakami [198] balanced occupants' needs and energy consumption by developing an automatic control logic in an office space that resulted in energy savings of 20% without increasing occupant dissatisfaction. Another office study achieved 24% energy savings in HVAC systems when using a user-centric distributed control system compared to conventional HVAC control. The proposed system learns individual occupants' thermal preferences using linear discriminant analysis. Jazizadeh et al. [199] also integrated user feedback into an actual building, using the fuzzy logic model to create comfort profiles integrated into HVAC control. They achieved 39% energy savings in HVAC while improving occupant comfort. Some other integrations using elevated versions of PMV that variate with time were reported to achieve fully satisfied occupants with the indoor conditions while yielding a 10.1% energy savings [200]. PMV combined with occupant feedback using a personalized regression model was also used in [11], [12]. They integrated these models into the control system of an office room, yielding up to 60% energy savings. However, the mentioned impact is mainly focused on energy savings and less on the effects it has on occupants. Hence, it is essential to provide more field studies that compare the before and after HCC implementation, especially on their impact on occupants.

While most studies integrating user preferences into control systems are focused on thermal comfort, some also address IAQ and visual comfort. Advanced ML models such as reinforcement learning were used to develop an HVAC controller in a university lab with 5 – 7 occupants, reducing CO_2 levels by 10% and energy consumption by 4 – 5% without compromising comfort [201]. Research [151] uses deep learning to predict PMV, CO_2 concentrations, and particulate matter (PM_{10} and $PM_{2.5}$) in a school building, achieving sufficient accuracy to be integrated into building control. They used simulations with EnergyPlus software and a controlled electric heat pump with a ventilator. A Q-learning-based control tested in a classroom with 72 occupants for one month resulted in 43% energy savings and a 24% reduction in CO_2 levels, while maintaining thermal comfort compared to air conditioning with fixed temperature of 25℃. HCC has also been applied to lighting control, with a 12-week field study [202] in six offices, showing a 13.4% reduction in energy consumption and improved occupant comfort. Furthermore, in [203] they used ML models to predict the user interaction with blinds to reduce the glare effect. The glare effect was reduced by 86.5 – 96.9% , making people more comfortable. Random forest was concluded to be the best-performing model for visual comfort predictions, followed by KNN and SVM.

The occupant perspective, experience, and insights are rarely investigated in research involving building control systems interacting with occupants. Some survey-based studies explore user preferences to interact with control systems [40]. However, interviews provide deeper insights and uncover underlying indicators that surveys cannot capture. Semi-structured interviews with 170 occupants in 23 Canadian university campus buildings revealed a correlation between perceived comfort and the ability to control the environment [204]. Occupants expressed a solid desire to adjust their surroundings, such as lighting and windows, based on their needs. Another study with 27 occupants in 13 buildings explored the use of building control systems by occupants. Their results indicated that the design of many building control systems holds unrealistic assumptions about occupants' knowledge and ability to interact with them. As HCC is a new concept, there is limited evidence of occupant experiences with HCC. Therefore, interviews with participants interacting with HCC are crucial to understanding their perceptions and interactions with these systems.

4.2 Methods

This chapter provides a framework for integrating user preferences into automated control systems using data-driven PCMs. A field study was conducted at the RCK Ruder Boskovic high school in Zagreb, Croatia, integrating user preferences into the conventional (PID-based) control system in the building. Indoor setpoints were adjusted based on user feedback from 24 participants in a classroom. A survey approach and semi-structured interviews are used to evaluate the impact of integrating user preferences into building control on occupants.

4.2.1 Proposed framework to integrate user preferences into automated building control systems

The proposed framework for integrating multiple user preferences into a building control system, is presented in Figure 4.1 .The struggle to balance preferences among multiple occupants is a known challenge for indoor environments with multiple users. Hence, the aim was to include the preferences of all users by creating a bound or range of setpoints where most users reported being comfortable. The comfort bound was created using simple statistics, identifying the comfort boundaries of each user with standard deviations to include the most frequent setpoints (i.e., air temperature, CO_2 level, or lighting level) for which users felt most comfortable. The standard deviations help to remove the outliers and create the upper and lower boundaries that translate to the setpoints, allowing the controller to adjust within these limits (Figure 4.2). While this might not be a "one-size-fits-all" approach that always satisfies all the occupants, it aims to reduce the number of dissatisfied people by considering their preferences.

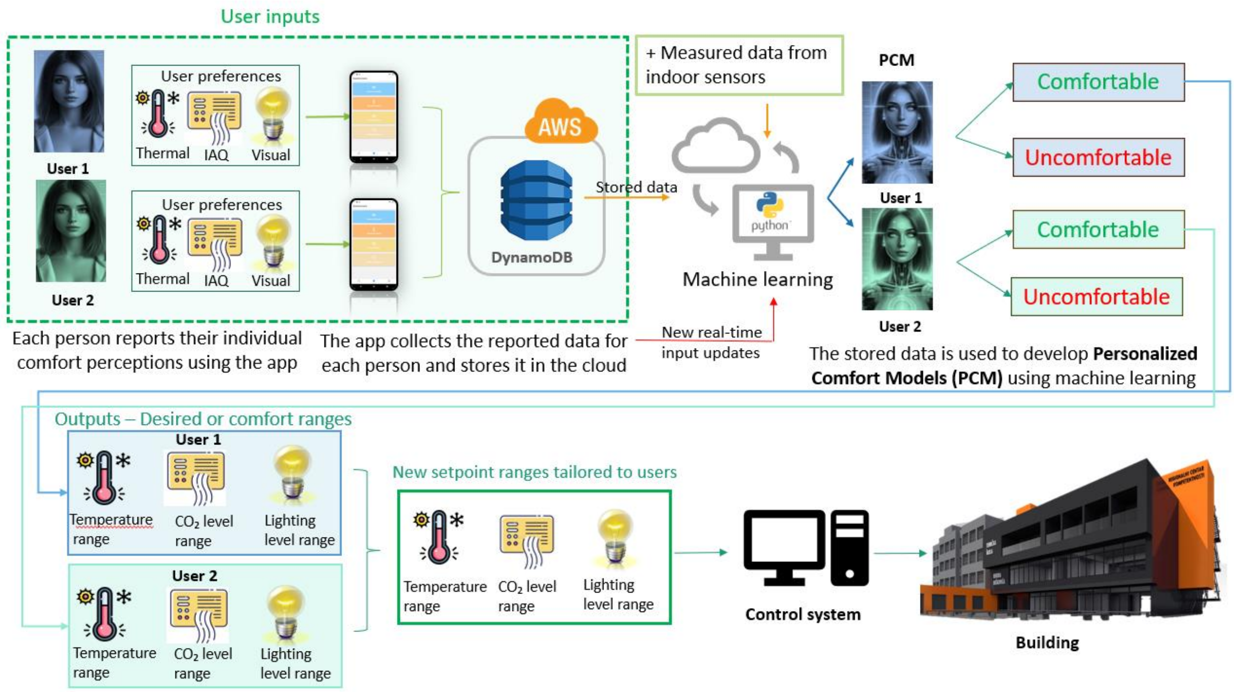

Figure 4.1 Framework for the integration of user preferences into building control systems using personalized comfort models of multiple users

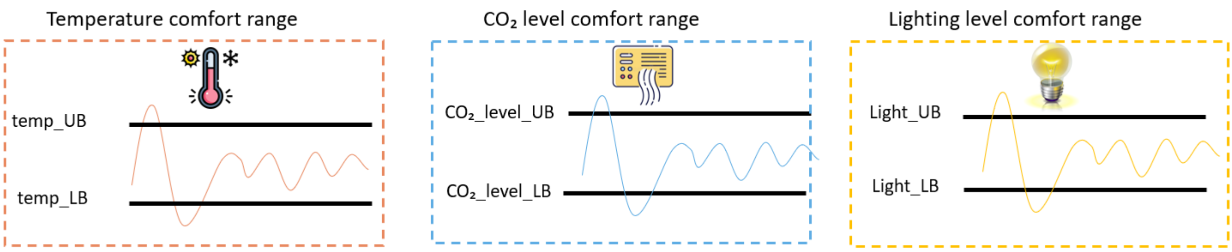

Figure 4.2 The output of the PCMs for multiple users is translated into the upper boundary (UB) and the lower boundary (LB), indicating the desired comfort ranges

Identifying the upper and lower boundaries begins by selecting all the data when users feel comfortable. This involves filtering data to include only instances when the user reported feeling comfortable (e.g., air temperature, CO_2 level, lighting levels). The proposed steps to determine the range of setpoints (using air temperature as an example, but applicable to CO_2 and lighting levels as well) are presented below and shown in Figure 4.3. The procedure is as follows:

1. Check data distribution: use a Kernel Density Estimation (KDE) plot to check the data distribution for all users. Does it resemble a normal distribution? (Figure 4.3, a.).
2. Calculate the mean setpoint (μ_i) for each user i. This shows the central value around which the preferred setpoints are centered. The mean value for all users is x. (Figure 4.3, b.).
3. Calculate the standard deviation (σ_i) for each user i. This shows the variation or dispersion of preferred setpoints from the mean setpoint (Figure 4.3, c.).
4. Assume the normal distribution for which the probability density function (PDF) [205] is calculated as:

$$f(x \mid \mu_i, \sigma_i) = \frac{1}{\sigma_i\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right)$$

5. Determine the confidence interval, which shows the percentage of data around the mean setpoints to be considered. In normal distribution, the confidence intervals can be 68% (corresponding to one standard deviation away from the mean setpoints $[\mu_i - \sigma_i, \mu + \sigma_i\ ]$), 95% or 99%. For this analysis, the 68% and 95% confidence intervals were selected, corresponding to one standard deviation and two standard deviations from the

mean value, respectively. The reason for choosing 68% is that it provides a clear and focused understanding on the central tendency and distribution of user comfort preferences. On the other hand, 95% confidence intervals include a more comprehensive range of temperatures that allow for more flexibility regarding the indoor conditions, and therefore, higher energy saving potential (Figure 4.3, d.).

6. Identify the comfort range between the lower and upper standard deviations, which shows the range of setpoints for which most users are satisfied (e.g., based on the 68% confidence interval, the comfort range in this study was 22.6 – 24.2°C, and for the 95% confidence interval, it was 21.8 – 24.8°C. Depending on user input, ranges may vary slightly and should be adjusted as more feedback becomes available. This range aligns with the thermal zone of 21.5°C-26.6°C yielded from feedback collected in a field study including 258 occupants from six countries measured for 8 to 21 months [206].

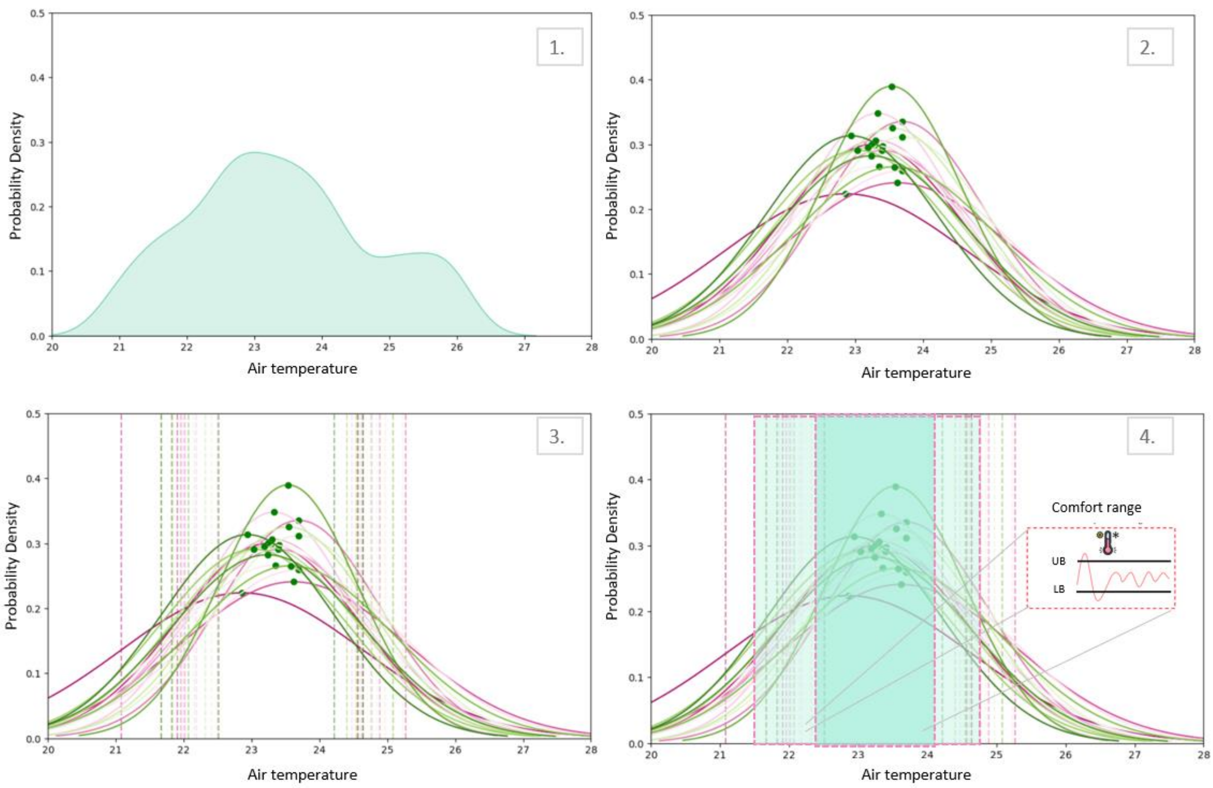

Figure 4.3 The proposed procedure to finding a range of comfort boundary *setpoints for multiple occupants sharing a space. Step 1: plot and inspect the data distribution when users feel comfortable. Step 2: calculate mean values for each user. Step 3: calculate standard deviations for each user. Step 4: determine the comfort range of setpoints assuming normal distribution*

4.2.2 A field study integration of user preferences into a building control system

A field study was conducted at RCK Ruder Boskovic high school in Zagreb, Croatia, to test the impact of integrating user preferences into an actual building. Before the implementation, the experiment used the building as a living laboratory to develop PCMs that predict user comfort (as explained in Chapter III). Over two weeks in the spring, indoor measurements and user feedback data were collected to report on indoor air quality (IAQ), thermal, and visual comfort and to learn about occupant preferences. The desired comfort ranges were then calculated based on the procedure explained in Section 4.2.1. For the last three days, the indoor setpoints were regulated based on learned preferences from PCMs, creating a tailored environment. Finally, user satisfaction was evaluated through individual interviews with each user.

A SCADA (Supervisory Control and Data Acquisition) building control system with a conventional control was used to change the indoor conditions in the classroom, serving as the experimental test bed. The RCK Ruder Boskovic high school is equipped with advanced HVAC systems. More specifically, the classroom chosen for the experiment is one of the most advanced living laboratories, equipped with four different types of ventilation systems (natural ventilation, mixing ventilation, displacement ventilation from the floor, and displacement ventilation from the walls) and three types of heating and cooling systems (fan coils, thermally activated building surfaces, and all-air system). Figure 4.4 shows the school building (a), the SCADA system in the control room (b), and the HVAC systems in the classroom (c). Chapter III thoroughly outlined the experiment design, showing that indoor conditions were measured 3 – 7 times daily. Simultaneously, occupants provided feedback during the same measurement intervals. The experiment design is briefly summarized in Table 4.1.

Figure 4.4 a) RCK Ruder Boskovic school building used as a living laboratory, b) SCADA system in the control room, c) various HVAC systems installed in the classroom that was used as a test bed

Table 4.1. The experiment design shows varying indoor settings across different days, spanning from 18. 04. 2024 to 03. 05. 2024

Days	1	2	3	4	5	6	7	8	9	10
Settings	A*	B	C	C	C	C	B	D	D	D

* A – Free floating building (HVAC systems turned off)
B – Standard setpoints
C – Intervention days (hot, cold, change in ventilation rates, change in lighting levels)
D – Human-centered control (integrating user preferences into the controller)

4.2.3 The impact of integrating user preferences into the control system on occupant comfort and satisfaction

Two approaches were used to evaluate the impact of integrating user preferences on occupant comfort and satisfaction: quantitative and qualitative analysis. Quantitative analysis included collecting survey-based responses reported by users via the app throughout the two-week field experiment. The qualitative study included semi-structured interviews with the participants to get insights into their experience interacting with HCC.

The experiment included standard operating days, intervention days, and days when user preferences were used as new setpoints. To assess changes in user satisfaction before and after integrating their preferences, comparisons were made between standard operating days (e.g., temperature set at 21°C) and free-floating days (when HVAC systems is not used only natural settings) versus HCC days (when user preferences were considered). Intervention days, when occupants were intentionally made uncomfortable, were excluded from this comparison. At the beginning of the experiment, the participants were informed about the concept of HCC and that they should report their comfort feedback sincerely, but they were not informed on which days of the experiment included their preferences.

Short, semi-structured interviews were conducted at the end of the two weeks of the experiment to gather qualitative insights and firsthand experiences of participants interacting with HCC. These are interviews conducted conversationally with one participant at a time to get more insights from them [207]. Of the 24 people that participated in the experiment, 19 of them participated in the interviews. The aim was to understand their experiences, opinions on HCC, beliefs about its potential, difficulties encountered, complaints, suggestions, and willingness to engage with such systems in the future. The list of questions is presented in Table 4.2 but it was expanded during the conversation-like interviews. The interviews were recorded with the participant's permission and later transcribed and translated from Croatian to English by native speakers with expertise in building control systems.

Table 4.2 Semi-structured interview questions to elicit insights from the participants on the interaction with HCC

1. How would you describe your overall experience during the experiment?
2. What are your thoughts on the concept of integrating your preferences into an automated control system?
3. Do you believe that implementing a control system that responds to user feedback has the potential to enhance comfort and satisfaction in indoor environments?
   (Follow up: Even in buildings outside this experiment?)
4. How did you feel interacting with the controller through the app during the experiment? Were there any challenges or difficulties? (For example, did you feel tired of reporting? Annoyed? Was it too frequent? Too many questions?)
5. Did you notice any changes in your satisfaction with indoor conditions during this week?

6. Do you have any suggestions or recommendations on what would make you feel more satisfied with the building control? (For example, would you like to be able to control the indoor environment? If yes, how?)
7. Would you keep reporting feedback if you could control the indoor conditions (not that frequently, but only when you feel like changing the conditions?)

4.3 Results

The aim of the school field experiments is to integrate user preferences into the open-code building control system. The focus is on improving user satisfaction by gathering insights from occupants through mini-surveys and interviews to learn from their experience interacting with HCC.

4.3.4 Findings from the field study on integrating user preferences into the building control system

The change of indoor parameters before and after integrating user preferences into the building control system are shown in Figure 4.5. The changed parameters for this experiment included only indoor air temperature and CO_2 level as shown in Figure 4.5 (a) and (c), respectively. The other changes in parameters are shown just for information on how different days had different conditions during the standard days (one day with free floating (no HVAC) and two days with standard setpoints) and HCC days (with integrated user preferences). The CO_2 comfort boundaries according to user preferences aligned with standard values, so CO_2 level setpoints required minimal adjustments. In contrast, occupant preferred air temperature boundaries exceeded standard values, necessitating continuous changes of the temperature setpoints. Although CO_2 was also controlled, occupants primarily noticed the changes in indoor air temperature. Furthermore, the visual comfort or lighting levels were not controlled during this experiment because the novel systems required for this control were not yet set up during the experiment period, but this will be explored in future research.

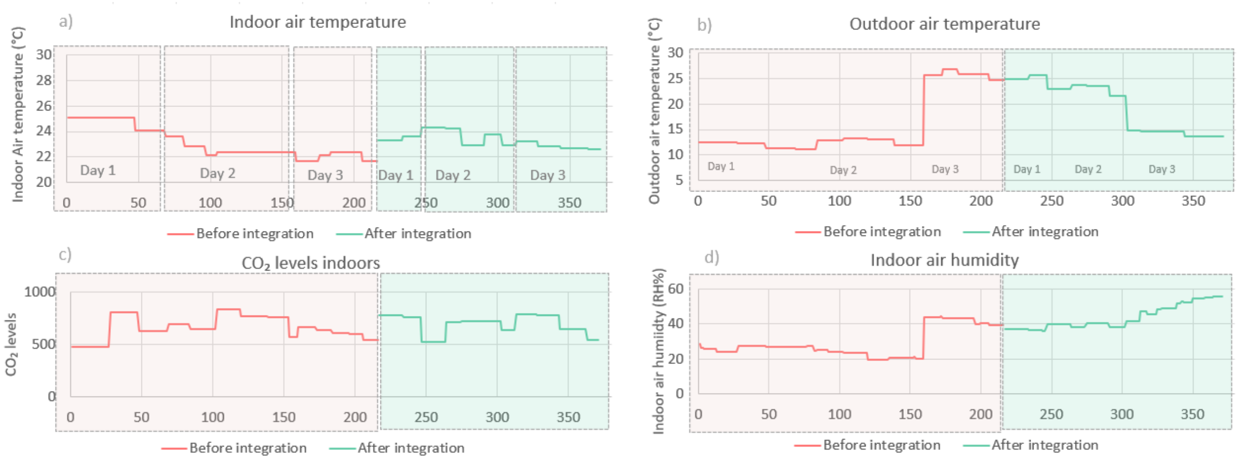

Figure 4.5 Change of indoor parameters before and after the integration of user preferences

The quantitative analysis of self-reported satisfaction during standard operating days and HCC days revealed significant differences in the perceived level of satisfaction among participants. For a meaningful comparison of user satisfaction before and after integrating their preferences, only standard setpoint and free-floating days (April 18, 19, 27) were compared to HCC days (April 30, May 2, 3). This is because the participants were expected to feel uncomfortable during intervention days when indoor conditions were intentionally set outside comfort boundaries. Figure 4.6 illustrates the difference in reported satisfaction. To avoid biased responses, participants were not informed which days the setpoints would be adjusted according to their preferences.

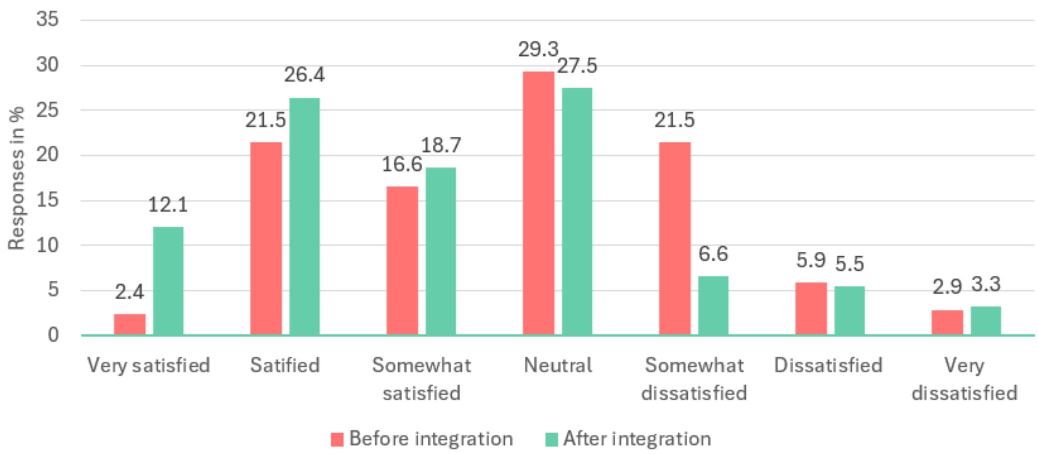

Figure 4.6 Comparison of reported satisfaction levels before (HVAC control using standard setpoints) and after integrating user preferences (setpoints defined based on user feedback)

The results indicate a significant improvement in overall user satisfaction, which increased by 16.7%, while dissatisfaction decreased by 14.9% (Figure 4.7), which is an important finding because only 11% of buildings reach 80% satisfaction [208], some have 42% dissatisfaction [209], and improving satisfaction by 17.6% would improve the overall occupant experience indoors, their comfort, and their well-being. **This finding supports the hypothesis of this PhD research that "The deployment of human-centered predictive control in a building by developing personalized data-driven comfort models significantly increases the occupants' indoor comfort satisfaction".** The semi-structured interviews discussed later further corroborate this conclusion.

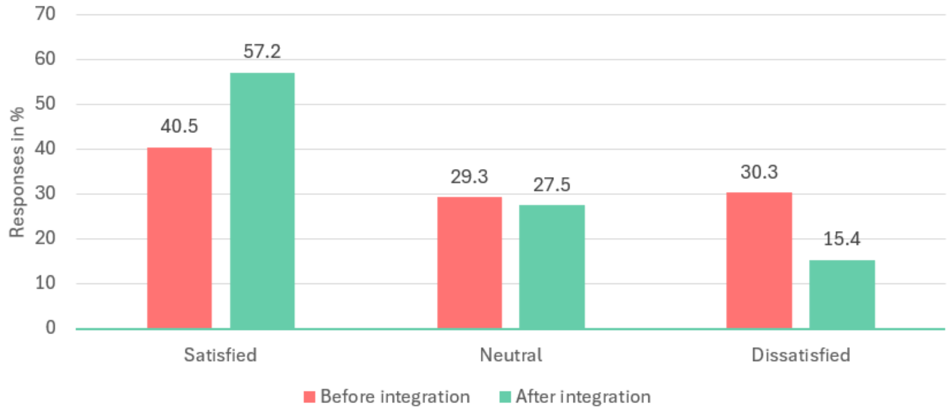

Figure 4.7 Comparison of aggregated user satisfaction levels grouping all responses into either the "satisfied" category (including "very satisfied, " "satisfied, " and "somewhat satisfied") or the "dissatisfied" category (including "very dissatisfied, " "dissatisfied," and "somewhat dissatisfied")

To provide a clearer picture, Figure 4.8 illustrates the number of satisfied participants before and after integrating user preferences. Initially, 10 out of 24 participants were satisfied. After the integration, the number of satisfied participants rose to 13 out of 24. Correspondingly, based on the percentages, it can be illustrated that the number of dissatisfied participants decreased from 7 to 4 out of 24 (Figure 4.8).

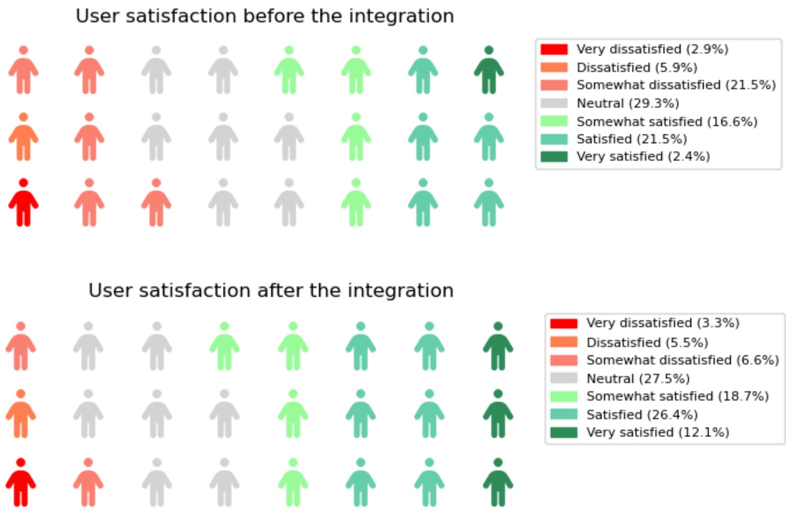

Figure 4.8 A visual representation of the number of participants satisfied and dissatisfied before and after integrating their preferences into the control system

4.3.5 Insights from occupants: findings from semi-structured interviews

The qualitative analysis of the semi-structured interviews elicited exciting insights from the participants' perspectives. These included insights on the participants' beliefs on the usability and potential of HCC, their experience reporting feedback, and their struggles and suggestions.

Belief in the usability of HCC: the belief that human-centered control can achieve the desired level of comfort and satisfaction varies among individuals. While some respondents express a positive sentiment and a stronger belief in the usability and functionality of HCC, others are skeptical but also a little optimistic. Lastly, some do not believe in the use of HCC.

"I find it interesting, and I like that it can listen to our opinions."

Respondent 2

"Do you mean that the "space" follows me?... I like the idea of the system recognizing me."

Respondent 12

Belief in the functionality of HCC: when asked whether they believe such a system has potential and could predict their comfort level and adjust the indoor conditions to their preferences, the responses varied. The majority expressed a positive sentiment (73.7%). In comparison, some were neutral and did not have an opinion (10.5%). Lastly, there were those who recognized the potential but were still skeptical about the benefits of HCC and liked traditional control better (15.8%). Some of their responses are as shown below:

"Yes, it makes sense to me. I believe in it because I think the system could recognize me. I would like it if the environment adapted to me; I like that concept."

Respondent 7

"I find this interesting, honestly. I like the idea of artificial intelligence determining the temperature for us based on our preferences."

Respondent 12

"Well, perhaps not perfectly, but it can make me comfortable."

Respondent 19

"*To be honest, I think that automatic control based on standards and norms, which is generally used, is fine, and it is unnecessary to do anything about it. … I don't think I should control the building since they are designed to accommodate many people."*

Respondent 5

"I don't think it's entirely pointless, but it's easier to open a window or turn on the air conditioning yourself. It's hard to see that in the future because doing some things yourself is easier."

Respondent 3

Evaluation of app and feedback reporting process: participants found it easy to interact with the controller by sharing feedback on perceived comfort conditions. The app was described as easy, simple, straightforward, and intuitive. The time required to complete surveys varied: 15 – 30 seconds (Respondent 12), 20 seconds (Respondent 24), 30 seconds (Respondents 2 and 4), one minute (Respondents 6 and 8), and two minutes (Respondent 19).

"It wasn't tiring; it was short,"

"The questions are simple, understandable, the answers as well, and it was straightforward to choose the answers."

"It's good; the questions and answers are short."

"It was intuitive."

"It's easy to access and get used to; it goes quite quickly after two or three times."

When it comes to frequency, a good share of participants were comfortable reporting once per hour (47.4%). In comparison, others preferred less frequent interaction (31.6%), while some had no opinion on this aspect (21.05%).

"It was frequent, but it also depends on the conditions. If they are changing quickly, then it is not too frequent, but if nothing changes, it doesn't make sense to report the feedback. There weren't too many questions, but sometimes it felt too frequent."

"If I imagined myself at work, I would probably prefer it to be a little less frequent."

"I would limit it to maybe 3 or 4 times daily."

"Once or twice a day."

Difficulties and struggles while reporting feedback: participants reported two main challenges with providing feedback. First, the app should be available in different languages, as it was in English while the participants' first language was Croatian. Second, they found it challenging to determine air humidity sensation, aligning with findings in Chapter III, suggesting that people often struggle to accurately perceive some indoor environment parameters, for instance, air humidity and CO_2 levels.

"It is great, but I would like it to be available in different languages. In the beginning, I had trouble with this English version of the app."

"The only thing that was a bit problematic was the air humidity question,"

"One of the questions I found difficult was reporting how I feel about air quality and how dry the air is. I wasn't sure how to determine that."

Occupant awareness of collective comfort in shared spaces: in shared environments, it is usually challenging to achieve a one-size-fits-all approach. Therefore, the aim is to achieve indoor conditions that satisfy most users. As participants reported, sharing the control autonomy with other participants in the room is not an inconvenience for them.

"If the majority's preferences are considered and then applied, that is fine with me. I think it would be silly if only my preferences were considered."

Respondent 19

"I think finding a temperature that suits 24 people is tough. I don't even know how that should be adjusted. But if the survey indicates that more people feel hot than cold, the system should automatically at least crack open the windows."

Respondent 12

Willingness to use HCC in the future: despite some being somewhat skeptical about using such systems in the future, all 19 respondents expressed readiness to use such systems in the future. However, some prefer a hybrid form of control that, despite the controller taking their preferences into account automatically, allows them to adjust some conditions manually. 36.8% of participants reported that they would like to be able to open the windows manually, while 21% also mentioned wanting to adjust the lighting levels manually.

"It would be good if this new system doesn't meet our preferences; we can just open the window ourselves."

Respondent 9

"I think the best would be when the building was controlled automatically, according to some standards, and then if I felt bad or uncomfortable, I would like to influence the building conditions.

Respondent 14

The impact of social influences on interacting with HCC: recalling the results in Chapter II on the social influence on users to report feedback, the interviews brought forth the distinct impact of social norms. Specifically, people are more likely to interact with a controller if they believe they will positively impact their peers and people around them and that their actions will be of service to someone.

"Of course, I would continue to report feedback if it would benefit me and others, students, and teachers."

Respondent 11

Perceived satisfaction with the indoor conditions: when asked about the perceived level of satisfaction, most respondents reported increased satisfaction during the last three days of the experiment, when the room was controlled with updated setpoints yielded according to user preferences. It is important to note that the participants were not informed on which days the setpoints were changed according to their preferences. Their awareness of their surroundings increased; they could even remember a day with the perfect temperature.

"…especially on one day, though I can't remember exactly which, the temperature was perfect. I don't know if it was Tuesday; I think it was Tuesday. The temperature and airflow were perfect."

Respondent 11

"*These last few days were great."*

Respondent 14

A smaller number of participants, around 15%, perceived all days as more or less the same, including the intervention days when the temperature was set too high or too low the other day, the air was stuffy some days, and the lighting was purposefully bad. These respondents had low variability in their reported data and are part of the "Always satisfied" group of respondents.

"I was neutral most of the time or comfortable. Only rarely did I feel any large discomfort."

Respondent 22

"…well, the conditions were the same, more or less. It was comfortable all the time."

Respondent 10

Practical suggestions and recommendations from the participants: participants made several valuable suggestions for the app. One suggestion was incorporating more nuanced comfort levels (e.g., the ASHRAE comfort scale). However, this approach was intentionally avoided to simplify responses and limit prediction categories to two classes (comfortable and uncomfortable) when developing PCMs. However, this could be implemented by getting nuanced responses from the occupants and then grouping the responses into two categories for ML models. Another suggestion for the app was to predict user responses based on indoor conditions so it could suggest responses instead of asking users to select them. For example, the app could tell the response "wants colder" if the user prefers cooler conditions. This feature could be explored in the future.

"I would prefer more choices regarding comfort or discomfort. If I had only the option of being comfortable or uncomfortable, I would feel in between most of the time."

"The app should be super simple and easy to use. Like short questions, so that the app learns your preferences and even offers you the answers it expects you to say immediately."

Some respondents even came up with ideas on incorporating HCC in future buildings. Their ideas resembled some current state-of-the-art research on personalized comfort and HCC. For instance, two respondents suggested ideas to use localized climate control, which aligns with the so-called Personalized Comfort Systems or spaces [210], [211], which is a well-researched topic currently. Furthermore, some mentioned grouping people with similar interests, which is also being explored by various research groups [4].

"The whole idea is good, but in my opinion, impossible to incorporate. Because many of us have different wishes and preferences regarding the conditions in the room, satisfying everyone is impossible. It would be possible if there was a way of cooling a specific part of the room. But currently, I don't see a possibility of doing this in real life… However, the idea of listening to building users seems good."

Respondent 14

"I think it has potential, but only if the rooms could be divided into zones so that each occupant has its microenvironment. The only way of doing this in practice is in the rooms where the occupants have similar preferences. For example, an office with people generally always feeling hot."

Respondent 22

From all the interviews, a word count analysis was conducted using MAXQDA software [212], demonstrating an overall positive sentiment. The results are in Figure 4.9, showing the most frequent words (more prominent ones used more frequently). The interview transcripts were cleaned, meaning that the stop words were removed, and articles and other words that did not contain any valuable meaning were removed. Furthermore, the questions from the interviews were also removed, and only the answers were included in the text analysis. The results were tested with and without lemmatization (shortening words to their base root form). Since the results did not differ much, Figure 4.9 shows the word cloud without lemmatization.

Figure 4.9 Word cloud visualization of the most frequent word used by respondents during the structured interviews

4.4 Discussion and conclusion

This chapter explores the impact of integrating user preferences into a building control system using PCM. It provides a framework for this integration, addressing multiple occupants in a shared space and various comfort aspects, including IAQ, thermal, and visual comfort.

This was enabled through a field study in a classroom of the RCK Ruder Boskovic high school, involving 24 participants. Over two weeks, this classroom served as a living laboratory to test and observe interactions with HCC. The indoor environment was managed using an open-source automated control system, allowing for real-time adjustments of indoor parameters as needed. The field experiment had distinct phases with specific indoor conditions. One day, the experiment featured free-floating conditions without HVAC. For two days, the experiment maintained standard HVAC settings. During the four-day intervention phase, comfort boundaries were tested by varying indoor air temperatures, ventilation rates, and lighting levels. Lastly, the HCC days highlighted the occupant-centered approach by integrating user preferences into the indoor environment regulation, with setpoints adjusted based on participants' self-reported preferences.

The proposed framework to integrate user preferences into the controller is a simple yet effective approach that considers all user preferences by removing outliers. If necessary, weights can be assigned to different occupants so that their responses impact the comfort ranges more. Based on the two experiments conducted, the one in the faculty lab (presented in Chapter III) and one in the school building, shared spaces such as offices or classrooms reveal that while individual comfort perceptions vary, there is often significant overlap in preferences. This allows us to define approximate comfort ranges or boundaries that satisfy most users, even if not all of them. According to standards such as ISO 7730:2005 [213], around 90% of people indoors need to be satisfied with the indoor conditions for thermal comfort, whereas ASHRAE 55-2004 states the same limit by adding an extra 10% dissatisfaction that might occur due to local discomfort and asymmetries. According to ASHRAE 62.1 [214], an acceptable IAQ level is achieved when 80% or more of the occupants do not express dissatisfaction. This shows that not all users can be satisfied. The aim is to consider occupants' preferences, and by using comfort ranges for all users individually, the indoor environmental settings can be tailored as close to their preferences as possible to improve their comfort and wellbeing.

The findings from this chapter show a 16.7% increase in self-reported user satisfaction after integrating user preferences into the controller, with satisfaction levels including very satisfied, satisfied, and somewhat satisfied. Dissatisfaction with indoor conditions decreased by 14.9% when comparing days with free-floating conditions, natural ventilation, and standard setpoints to those with HCC setpoints. Intervention days were excluded from this comparison as occupants were intentionally made uncomfortable, which was expected to result in lower satisfaction. In context, a survey of 62 360 occupants in 617 office buildings in the US, Australia, Canada and other locations, found that 38% were dissatisfied with the temperature in indoor conditions and 20% dissatisfied with air quality [215]. Another study with 34 000 office occupants in 215 buildings in US, Canada and Finland, reported only 11% of buildings reaching 80% satisfaction [208]. A study in Portugal with 425 elderly care center occupants showed 42% dissatisfaction, rating conditions as "slightly cool" despite standard heating operations [209]. These studies highlight that many buildings fail to meet occupant comfort requirements. Thus, a 16.7% increase in satisfaction would be significant as it is known that enabling user access to control increases their satisfaction [3], [191].

During the field study, 19 out of 24 participants shared their experiences interacting with HCC through semi-structured interviews. Participants expressed varying beliefs about the usability and functionality of HCC systems. Around 73.7% believe that HCC could learn and meet their preferences, 10.5% were neutral, and 15.8% were skeptical, favoring conventional control systems. These findings align with Chapter II, where 60.9% of 1 000 surveyed individuals believed in the functionality of HCC, even without prior interaction with such systems. This suggests that direct interaction with HCC might increase user acceptance and willingness to engage. Moreover, this interaction increases their awareness of the indoor environment, making them more likely to take conscious actions in regulating indoor parameters when they understand the impact of such actions. Another influence was the social factors, as the participants expressed that they would interact more if they contributed positively to their peers and teachers. This finding aligns with the insights from Chapter II, which identified attitude, ease of use, and social influences as the main factors influencing willingness to interact with HCC and share data [216]. All participants, including those initially skeptical about its functionality, expressed a willingness to use HCC in the future if given the opportunity. The skeptical group, however, emphasized the need for hybrid controls operating on standard settings while allowing user interaction in automated control when needed. In a natural environment, it is expected that not everyone will choose to engage with HCC, which is acceptable. The goal of HCC is to enable occupants access to control to adjust the indoor environment through PCMs. At the same time, those who prefer not to interact can be accommodated within the onset conditions.

The field experiment also assessed the practicality of interacting with HCC. Participants indicated that the feedback reporting process was easy, straightforward, and intuitive, taking them between 15 seconds and 2 minutes to complete. Regarding the feedback frequency, the results suggest that 47.4% of the participants were comfortable reporting feedback every hour, 31.6% preferred less frequent interaction, and 21.0% had no opinion. However, these results may be biased as the participants, being school students, expressed pride in participating in the novel research and might have felt the need to provide favorable responses. However, bias is somewhat expected in semi-structured interviews and can come from many sources, such as leading questions or selection bias of the participants [217]. The responses that might be more realistic are those reported in survey responses from Chapter II, stating that from 1 000 individuals only 1.9% were willing to provide feedback every hour, 14.4% every few hours, and 73.3% only when they felt uncomfortable.

During interviews the participants also suggested a few strategies to accommodate collective comfort in shared spaces, and those strategies align with current research on occupant comfort. One of the proposed strategies includes the development of Personalized Comfort Systems (PCS) to create localized microclimates for occupants sharing the same space [210], [218], [219]. The PCS could be using heating chairs [220], leg warmers [221], personalized ventilators [222], [223], etc. Another suggested strategy involves grouping people with similar indoor environment preferences to sit in the same proximity [4]. The interviews also indicated that collective comfort is a common expectation in shared spaces. Consequently, the willingness to share the control autonomy with others is generally high, with participants expressing that it is expected to consider the preferences of the majority.

The challenges and difficulties encountered by the participants include the fact that the participants struggled to respond to some perceived indoor air parameters, such as air humidity. This shows that some parameters are complex for users to sense. Furthermore, some reported language barriers to understanding the app questions, which had to be translated. This suggests that it is important to know the audience and, if possible, to tailor the interface to be more acceptable to users or the target group. Participants also gave some suggestions, such as having the interface to predict their responses initially so that they could directly skip some questions.

The field study uncovered some practical implications that somewhat align with the findings of Chapter II. Some of the takeaways are:

- Framework for integrating user preferences: the recommendation is to implement a simple yet functional framework that integrates user preferences into building control by removing outliers (for instance, someone being comfortable when the temperature is 26.5 ℃, while everyone else was uncomfortable in those conditions). This approach accounts for most user preferences, which are useful in shared spaces, allowing for approximate comfort ranges that satisfy most users.
- Increased user satisfaction: integrating user preferences into the building control system using PCMs led to a 16.7% increase in overall user satisfaction, indicating that HCC can significantly enhance occupant indoor satisfaction.
- Ease of interaction: participants found the feedback reporting process (through the proposed HComfort app) easy and intuitive. It took 15 seconds to 2 minutes to provide

feedback. This suggests that designing user-friendly interfaces can facilitate greater user engagement with HCC systems.

- Feedback frequency preferences: nearly 50% of the participants were comfortable providing feedback every hour, but a significant portion preferred less frequent interaction. This highlights the need to balance the frequency of user interactions to avoid potential user fatigue.
- Multilingual interfaces: to accommodate diverse user groups, it is recommended to ensure that the HCC system interfaces are available in multiple languages, especially in environments with participants who may not be fluent in other languages.
- Hybrid control systems: it is recommended to implement hybrid control systems that run on standard settings but also enable adaptive control and user interaction. This caters to both groups of occupants, those who prefer automated control and those who want some level of manual control.
- Challenges with sensing parameters: it is recommended to provide more intuitive measurement tools or visual aids to address users' difficulties in sensing specific indoor parameters, such as air humidity.

This study has some limitations:

- Due to time constraints, the experiment lasted only ten working days. However, the open-access control system created enough varying indoor conditions to collect sufficient data. As Chapter III indicated, 50-60 data points are the minimum needed to learn occupant preferences. The frequent feedback of occupants under different conditions helped compensate for the short duration of the experiment.

- The experiment was focused only on one classroom, and in the future, it can be expanded to include the whole building.

- The building was newly built, which could also impact the participants' sense of participation as the entire environment was a novelty. Furthermore, the new building also might have impacted their IAQ comfort as one participant mentioned the smell of freshly painted walls, which might be the reason that they expressed discomfort even for normal CO_2 levels.

- The positive predisposition of the participants can also be slightly biased by their sense of pride in participating in such a novel experiment. This was also indicated in some of the responses.

"I was quite pleased to participate in the experiment. I feel honored to have been in the class where I was. It was interesting here. I experienced something new."

Respondent 8

In future studies, expanding this experiment to other buildings, such as residential and commercial buildings, and for more extended periods would be beneficial. Furthermore, increasing users' awareness of energy-efficient and environmentally friendly behaviors in buildings is imperative.

"…well, I would like to see someone doing it [implementing HC] for their own home. That their house generally adapts to the homeowner. That people can enter the building with their phones, and by itself, the system already knows they've entered, and then the system can turn on and adjust itself."

Respondent 12

Chapter V.

5. Impact of human-centered control on grid flexibility

"The secret of change is to focus all of your energy, not on fighting the old, but on building the new."

Socrates

Occupant behaviour significantly impacts the overall energy consumption in buildings and can potentially increase it by one-third [189]. Therefore, changing the energy consumption behaviour towards more sustainable actions can have a positive outcome on energy efficiency and environmental impact. Encouraging occupants to engage in energy-efficient actions, such as grid flexibility or demand response actions, is a promising approach to reducing energy usage in buildings. On the other side, the high penetration of renewable energy sources in the electricity grids of developed countries has created imbalances between electricity supply and demand. For instance, during peak hours, solar energy generation can exceed demand, leading to fluctuations in electricity prices. In this case, it is essential to have consumers who can utilize this excess electricity. Conversely, during peak hours, the grid becomes overloaded, leading to high electricity prices and necessitating reduced energy consumption. This situation presents an opportunity for demand-response actions within the grid. Buildings account for around 40% of the overall energy consumption [224], and around 75% of electricity consumption only in the US [225], contributing to 80% of peak demand, have significant potential to participate in these actions. Advanced control systems in buildings, such as Human-Centric Control (HCC) with Model Predictive Control (MPC), empower occupants to be active participants in the energy management process. This is achieved through information exchange between the grid, buildings, and users. When the electricity grid is overloaded, occupants can be prompted to modify their energy consumption to alleviate the load from the grid. For example, informed occupants could reduce energy use by temporarily lowering temperature setpoints during the heating season or turning off certain appliances. HCC highlights the crucial role that buildings can play in enhancing grid flexibility. However, due to its novelty, the impact of HCC on grid flexibility still requires further exploration.

In this chapter, the definition and quantification of the impact of HCC on grid flexibility are examined using simulations. The powerful TRNSYS software and MATLAB are utilized to run simulations representing the building behaviour of the RCK Ruder Boskovic high school in Zagreb, Croatia. Five scenarios are analyzed to demonstrate the impact of various control strategies on building energy performance and the role of HCC in grid flexibility.

5.1 Literature review

The increasing electric demand with varying dynamics and the rise in renewable energy sources characterized by their intermittent power generation, have heightened the complexity of power grids, making it more challenging to balance supply and demand. [226], [227]. To achieve balance, flexibility is needed [228]. Flexibility can be provided on the grid side, where the grid enables flexibility through measures like flexible electricity generation [228]. It can also be on the demand side, where consumers adjust their energy use to support grid stability [229]. Demand-side management (DSM) [230] enables flexibility through various strategies, including energy efficiency, which involves reducing overall energy consumption compared to a baseline by improving building insulation and using more efficient HVAC systems [231]. Another strategy within DSM is demand-response (DR), which decreases electricity demand when the power grid is overloaded [232]. Additionally, energy flexibility, also known as demand flexibility, encompasses the ability to reduce, shed, shift, modulate, or generate electricity [230]. For instance, energy flexibility includes reducing energy consumption from the grid using renewable energy systems, rescheduling HVAC systems, shifting occupant demand through changed behaviour [233], [230], etc. Load shifting strategy is the most researched one, according to [227], which involves moving energy use to off-peak times. DR programs can be either incentive-based or price-based and aim to shift energy consumption away from peak hours [234]. The price-based program is the most commonly used approach in research, according to Jurjevic et al. [230].

The notion of flexibility is still not yet clearly defined and continues to be debated [235]. This challenge is being tackled by The International Energy Agency (IEA) Energy in Buildings and Communities Program Annex 67 [224], where they aim to define and quantify the energy flexibility in buildings. Definitions of some common terms related to flexibility are shown in Table 5.1. However, the quantification of flexibility is an ongoing quest as it varies based on the approach level (system, building, or community/district), building controls, flexible building operations [236], and model type (physics-based, data-driven, or hybrid).

5.1.1 The role of buildings in grid flexibility

As significant energy users, buildings can effectively facilitate DSM by adjusting their energy consumption and timing of energy usage. This makes them valuable for DR actions, which help reduce grid stress by altering electricity demand when needed [241]. In buildings, HVAC systems, washing machines, dishwashers, and electric vehicles are considered controllable loads to enable reducing and shifting energy peaks, whereas computers and televisions are considered non-controllable loads [230]. Additionally, thermal and electric storage can also provide flexibility. Thermal storage options include passive storage or the thermal mass of the building [242] or active storage solutions like water tanks and, less commonly used, phase change material tanks [228]. In commercial buildings, the HVAC systems alone account for 40 – 50% of the total electricity consumption [243], which makes them a primary target for DR research related to buildings.

Table 5.1. Definitions of common terms used for flexibility solutions

Source	Name	Definition
Energy Agency (IEA) [237]	Grid flexibility	"The ability of a power grid to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales, from ensuring instantaneous stability of the power system to supporting long-term security of supply"
The Electric Power Research Institute (EPRI) [238]	Demand side management (DSM)	"DSM is the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., time pattern and magnitude of a utility's load. Utility programs falling under the umbrella of DSM include load management, new uses, strategic conservation, electrification, customer generation, and adjustments in market share."
Energy Agency (IEA) Annex 67 [239]	Energy flexibility	"The ability for a building to manage its demand and generation according to local climate conditions, user needs, and grid requirements"
Energy Agency (IEA) [240]	Demand response	"Demand response refers to balancing the demand on power grids by encouraging customers to shift electricity demand to times when electricity is more plentiful or other demand is lower, typically through prices or monetary incentives."

Two main control architectures enable grid-building interaction: centralized and decentralized controls [230]. Centralized control is managed from the grid side using a top-down approach for the end users. In contrast, decentralized control operates at the building level, requiring a local controller to adjust building or appliance behavior in response to grid signals. This controller can function at the appliance level, managing smart energy-consuming devices, or as part of a building control system managing the entire building [234]. Depending on the control system used, DR at the building level can be implemented in various ways. The simplest method involves on-off control of appliances or HVAC systems, such as turning heating or cooling on and off at specific times to reduce energy consumption. Rule-based control operates on if-else conditions, managing appliances or HVAC systems to avoid exceeding restrictions when electricity prices are high. For example, if electricity prices are high, the system might reduce the water inlet temperature of heat pumps. Advanced controllers optimize building system operation and energy consumption, balancing costs and comfort by considering various factors such as weather predictions, occupancy, and electricity price forecasts [228]. Research [244] presents a review on the use of rule-based control and MPC systems using HVAC with heat pumps for energy flexibility in buildings.

Different benefits can be achieved depending on the control strategy employed for energy flexibility through HVAC in buildings. For instance, rule-based controllers can reduce energy consumption but may compromise costs or comfort. On the other hand, advanced controllers offer great flexibility for load shifting and cost reduction but may increase the aggregated amount of energy usage. The effectiveness of various control systems in buildings that aim to reduce energy consumption and enable energy flexibility shows total and peak energy consumption reductions ranging from 20 – 30% under different control schemes [230]. In residential buildings, the literature reports peak power reductions ranging from 0.5% to 65%, energy savings up to 60%, operational cost reductions from 0.8% to 48%, and greenhouse gas emissions reductions between 0.4% and 29% [235]. Lee et al. [245] achieved up to 80% energy consumption reduction during peak hours in the cooling season and 64% in the heating season. Carvalho et al. [246] reported energy cost reductions between 17% and 34%.

Model Predictive Control (MPC) is an advanced control strategy that presents a great enabler for demand response (DR) because, during peak hours, it can reduce or shift energy consumption to more favorable times. MPC optimizes an objective function to minimize targets such as energy costs and occupant discomfort, among other targets. It leverages prediction horizons that account for disturbances like weather, occupancy, and dynamic electricity pricing to optimize building operations effectively. Economic MPC, which aims to reduce electricity costs, is the most commonly used approach [244]. For example, research [247] used economic MPC to compare energy consumption and costs under three electricity tariff scenarios: flat rate, day-night tariff, and time-of-use prices. The results showed up to 15% electricity cost savings and 80% load shifting, though overall energy consumption increased by 20% outside peak hours. This demonstrates that energy flexibility, which shifts consumption to more favorable times sometimes increases amount of energy usage, but that energy is used in off-peak times and should not be penalized [241]. In another study, MPC with simple day-night tariffs in an actual office building in Brussels achieved a 30 – 40% cost reduction compared to conventional rule-based control [248]. Similarly, research [249] using MPC with floor heating and a ground source heat pump reported 35% cost savings with dynamic electricity pricing. In [250], MPC is used in a multi-room house in Denmark to adjust the heat consumption depending on dynamic electricity prices, and it achieves up to 37% reduction in electricity costs per week. MPC has also been used for visual comfort by controlling blinds for sufficient daylight and for indoor air quality (IAQ) to ensure proper ventilation [251]. This shows the great potential of MPC for energy efficiency and energy flexibility in buildings. However, these studies focus primarily on energy efficiency and cost savings and less on the impact on occupant comfort, satisfaction, and acceptability of such systems.

Research on incorporating the human dimension in MPC is limited, but some studies show the feasibility of implementing HCC with MPC in buildings, as shown Table 5.2. Experimental studies were conducted in office rooms, open-plan offices [10], [11], [252], academic buildings [13], and a chamber experiment [14]. Additionally, two simulation studies [253] , [254] were not validated in natural environments but included the human dimension. The limited number of field implementations highlights the need for more research in real-life settings, particularly in multi-zone buildings with more occupants, to confirm the feasibility of such control systems.

5.1.2 The role of occupants in grid flexibility actions

The human dimension plays an important role in enabling energy flexibility. Energy consumers can participate in flexibility solutions either actively, by adjusting their energy consumption behavior and timing according to grid price signals, or passively, by agreeing to a control program managed by the grid [255]. Ensuring long-term consumer participation in DR actions is still a significant challenge [256]. Therefore, a participatory approach that engages users in the design and implementation, enhances occupant experience and raises awareness of the benefits of energy flexibility can improve acceptance and user engagement in DR actions [241]. Additionally, prioritizing occupant comfort and understanding the impact on occupants is crucial for successfully deploying and accepting HVAC control strategies. According to [235] there is a gap in integrating occupant impacts into the quantification of energy flexibility. Moreover, the future of developing and implementing demand response greatly depends on incorporating user feedback [257]. Therefore, estimating how the users can impact energy flexibility is essential.

Table 5.2. Studies on the integration of the human dimension in buildings using MPC focusing on user-provided feedback, not occupancy

Reference	**Year**	**Building**	**People**	**Type**	**Human dimension**
[258]	2020	Campus building-one zone		Experiment	PMV, physiological sensing using IoT
[10]	2019	Open-plan office	9	Experiment &Simulation	Thermal preference/feedback
[13]	2017	Academic building	22	Experiment	Thermal preference/feedback
[14]	2016	Chamber	4	Experiment	AMV-actual mean vote
[11]	2013	Office room	1	Experiment	Thermal preference/feedback, occupancy
[252]	2013	Office room	1	Experiment	Thermal preference/feedback, occupancy
[253]	2014			Simulation	
[254]	2015			Simulation	

Integrating occupant preferences and comfort into control strategies involves either using comfort temperature ranges or group-based comfort models like PMV (Predicted Mean Vote), PPD (Predicted Percentage of Dissatisfied), or personalized comfort models (PCMs). In MPC, comfort can be addressed as a constraint that should not be violated or within the objective function by penalizing deviations from a setpoint. In the first approach, the use of comfort temperature ranges varies significantly in the literature. For example, research [259] uses $21 - 24°C$, while research [247] uses $20 - 22°C$ during occupancy hours $(07{:}00 - 22{:}00)$ with no constraints outside these hours. Yoon et al. [260] use $22 - 27°C$ in a dynamic demand response controller that adjusts indoor temperature based on real-time electricity pricing. This controller was also tested in another study [261], calculating the percentage of hours within $25 - 28°C$ for medium and large houses. Other studies, such as those by Yu et al. [243], use a multi-agent framework to control HVAC systems in commercial buildings, setting comfort boundaries based on minimum and maximum comfortable temperatures. However, this approach can include outliers and cause discomfort in multi-occupant settings. Therefore, considering individual comfort ranges and finding a collective comfort range in multi-occupant settings can minimize dissatisfaction.

The second approach is often used with group-based comfort models like PMV or PPD. For instance, in [262], simulations in TRNSYS achieved $10 - 15\%$ cost savings while maintaining comfort by integrating PMV into the MPC objective function. In [263], PMV was considered in a predictive controller for public buildings, estimating energy savings greater than 50%.

The third approach involves integrating personalized occupant preferences using PCMs. Ghahramani et al. [18] optimized energy consumption with a knowledge-based control strategy that considered personal thermal comfort. Kim et al. [264] developed PCMs using neural networks for each occupant. They implemented them into a predictive controller for demand response, achieving a 17.3% cost reduction and a 25% reduction in discomfort without significant changes in energy consumption during peak hours. In a recent study [265], the integration of PCMs in optimization-based controllers was analyzed using the proposed PICO (Personalization-Integrated Co-Optimization) framework. This simulation-based study used EnergyPlus software with August weather data to develop average comfort probability profiles for all occupants, aiming to satisfy most of them. Data were used from a previous study by the same authors [266] collected thermal votes (uncomfortably warm, comfortable, and uncomfortably cold) via a smart thermostat, processed using a Bayesian network. The predictive model aimed to minimize energy costs while penalizing collective discomfort. Various scenarios were tested, including one where occupants accepted 50% less comfort for greater energy flexibility. With a comfort probability reduced to 50%, the acceptable temperature range widened from 21°C to 26.6°C. However, the preferred comfort range based on occupant profiles was 20.63°C to 24.67°C. Results measured energy consumption, costs, and comfort during peak hours and the entire day. The study achieved a peak energy consumption reduction of 18.7% to 24.2% compared to a fixed setpoint controller, with a comfort reduction of 7% to 17.6%. This demonstrates that using PCMs consistently meets various thermal comfort needs, enhancing occupant experience and potentially improving acceptance.

The assumed peak times of grid load vary across studies, but most use fixed schedules, for example, Kim et al. [267] assumed peak times from 13:00 to 17:00, Yoon et al. [260] from 15:30 to 17:30, and research [265] considered peak hours from 14:00 to 15:00 based on the highest electricity price on August 1st when they did their simulation. Lee et al. [245] assumed peak hours from 14:00 to 17:00 in summer and 17:00 to 20:00 in winter, while Carvalho et al. [246] assumed peak hours from 09:00 to 10:30 and 18:00 to 20:30. On a more general principle, late afternoons or early evenings between 16:00 to 21:00 are considered peak hours, although this can vary by region [268], [269], [270]. However, [245] mentions that fixed schedules lack adaptation to natural conditions and vary seasonally, yet they are the more straightforward option.

5.2 Methods

This chapter uses comprehensive simulations to evaluate the impact of HCC on grid flexibility and various control systems on building energy performance, costs, and comfort. The case study building for the simulation is the same high school building, RCK Ruder Boskovic, mentioned in Chapters III and IV. These simulations are built upon a collaborative research effort with PhD candidate Nikola Badun [271],[272] using TRNSYS software and MATLAB programming. Two different control strategies are employed for these simulations. The first is the conventional Proportional-Integral-Derivative (PID) control, and the second is the advanced MPC. These control strategies are tested for different indoor air setpoints, including standard setpoints of $20 - 22°C$, where $20°C$ was used for heating and $22°C$ for cooling. Additionally, setpoints based on user preferences (Human-centric (HC) setpoints) with temperature ranges of $21.8 - 24.8°C$, were extracted as the desired comfort range from the field study in Chapter III.

To explore the impact that various control strategies have on the building energy performance, grid flexibility, costs, and comfort, five scenarios are presented and analyzed:

- **Scenario 1 – Standard PID**: PID control with standard setpoints $(20 - 22°C)$ and dynamic electricity prices. It is important to note that while electricity prices do not influence the PID control function, dynamic pricing impacts the overall energy costs.

- **Scenario 2 – HC-PID**: PID control with adjusted setpoints based on user comfort boundaries ($21.8 - 24.8$°C) and dynamic electricity prices.
- **Scenario 3 – Standard MPC**: MPC with standard setpoints ($20 - 22$°C) and dynamic electricity prices when the space was occupied and ($15 - 30$ °C) when the space was unoccupied.
- **Scenario 4 – HC-MPC**: MPC with adjusted setpoints based on user comfort boundaries ($21.8 - 24.8$°C) and dynamic electricity prices, and ($15 - 30$ °C) when the space was unoccupied.
- **Scenario 5 – DR-HC-MPC** (demand-response HC-MPC): combines user engagement in demand-response (aiming to provide grid flexibility) with MPC control. The assumption is that occupants are willing to reduce energy consumption by adjusting their comfort boundaries by 2°C to less favorable conditions for two hours during peak times. This assumption is based on survey responses from Chapter II. In the survey, nearly 48% of the 1 000 respondents indicated a willingness to participate in grid flexibility actions for only $1 - 2$ hours per day, assuming they would accept two hours with reduced comfort for energy flexibility. Peak hours were considered 17:00-19:00 in January and 18:00-20:00 in August, based on the highest average hourly electricity prices per day for a month (Figure 5.1). Although the actual peak for August was 19:00-21:00, it was adjusted to 18:00-20:00 to include occupied hours for the consumption reduction analysis. The actual dynamic electricity prices of Denmark for 2023 [273] are used as an example to simulate a realistic electricity market with dynamic prices. These prices are applied to the simulated building in Zagreb, Croatia, to illustrate how the system would function under similar conditions.

These scenarios are analyzed for both the heating season, using January as an example, and the cooling season, using August as an example, assuming a consistent occupancy schedule where the building was occupied from 06:00 to 20:00.

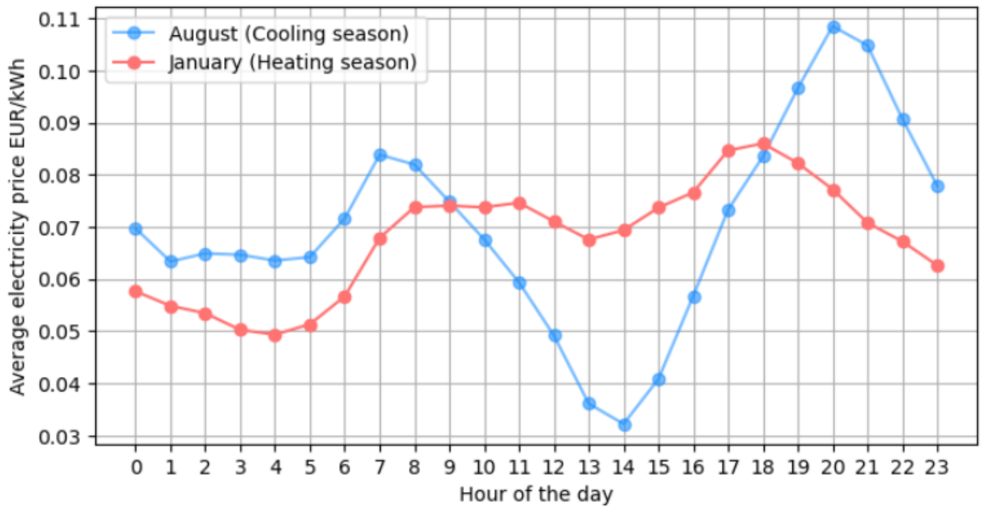

Figure 5.1. Hourly average electricity prices for Denmark during January and August 2023 [273]

PID Control – is a conventional, often-used control strategy due to its simple structure and ease of implementation [274]. It entails three mode algorithms such as proportional (P), which determines the reaction to the current error; integral (I), which determines the response based on the sum of past errors; and derivative (D), which predicts future errors based on the trend of change. It adjusts the control inputs to minimize the difference between the measured parameters (i.e., air temperature) and the desired setpoint (i.e., desired air temperature). According to [274], the control in parallel PID is computed using:

$$u(t) = K_c\left(e(t) + \frac{1}{T_i}\int e(t)dt + T_d\frac{de(t)}{dt}\right)$$

where $K_p = K_c$ is the proportional gain, $e(t)$ is the error at time *t* (e.g., the difference between the setpoint and the measured temperature), $k_i = \frac{K_c}{T_i}$ and T_i is the integral time, $k_d = K_c T_d$ and T_d is the derivative time.

MPC is an advanced control strategy that uses a model of a system (i.e., building) to predict future states (i.e., air temperature) and optimize control inputs over a prediction horizon [275]. It continuously solves optimization problems that aim to minimize a cost function. In this case, the cost function is designed to minimize both electricity costs and thermal discomfort violations. The objective function used for the MPC is as follows:

$$EC_{\text{tot}} = \sum_{k=1}^{PH} [EC(k) + Penalty(k)] \tag{1}$$

Where the $EC(k) = E_{\text{total}}(k) \cdot El_{\text{price}}(k)$ presents the electricity cost, calculated based on the total energy consumption by the heat pump and the electricity price. The $Penalty(k)$ indicates the discomfort violation, which occurs when the actual zone temperature $T_{\text{z}}(k)$ exceeds the comfort boundaries, either above the upper boundary or below the lower boundary. The zone temperature $T_{\text{z}}(k)$ is simulated using an ARX grey-box model, which captures the behavior of the simulated building. The details of the building model and MPC formulation can be found in [272]. This model expresses the zone air temperature $T_{\text{z}}(k)$ as a function of the ambient temperature ($T_{amb}(k)$), the heat of the water ($Q_w(k)$), internal heat gains ($Q_{int}(k)$), and solar gains ($Q_{sol}(k)$):

$$T_{\text{z}}(k) = f(T_{\text{amb}}(k), Q_{\text{w}}(k), Q_{\text{int}}(k), Q_{\text{sol}}(k)) \tag{2}$$

5.2.3 The performance evaluation and grid flexibility quantification

To evaluate the performance of different control strategies and the impact of HCC on grid flexibility, various Key Performance Indicators (KPIs) were calculated. The standard PID is considered a baseline or reference scenario, and the other scenarios are compared to it. The data analysis from simulations followed this procedure:

1. Data selection: data were selected for peak hours when the grid is generally more overloaded. The peak hours were chosen based on the hourly average electricity prices for the chosen electric pricing dataset. Peak hours were considered 17:00 to 19:00 in January and 18:00 to 20:00 in August. Only afternoon peak hours were considered for simplification and complying with the general knowledge that, on average, late afternoons or early evenings between 16:00 to 21:00 are usually considered peak hours [268], [269], [270]. Furthermore, the data for the entire day was also analyzed to achieve a broader overview of how the scenarios impact not only peak hours but the entire day; this is shown in Annex F.

2. Energy consumption calculation: The total energy consumption of the heat pumps (E_{total}, kWh) was calculated for these peak hours and entire days over one month

during the heating and cooling seasons. Additionally, the total energy consumption for both seasons combined was also calculated. The difference in energy consumption (energy savings ($\Delta E, kWh$)) between the reference scenario (standard PID) and other scenarios was calculated. Lastly, the difference in energy consumption in percentage ($\Delta E(\%)$) is also shown, highlighting the variations in energy consumption.

$$E_{total} = \sum_{i=1}^{n} E_i \tag{3}$$

$$\Delta E = E_{ref} - E_{scenario(i)} \tag{4}$$

$$\Delta E(\%) = \frac{E_{ref} - E_{scenario(i)}}{E_{ref}} \cdot 100\% \tag{5}$$

3. Energy cost calculation: energy costs for the heat pumps were also calculated, including total energy costs (EC_{total}, €), savings in energy costs (ΔEC, €), and savings as a percentage (ΔEC, %).

$$EC_{total} = \sum_{i=1}^{n} EC_i \tag{6}$$

$$\Delta EC = EC_{ref} - EC_{scenario(i)} \tag{7}$$

$$\Delta EC(\%) = \frac{EC_{ref} - EC_{scenario(i)}}{EC_{ref}} \cdot 100\% \tag{8}$$

4. Load shifting ability calculation: the load shifting ability was assessed using the KPI proposed by IEA EBC Annex 67 [276]. This equation measures how effectively a system shifts energy usage to optimize consumption. A higher value indicates better performance, meaning more energy was shifted from peak to off-peak times. The numerator captures the maximum positive differences between reference energy

consumption ($E_{\text{ref},i}$) and the energy consumption for the flexibility scenario ($E_{\text{flex},i,}$). The zero ensures positive energy savings are counted to measure load-shifting effectiveness accurately.

$$Load\ shifting\ ability = \frac{\sum_{i=1}^{n} max(E_{\text{ref},i} - E_{\text{flex},i,}, 0)}{\sum_{i=1}^{n} E_{\text{ref},i}} \quad (9)$$

5. Comfort impact calculation: the impact on comfort is calculated using the thermal discomfort over a given period of time, as described in the BOPTEST documentation [277]. This method measures the integral of temperature deviation compared to the comfort boundaries over a specified time period. $D(t_0, t_f)$ is the total discomfort between start (t_o) and end (t_f) time, z is the index of the zone for N zones, $s_z(t)$ is the deviation outside the comfort boundaries at the time t. In these scenarios, uncomfortable conditions are defined as indoor air temperatures falling outside the comfort boundaries of $21.8 - 24.8$°C, as determined during the field experiment in Chapter III.

$$D(t_0, t_f) = \frac{\sum_{z}^{N} \int_{t_0}^{t_f} \|s_z(t)\| dt}{N} \quad (10)$$

5.3 Results

The results from the simulations show the impact of HCC on grid flexibility and various control systems on building energy performance, costs, and comfort. Five scenarios using different settings for various control strategies for the same building are presented.

5.3.4 Findings from the building performance simulations

Integrating user preferences into the building control changes the building behaviour compared to standard setpoints. For instance, when the building is controlled based on the thermal comfort boundaries expressed by users ($21.8 - 24.8$ °C), it significantly changes compared to the conventionally used $20 - 22$°C. Figure 5.2 shows how the indoor air temperature and energy consumption vary depending on the control strategy used and the temperature range inserted as an input into the controller during winter. The indoor air temperature was controlled only when the building was occupied. As expected, when using HC-PID or HC-MPC, the air temperatures are higher in winter as occupants prefer warmer temperatures. In contrast, in summer, temperatures are maintained near the upper boundary. Consequently, the variation in indoor air temperature incurs varying energy consumption of the HVAC system (Figure 5.2). The graph shows that the energy consumption using standard-temperature PID and MPC is lower in winter than HC-PID and HC-MPC because the standard temperature was lower, needing less heating than the occupants' desired temperature range, which is higher and requires more energy. Engaging users in demand-response actions (DR-HC-MPC) leads to lower energy consumption during peak hours because users accept lower temperature ranges for 2℃ which requires less energy from the heat pumps. These findings are numerically supported in 5.3.5 for a more precise description.

For the summer season (August), when cooling is needed, Figure 5.3 shows the energy consumption for different scenarios. The findings show that standard PID and standard MPC have the highest energy consumption during summer because the standard setpoints are lower, requiring more energy for cooling. HC-PID and HC-MPC consume less energy than conventional PID since occupants prefer higher temperatures, needing less cooling, and using less energy. Yet, a limitation of this is that the comfort boundaries ($21.8 - 24.8$ ℃) were decided during a transition period (spring), and these can be lower or higher during summer. For some days, standard MPC and HC-MPC consume less energy during the day than PID because the energy consumption was shifted at night.

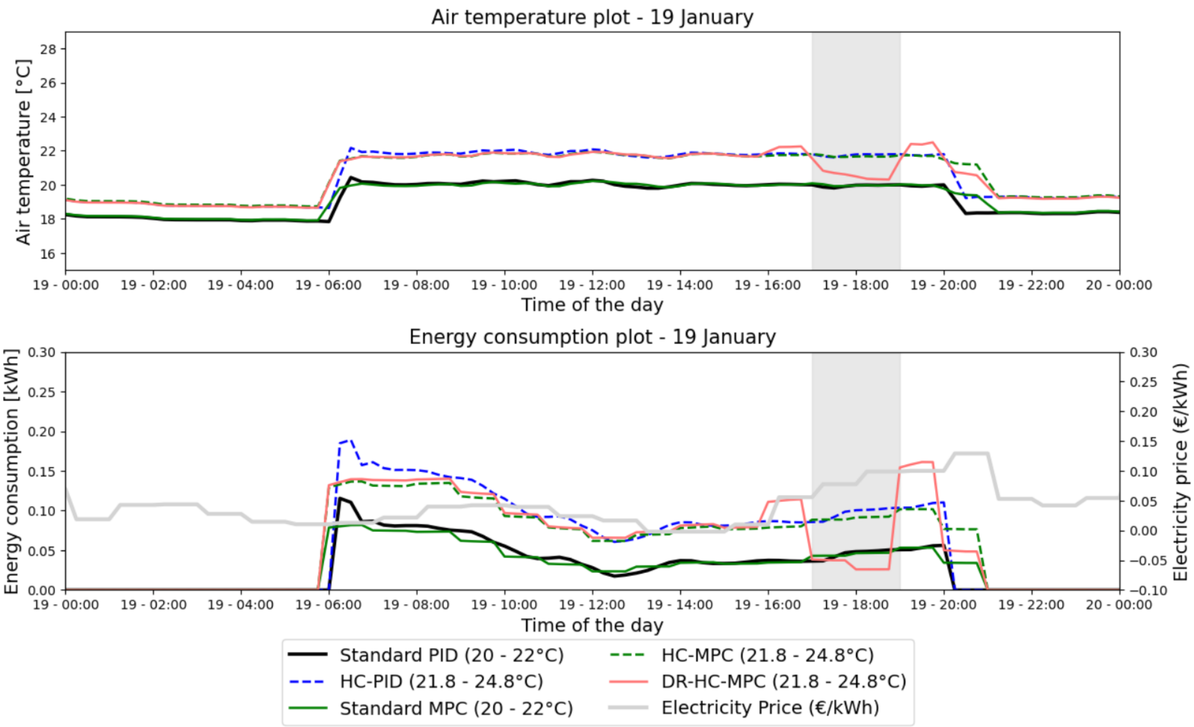

Figure 5.2 Air temperatures (upper) and energy consumptions (lower) when using different control strategies and different setpoint ranges of temperatures during winter (heating season) for one day taken as a representative day.

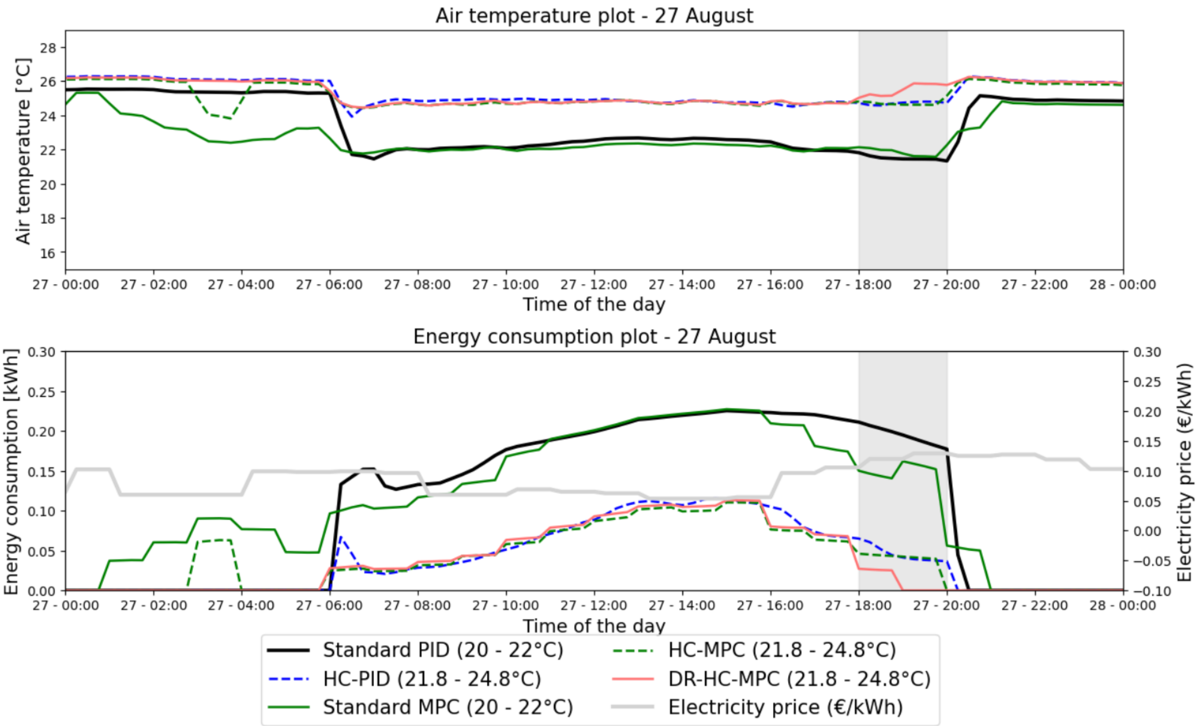

Figure 5.3 Air temperatures (upper) and energy consumptions (lower) when using different control strategies and different setpoint ranges of temperatures during summer (cooling season)for one day taken as a representative day

5.3.5 Evaluation of the impact of HCC on grid flexibility

This chapter aims to define the impact that HCC has on grid flexibility. For simplicity, this analysis focuses on KPIs during peak hours. Comparisons for the hours during occupied times from 06:00 – 20:00 are also included for the reader but are shown in Annex F for brevity. Figure 5.4 shows how different scenarios perform for energy savings, cost savings, load shifting, and comfort. The presented data includes the winter season (heating period – January) and the summer season (cooling period – August). The KPIs are calculated separately for both seasons, and the combined or cumulative results are shown later in Figure 5.5 within this section. The key findings presented in Figure 5.4, for separate summer and winter seasons, show that:

- Energy savings: During heating season for peak hours, engaging users in demand-response actions (DR-HC-MPC scenario) achieves only 3.9% energy savings compared to the baseline scenario with standard PID. This minimal increase is due to the high preferred temperature ranges of occupants. Although occupants accept less comfort for energy flexibility, the high initial temperatures ($21.8 - 24.8$°C) mean that reducing the temperature by 2°C still requires more energy than using the standard $20 - 22$°C range. Standard MPC, with standard setpoints, achieved 7.6% energy savings for winter compared to standard PID, whereas integrating preferred temperature ranges of occupants to MPC, the energy consumption increased by 95% during peak hours. Again, this results from the high initial desired temperatures for the heating season. Furthermore, the highest increase in energy consumption is caused by integrating user preferences into PID control. The increase in energy consumption goes up to 121.8%, as it doesn't try to optimize the energy consumption. This demonstrates if occupants prefer higher temperatures and PID is used for control, high energy consumption is expected. However, integrating user-desired temperatures higher than standard setpoints during the summer or cooling season significantly increases the energy savings from 78.6 – 87.0% for DR-HC-MPC, HC-MPC, and HC-PID, respectively. This is because, with higher accepted indoor temperatures, less energy will be used for cooling (Figure 5.4 (a)).
- Energy cost savings: During winter peak hours, the DR-HC-MPC scenario achieved 4.6% cost savings compared to the baseline scenario with standard PID. Standard MPC achieved 7.9% cost savings compared to the baseline. While standard MPC achieved higher savings, DR-HC-MPC considered occupant preferences, aligning with HCC

primary goal to put occupants first. However, integrating user preferences into PID and using MPC with standard temperatures increased electricity costs: HC-PID costs were 237.4% higher, and HC-MPC costs were 95.2% higher than the baseline due to the extra heating needed in winter. During peak hours in summer, all scenarios achieved cost savings from 20.9% for standard MPC up to 97.9% for DR-HC-MPC, showing the great potential of HCC during summer. Standard MPC (20.9%) performed lower than HC-PID (83.4%) because the latter had higher temperature setpoints, needing less cooling and consequently lower costs. (Figure 5.4 (b)). Detailed costs and energy savings are shown in Annex F.

- Cost variations depend on electricity pricing. Although PID control is price-agnostic and does not consider electricity prices, electricity costs are still affected by the pricing model used. The baseline scenario with standard PID was tested under fixed and dynamic electricity prices, and cost savings for all scenarios were analyzed. For instance, dynamic prices increased HC-PID costs by 237.4%, as mentioned above, whereas fixed prices raised them by 121.8% compared to baseline. The pricing approach also slightly affected other scenarios, with detailed results available in Annex H.
- Load shifting: During winter peak hours, DR-HC-MPC achieves the highest load shifting ability at 27.0%, indicating significant flexibility in shifting energy consumption to off-peak periods. Standard MPC shows an 11.6% load-shifting ability, while HC-MPC, which integrates user preferences, fails to shift any load during winter due to the high energy needed to maintain preferred high temperatures. During summer peak hours, DR-HC-MPC shows the highest load-shifting ability at 88.5%, followed by HC-MPC (85.1%). This is because the DR scenario expanded the comfort range by 2°C, raising the upper limit from 24.8°C to 26.8°C, which allows for greater flexibility (Figure 5.4 (c)).

- Comfort: Integrating user preferences significantly improves comfort in both PID and MPC. During winter peak hours, HC-PID achieves low discomfort values of 2.9 Kh compared to 95.3 Kh with standard PID. HC-MPC achieves 5.1 Kh, which is also significantly better than the baseline. This measure is degree-hours, indicating fewer hours and temperature points outside the comfort boundaries. However, engaging users in grid flexibility or DR during winter peak hours results in higher discomfort at 51.9

Kh, although lower than the standard PID baseline but higher than HC-MPC (5.1 Kh). This indicates that while demand response actions can reduce overall discomfort compared to traditional PID, there is a considerable increase in discomfort compared to advanced control strategies explicitly prioritizing user comfort, like HC-MPC. In summer, standard PID discomfort is low at 4.4 Kh, with HC-PID and HC-MPC achieving even lower values at 0.1 Kh and 0.7 Kh, respectively. The controllers keep the air temperature within the occupant-desired comfort range. Conversely, discomfort in DR-HC-MPC rises to 9.7 Kh, indicating a slight increase compared to the baseline (4.4 Kh) and HC-MPC (0.7 Kh). This trade-off, or “collateral damage,” is necessary to achieve significant cost savings: 97.9% compared to the baseline and 8.4% higher than HC-MPC with 89.5% savings. This highlights the balance between achieving energy cost savings and maintaining occupant comfort when engaging in DR actions. (Figure 5.4 (d)).

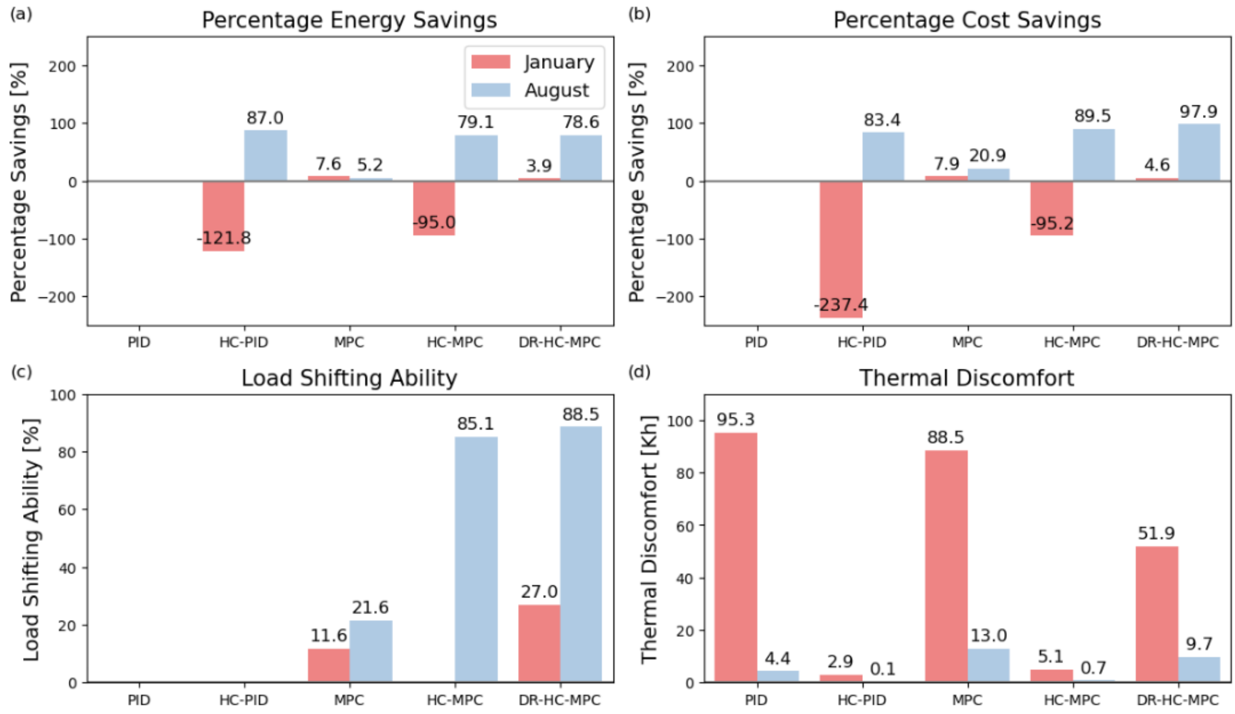

Figure 5.4. Key Performance Indicators (KPIs) during peak hours for energy consumption savings (a), cost savings (b), energy flexibility (c), and comfort (d) are presented separately for the winter season (heating periods, in red) and summer season (cooling periods, in blue)

To illustrate the overall impact of integrating user preferences and engaging occupants in grid flexibility actions in general with data from two representative months, a cumulative approach was used by combining the data from January (heating season) and August (cooling season). The analysis focused on peak hours for both months, revealing the following results:

- Energy consumption: engaging users in DR actions during peak hours in both seasons can result in up to 44.6% energy savings compared to the standard PID control. This is achieved by combining an advanced controller (MPC), a wider comfort range agreed upon by occupants, and considering electricity pricing. This demonstrates the significant potential of demand response actions to reduce energy consumption by targeting peak hours. Without DR, the MPC that integrates user preferences (HC-MPC) does not yield overall energy savings when aggregating data for both cooling and heating seasons. Although there are energy savings in summer, the higher energy consumption in winter due to preferred high temperatures cancels out these benefits. (Figure 5.5 (a)).
- Energy costs: DR actions during both seasons result in a 59.4% reduction in energy costs compared to the PID baseline. In contrast, HC-MPC achieves 13.3% savings, and standard MPC achieves 15.5%. However, integrating user preferences into PID control increases energy costs by 49% compared to standard temperature PID. This demonstrates that the highest savings are achieved with DR actions, even when integrating user preferences, showing that occupants can be prioritized without compromising costs by leveraging advanced controllers like MPC, dynamic electricity prices, and short curtailment actions (Figure 5.5 (b)).
- Grid flexibility: engaging users in DR actions improves the load-shifting ability of the building during peak hours by 60.6% as it uses wider temperature ranges, allowing for more flexibility. In comparison, MPC with user preferences (HC-MPC) achieves a 46.4% improvement for both seasons, and standard MPC is 17.1%. (Figure 5.5 (c)).
- Comfort: integrating user preferences significantly improves comfort conditions in both PID and MPC. HC-PID achieves the lowest discomfort violation at 3.0 Kh, followed by HC-MPC at 5.8 Kh, compared to the standard PID baseline of 99.6 Kh. This indicates fewer hours and temperature points outside the comfort boundaries when integrating user preferences. However, engaging users in DR actions increases discomfort to 61.6 Kh. While this is lower than the standard PID discomfort of 99.6 Kh, it is higher than HC-MPC (5.8 Kh). This shows that although DR-HC-MPC improves comfort by integrating user preferences, comfort is compromised for 2 hours during peak periods, although agreed upon by occupants. This is the trade-off for DR

actions to achieve significant cost savings of 59.5% when aggregating heating and cooling season data. (Figure 5.5 (d)).

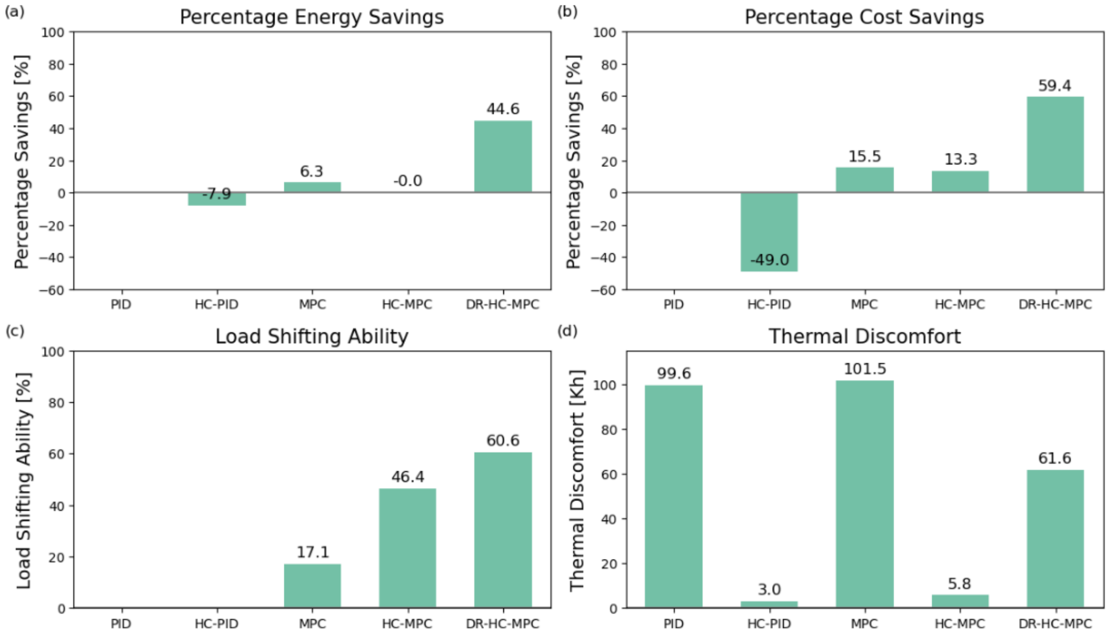

Figure 5.5 Key Performance Indicators (KPIs) during peak hours for both winter (heating periods) and summer (cooling periods) seasons, for energy consumption savings (a), cost savings (b), energy flexibility (c), and comfort (d)

5.4 Discussion and conclusions

In this chapter, the definition and quantification of the impact of HCC on grid flexibility are examined using comprehensive simulations. The simulations are conducted using TRNSYS and MATLAB, two widely recognized tools in the field, to run simulations representing the building behaviour of the RCK Ruder Boskovic high school in Zagreb, Croatia. Five scenarios are analyzed to demonstrate the impact of various control strategies on building energy performance and the role of HCC in grid flexibility. The key findings are:

- Significant peak energy consumption reductions during heating and cooling seasons can be achieved using occupant-based comfort ranges while engaging users in grid flexibility actions. By allowing indoor air temperatures to adjust to less favorable conditions during peak hours, energy savings of up to 44.6% can be achieved with the DR-HC-MPC scenario compared to the reference scenario using PID control with standard temperatures. This result is within the reported value where energy savings reached up to 60% [235]. Research [230] states that peak energy reductions range from 20 – 30% under different control schemes and more than 50% in [263]. Moreover, the results also show that winter savings reach 3.9%, while summer savings can be as high as 78.6% during peak hours. Compared to other studies considering occupant comfort with PCMs [265], which achieved an 18.7 – 24.2% peak energy consumption reduction during the cooling season in August by assuming a 50% reduction in comfort, the results of this study are significantly higher. Despite using a similar comfort temperature range (21°C to 26.6°C in their study and 21.8°C to 24.8°C in this study), the additional ±2°C deviation during peak hours for DR activity in this chapter resulted in much more significant energy savings. Yet, Lee et al. [245] achieved up to 80% energy consumption reduction during peak hours in the cooling season and 64% in the heating season. However, they used standard temperatures, and in this study, the summer season exceeds these mentioned savings. This demonstrates the substantial potential of the DR-HC-MPC to reduce energy consumption by engaging occupants as active participants in DR actions for only 2 hours (as assumed in this research) if they engage for longer or if the agreed upon comfort boundary exceedance changes (other than ±2°C), then the savings will also significantly change. Hence, engaging participants in a participatory manner is important to make DR actions as acceptable to them as possible, including various motivation factors to increase flexibility, energy savings, and other benefits.

- The DR-HC-MPC control strategy enables significant load shifting, averaging 60.6% for both heating and cooling seasons. During the heating season, it achieves a load shift of 27.0%, while in the cooling season, it reaches 88.5%. The heating season performed lower as it deals with higher temperature setpoints per occupants' preferences, increasing the need for more energy. Whereas the summer results align with reported findings of 80% load shifting in [247].This highlights its potential to move energy consumption from peak to off-peak hours, reducing grid overload and taking advantage of lower electricity prices.
- The DR-HC-MPC control strategy enables an average electricity cost saving of 59.4%. This goes in line with other cost savings reported in the literature, such as 0.8% to 48% reported by [235], 17 – 34% reported by [246]. In winter, savings can be achieved by up to 4.6%, while in summer, savings can reach up to 97.9%. The higher overall savings occur during summer as the comfort ranges for the occupants are higher, leading to less energy usage for cooling and resulting in higher savings. The other studies usually use

standard setpoints. This demonstrates that demand-response actions combined with user-preference-based setpoints are particularly beneficial financially. However, these outcomes are specific to the selected comfort boundary of 21.8 – 24.8℃ and may vary with different comfort boundaries.

- The DR-HC-MPC strategy has a relatively high discomfort rate, reaching up to 61.6 Kh which is still lower compared to the standard PID baseline with 99.6 Kh, but higher than the HC-MPC (5.8 Kh) which primarily focuses on occupant comfort. This increase in discomfort is the trade-off for achieving 59.4% cost reduction and 44.6% energy savings during peak hours, on average, for both cooling and heating season. Most discomfort occurs during winter, with 51.9 Kh, and summer, with 9.7 Kh. These findings indicate that engaging occupants in grid flexibility actions can decrease their comfort. In this study, discomfort increased from 5.8 Kh to 61.6 Kh when using DR-HC-MPC instead of HC-MPC, though it remained lower than the 99.6 Kh of the standard PID baseline. This indicates that advanced controllers like MPC with user integration and engagement in flexibility actions can still improve comfort, albeit less so than using advanced controllers with user preferences integration alone without DR actions.
- Integrating user preferences into conventional control strategies like PID significantly improves overall comfort for both seasons, reducing discomfort to as low as 3.0 Kh. However, this improvement results in a 7.9% increase in energy consumption and a 49.0% increase in costs compared to the standard PID baseline. This shows that when prioritizing occupants in buildings that use PID, higher energy consumption and higher costs are expected, especially during the heating season, considering that people prefer higher temperature ranges than standard ranges.
- Using standard setpoint temperatures of $20 - 22$ ℃, in both MPC and PID, control strategies cause high thermal discomfort with values up to 99.6 and 101.5 Kh, respectively. The standard MPC reduced electricity costs by 15.5% compared to the standard PID for aggregated data during peak hours. This goes in line with other values reported in studies like 15% electricity cost savings in [247] and 17% to 34% in [246]. Additionally, it enables 17.1% of the consumed energy to be shifted to off-peak periods. This indicates that while standard setpoints are commonly used, advanced control strategies like MPC can reduce energy costs, though they may not prioritize overall occupant comfort.

5.4.6 Practical implications and recommendations

The findings from this chapter are valuable for designers and developers of advanced control systems in buildings, as well as practitioners and other stakeholders. For convenience, some key takeaways, practical implications, and recommendations are presented below:

- Significant energy savings: implementing occupant-based comfort ranges and engaging users in grid flexibility actions can substantially reduce electricity consumption. For example, the DR-HC-MPC control strategy can achieve up to 44.6% savings in electricity usage, demonstrating a promising approach to balancing energy efficiency with occupant preferences.
- Increased load shifting: the DR-HC-MPC control strategy shows significant potential for load shifting, with an average ability of 60.6% for both heating and cooling seasons. This ability to shift energy consumption from on-peak to off-peak hours can help reduce grid overload and leverage lower electricity prices.
- Cost savings: integrating demand-response actions with user-preference-based setpoints in the DR-HC-MPC control strategy results in an average electricity cost saving of 59.4%. Seasonal variations are notable, with up to 4.6% cost savings in winter and 97.9% in summer. This suggests that the potential can also significantly change depending on climate zones. This financial benefit emphasizes optimizing control strategies based on user preferences and grid conditions.
- Trade-offs in comfort: while the DR-HC-MPC strategy offers significant energy and cost savings, it comes with a lower discomfort rate ($61.6\ Kh$) compared to the standard PID baseline ($99.6\ Kh$), but higher discomfort compared to HC-MPC ($5.8\ Kh$). This indicates that advanced controllers like MPC with user integration and engagement in flexibility actions can still improve comfort, albeit less than using advanced controllers with user preferences integration alone without DR actions. This suggests balancing energy reduction and grid flexibility goals with occupant comfort, possibly by adjusting engagement times or temperature changes to minimize discomfort.
- DR-HC-MPC merges all vital points, including advanced controllers like MPC, occupant preference integration, and grid flexibility interaction, while still yielding cost savings, load shifting, and improved comfort compared to the PID baseline.

- User preferences in advanced control: incorporating user preferences into advanced control strategies like MPC significantly improves occupant comfort, reducing overall discomfort to $5.8\ Kh$. It achieves 13.3% cost savings compared to standard PID, but it has a lower load-shifting ability compared to the scenario when occupants are engaged in DR actions.
- Improved comfort with conventional strategies: integrating user preferences into conventional PID control also improves overall comfort, reducing discomfort to $3.0\ Kh$. However, this comes with increased energy consumption (7.9%) and costs (49.0%) compared to the standard PID baseline. The most significant increases occur in winter, suggesting that prioritizing occupant comfort in PID-controlled buildings may lead to higher energy usage and costs, especially during heating seasons. This means that MPC is the better option to integrate user preferences for HCC.
- Challenges with standard setpoints: using standard setpoint temperatures ($20 - 22$°C) in MPC or PID, control strategies result in high thermal discomfort (up to 99.6 and $101.5\ Kh$, respectively). Although standard MPC reduces energy costs by 15.5% and enables a 17.1% load-shifting ability, it does not prioritize occupants as the desired comfort boundaries differ from the standard. This indicates a need for more advanced strategies to balance cost savings with comfort.

For future studies, it is important to test these scenarios in real-world buildings, incorporating dynamic electricity pricing and engaging occupants in demand response actions. This research included several assumptions, such as the willingness of occupants to participate in grid flexibility actions for only two hours. Exploring other scenarios, such as interactions lasting one or more hours or temperature exceedances of more or less than two degrees outside the desired comfort boundary, would be beneficial. Additionally, expanding the study to include the impact of HCC on grid flexibility when using other systems, such as ventilation or lighting, would provide valuable insights. Moreover, according to the findings from Chapter II, people have different expectations regarding incentives. Exploring how incentives impact interaction and motivation for long-term engagement in grid flexibility actions would be interesting. Overall, the role of occupants in enabling grid flexibility, when combined with advanced controllers like HCC with MPC, shows great potential for creating energy-flexible buildings and smart, sustainable grids, all while prioritizing occupant comfort.

Conclusions

6. Summary and Conclusions

This thesis significantly advances the knowledge of the potential of integrating Human-Centered Control (HCC) systems in buildings, prioritizing occupant preferences and needs to improve comfort and satisfaction with indoor environments. The study presents an interdisciplinary research approach that combines technical and social sciences. It begins by examining user perspectives on control systems, including their opinions, preferences, and willingness to interact with HCC by sharing data or feedback for indoor environmental control and grid flexibility. This was accomplished using a survey-based study involving nearly 1 000 respondents in Zagreb, Croatia, with a diverse target group regarding age, sex, and technical knowledge. The research also introduces a novel theoretical framework using an established psychological theory known as the Theory of Planned Behavior to predict users' willingness to interact with HCC systems by sharing data for environmental control and grid flexibility interaction. This framework addresses the common issue of insufficient user-provided data in HCC systems by predicting if occupants are willing to interact with them. Moreover, this framework enables to identify factors that motivate or hinder occupants from interacting with HCC, such as the beliefs about the usability of such systems, the ease of use, type of preferred interface, time duration and frequency of the interaction, the impact of social norms and user trust in sharing data with such systems.

Building on these practical insights gathered by the survey, this research also developed a practical method, based on a user-led design to integrate user preferences into building control systems using personalized comfort models (PCMs). These models learn occupants' preferences over time, reducing the need for continuous user input. The models can predict future comfort levels by analyzing past user-reported comfort and discomfort states in specific indoor conditions (e.g., air temperature, CO_2 level, lighting). Data-driven PCMs were developed using Artificial Intelligence (AI), specifically supervised Machine learning (ML) models, for multiple comfort aspects, including indoor air quality, thermal and visual comfort. This is a significant step forward, as research found in literature has primarily focused on thermal comfort PCMs. Additionally, nine different ML models were developed and tested to find the optimal one for PCM development. These models use collected subjective data as feedback on perceived comfort from users through a specially designed smartphone application, as well as indoor measurements obtained from sensors. The data was collected during two field studies. The first field study involved four participants over three weeks in a faculty office, while the second study was conducted in a high school building with 24 participants over two weeks. In the high school study, the feasibility of integrating user preferences through PCMs into the control system of an actual building was tested by implementing HCC as a proof-of-concept study. The impact on occupant satisfaction was evaluated through surveys and semi-structured participant interviews. This evaluation demonstrated the practical implications and real-world effects of implementing HCC in an actual building.

Finally, simulations were employed to quantify the impact of integrating user preferences into control systems, namely the effect of HCC on grid flexibility, energy savings, electricity costs, and comfort. These simulations compared the effects of incorporating user preferences into conventional PID control and advanced systems like Model Predictive Control (MPC). More importantly, they demonstrated how combining HCC with MPC and user engagement in demand-response actions can significantly enhance grid stability and efficiency, emphasizing the crucial role of buildings in grid flexibility.

6.1 Scientific contributions

This thesis presents an interdisciplinary study that combines surveys, model development, field experiments, and simulations. It highlights the novelty and practicality of integrating user preferences into building control systems through PCMs, a method that can significantly improve occupant comfort and satisfaction. The research also demonstrates the potential of leveraging HCC with MPC in buildings for grid flexibility, marking a significant step toward smarter, more responsive buildings. The main scientific contributions, key findings, and practical implications of this research are as follows:

- The first scientific contribution includes a framework based on a psychological or behavioral science approach, namely the Theory of Planned Behaviour (TPB), that can be used to predict the willingness of users to report feedback on the perceived comfort conditions in a human-centered control system. A survey-based approach was used with almost 1 000 respondents to gather insights on their willingness to interact with HCC and their preferences regarding control systems in buildings. The key findings show that:

- Approximately 75.7% of respondents want access to control in buildings, but only 55.6% are willing to interact with HCC by sharing data or feedback for environmental control. Therefore, user interaction with controls dependent on user-reported data cannot be seamlessly assumed but can be predicted to increase the certainty that users will interact with controllers.
- The proposed framework for predicting users' willingness to interact with HCC by sharing data or feedback on perceived comfort can achieve a moderate prediction potential of $R^2 = 64\%$, which is satisfactory in behavioural sciences. This is useful for predicting user engagement in HCC, which relies on user-provided data.
- The proposed framework identified key factors influencing occupant interaction with HCC: beliefs about usability and benefits, ease of use, social impact, and trust in data privacy. Increasing awareness of the positive impact of HCC benefits on environmental control and grid flexibility can enhance user engagement. Behavioural approaches like comparison and gamification can boost social impact. Additionally, intuitive, easy-to-use interfaces are crucial for simplifying data sharing with HCC.
- Around 47% of respondents prefer more automated control systems while still desiring the ability to adjust indoor conditions. IAQ emerged as the most important comfort aspect (85%), followed by thermal (84%) and visual comfort (74%). Therefore, in addition to thermal comfort, IAQ control should also be given priority in building control systems.
- From the practical side, 66% of respondents prefer to use smartphones as interfaces to interact with the HCC as a more convenient interface. The findings suggest that smartphone applications should be simple, easy to use, and require less frequent feedback. Also, a high degree of privacy security should be ensured. Occupants want to interact or share data or feedback only when

discomfort arises (53.5%), and only 30% would like to receive nudges or reminders to share their data with HCC.

- Around 60% of respondents are open to engaging in grid flexibility actions by reducing their energy consumption when informed of grid overloads, and the expectations of incentives vary among respondents. Most respondents would only like to interact with demand-response action for short periods ($1 - 2$ hours).

- The second scientific contribution shows a method for the development of PCMs using multi-aspect comfort data collected as direct feedback from the occupants on their perceived indoor comfort. The PCMs enable the deployment of HCC in buildings with less user interaction, which was tested in an actual building. Two field studies or experiments were conducted to collect data for PCM development, the first in a faculty office experiment with four participants for three weeks and the second in a school building with 24 participants for two weeks. The school building was also used to test the feasibility of implementing HCC in an actual building. The key findings show that:
  - Data-driven PCMs using ML models can be developed for various occupants and comfort aspects (IAQ, thermal, visual). The decision tree ML model generally performs best, especially when there is less data available, with an average F1 score ranging from 0.7 to 0.86 across different participants and comfort aspects. Random Forest performs better with more data points. Tree-based models maintain high performance even with fewer input features, making PCMs feasible for deployment in diverse buildings with varying sensor setups and data availability.
  - The use of comfort-based (predicting comfortable or uncomfortable states) or preference-based PCMs (predicting desire for change, e.g., want warmer or cooler) does not significantly impact the model performance (predictive potential) when employing tree-based ML models. Specifically, the small deviation in F1 score ranged from 0 to 0.02 for tree-based models (on average across all users and comfort aspects). Hence, if the aim of PCMs is to be integrated into control systems in buildings, it is better to use approaches that are more intuitive to the users (e.g., it might be easier for the user to report if

they want warmer or cooler conditions than to state if they are comfortable or uncomfortable).

- Around 50 – 60 data points are needed for optimal PCM performance. Yet, the data need variability in the provided user feedback for a balanced dataset to train the ML models effectively.
- Participants reported comfort at higher indoor temperatures than standard setpoints. The lab experiment found a comfortable range of 22.5 – 25°C, while the field experiment in the school building found 21.8 – 24.8°C. Both experiments, conducted in different seasons, indicate a preferred temperature slightly above the usual setpoints of 21 – 22°C. The field studies revealed that while individual comfort perceptions vary, preferences often overlap significantly. Thus, implementing HCC with PCMs can optimize HVAC control by adjusting to comfort needs rather than static setpoints.
- The IAQ and visual comfort analysis found peak comfort at CO_2 levels around 800 ppm, aligning with the ASHRAE guideline that defines 1 000 ppm as the upper boundary for comfort. Despite indoor lighting levels being below the recommended 300 lux in the lab experiment, users reported feeling comfortable, indicating high adaptability to lighting levels.

This study included a field test in a school building to evaluate the feasibility of implementing HCC for multiple occupants. The proposed framework enables occupant access to automated control through PCMs by considering the comfort boundaries and temperature preferences of all occupants. This was tested during the two-week-long experiment, where the collected feedback from occupants was used to learn their preferences and then adjust the environmental setpoints based on their preferences for three days. This straightforward yet practical approach ensures most occupant preferences are accounted for by removing outliers, ultimately aiming to maximize satisfaction for most occupants. The real-world impact on occupant satisfaction was also evaluated using longitudinal surveys during the experiment and semi-structured interviews at the end of the experiment by comparing user satisfaction before and after the implementation. The key findings are:

- Integrating user preferences into the building control system led to a 16.7% increase in overall user satisfaction, indicating that HCC can significantly enhance occupant indoor satisfaction. This was concluded by comparing the self-reported satisfaction before and after the implementation of HCC without informing the participants on which days the setpoints were adjusted based on their expressed preferences. This also confirms the hypothesis of this research that "**The deployment of human-centered predictive control in a building by developing personalized data-driven comfort models significantly increases the occupants' indoor comfort satisfaction**."

- Semi-structured interviews conducted with 19 of the 24 participants after the field integration of HCC revealed that 73.7% believed HCC could learn and meet their preferences, 10.5% were neutral, and 15.8% were skeptical, favoring conventional control systems. HCC enables occupants to have control access to automated control systems. Yet, some participants preferred hybrid control systems that operate on standard settings but allow for manual interaction and adaptive control.

- Interviews revealed that collective comfort is a common expectation in shared spaces, with a high willingness of occupants to share control autonomy. Participants expect the preferences of the majority to be considered. Thus, the proposed HCC framework, which removes outliers to accommodate most occupants, aligns with occupant expectations and is not seen as a significant inconvenience.

- Participants found the feedback reporting process easy, straightforward, and intuitive, typically taking between 15 seconds and two minutes to complete. Regarding feedback frequency, 47.4% of participants did not mind reporting feedback every hour, 31.6% preferred less frequent interaction, and 21.0% had no preference. However, challenges were noted: some participants struggled to sense specific indoor air parameters, such as air humidity, indicating the complexity of these parameters for users. Additionally, language barriers were reported, with some participants having difficulty understanding questions in English, necessitating translations. This highlights the importance of tailoring the interface to the target group and having an intuitive app.

- The third scientific contribution is the definition and quantification of the impact of HCC on grid flexibility. This is achieved by using comprehensive simulations using TRNSYS software and MATLAB, two widely recognized tools in the field. The simulations represent the building behavior of the RCK Ruder Boskovic high school in Zagreb, Croatia. Five scenarios are analyzed to demonstrate the impact of various control strategies on electricity consumption, costs, grid flexibility, and comfort. The scenarios are standard PID and standard MPC (both with standard temperature setpoints ($20-22$°C)), human-centered PID (HC-PID), and HC-MPC (with expressed user preferences or human-centered (HC) setpoints ($21.8-24.8$ °C), retrieved from participants during the school experiment). Lastly, the DR-HC-MPC scenario integrates user preferences in HCC and user engagement in grid flexibility. This engagement is done during peak overloads by temporarily adjusting comfort boundaries to less favorable conditions, aiming to reduce energy consumption and alleviate grid load, upon agreement with occupants. For example, for the simulations, it was assumed the desired comfort boundary of occupants ($21.8-24.8$ °C) to be adjusted for ± 2°C for two hours when the electricity prices are on average the highest to decrease the heating need in winter and decrease the cooling need in summer. The key findings suggest that:

- The DR-HC-MPC shows significant potential to reduce electricity consumption (44.6%) and costs (59.4%) compared to the standard PID that was used as a reference scenario. This demonstrates a promising approach to balancing energy efficiency with occupant preferences. Furthermore, it comes with a lower discomfort rate (61.6 Kh) compared to the standard PID baseline (99.6 Kh), but higher compared to HC-MPC (5.8 Kh). This indicates that advanced controllers like MPC with user integration and engagement in flexibility actions can still improve comfort, albeit less so than using advanced controllers with user preferences integration alone without DR actions. This suggests balancing energy reduction and grid flexibility goals with occupant comfort, possibly by adjusting engagement times or temperature changes to minimize discomfort. The DR-HC-MPC control strategy shows significant potential for load shifting, with an average ability of 60.6% for both heating and cooling seasons. This ability to shift energy consumption from on-peak to off-peak hours can help reduce grid overload and leverage lower electricity prices.

- Incorporating user preferences into advanced control strategies like MPC significantly improves occupant comfort, reducing discomfort to 5.8 Kh, compared to standard PID with 99.6 Kh, for peak hours. This control strategy enables shifting energy consumption to off-peak hours, achieving a 13.3% cost saving and a 46.4% load-shifting ability, which is 14.2% less than when engaging occupants in demand response (DR-HC-MPC with 60.6%).

- Integrating user preferences into the conventional PID control improves overall comfort, reducing discomfort to 3.0 Kh. However, this comes with increased energy consumption (7.9%) and costs (49.0%) compared to the standard PID baseline. The most significant increases occur in winter, suggesting that prioritizing occupant comfort in PID-controlled buildings may lead to higher energy usage and costs, especially during heating seasons. Therefore, the results suggest that the MPC is the better option for integrating user preferences in HCC.

6.2 Limitations and future studies

This thesis employs multidisciplinary methods and approaches, yielding insightful findings that pave the way for implementing HCC using PCMs in buildings and leveraging HCC for grid flexibility actions. Yet, this research has some limitations. For instance, the survey-based study used in this research consists of a high number of respondents, but there is a relatively limited number of elderly and lower-education respondents because the survey was conducted in educational facilities. However, the current respondents are the most likely users of HCC, given that a broader implementation of such systems is still in the development phase. In future studies, expanding the survey to other buildings and including more diverse target groups besides those in educational buildings is beneficial. Furthermore, conducting more field studies to compare the respondents' expressed willingness to interact with HCC with their actual behavior after implementation in real-world settings would be valuable. Lastly, it would be interesting to explore how the engagement levels of users interacting with HCC change over time and what impacts that engagement in the long run.

The field studies that were conducted included a small group of people (four participants) in the faculty experiment and medium size group (24 participants) in the school experiment. Having more people participating would benefit the generalization of the findings. Furthermore, the experiments lasted for a short time, one during winter and the other during spring, therefore longer experiments across different seasons would cover more versatile conditions. Despite their brevity, these experiments provided sufficient variation to learn participants' preferences under varying conditions due to the planned intervention days. Moreover, the experiment of implementing HCC in an actual building was conducted only in one classroom and it mainly serves as a proof-of-concept study. This approach can be expanded to include the entire building or extended to other buildings to evaluate how the implementation of HCC performs in various settings, allowing for the assessment of its effects with a larger number of participants. Additionally, expanding the research to include other comfort aspects, such as acoustic comfort, would provide a more comprehensive understanding of comfort. The building used in the field experiment was newly built, which could also impact the participants' sense of participation as the entire environment was a novelty to them. The predisposition of the participants to respond positively can also be slightly biased by their pride in participating in such a novel experiment. However, this is a general concern in experiments involving people. Lastly, it would be interesting to test the impact of HCC on grid flexibility and the integration of user preferences into conventional and advanced control systems (e.g., MPC) in field studies rather than simulations. Furthermore, the impact of HCC on grid flexibility was tested with the assumption that the users are willing to engage in grid flexibility actions for only two hours when the grid is overloaded. This was done by changing the indoor temperature for $\pm 2℃$ to unfavorable conditions to reduce energy consumption. In reality, this highly depends on user acceptance. In future studies, testing more scenarios helps to evaluate how engagement duration and setpoint changes alter the impact of HCC on grid flexibility.

In conclusion, much intriguing research remains to be done on generalizing the integration of HCC in actual buildings. However, the goal is clear: buildings are built for people, and their comfort, well-being, and satisfaction should be prioritized. Comfortable environments can be created by leveraging IoT and AI in buildings to learn user preferences through PCMs and integrate them into the building control systems to tailor environments to occupants' needs. Combining this approach with advanced control systems (like MPC) and demand-response actions, empowers both occupants and buildings to contribute to grid stability and efficiency, with minimal impact on comfort for short periods with occupant agreement. This strategy enhances energy efficiency and helps shape a sustainable future while prioritizing occupants in buildings.

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Annex A

Table A.1. Questions from the questionnaire dealing with user preferences on control systems

Retrieved information	Code	Question	5-point Likert scale
Integration preference	CA	How important is it for you to have the possibility of adjusting the lighting, heating, ventilation (air quality, amount of fresh air), and cooling systems?	Not at all important/Very important
	ICA	To what extent would you prefer to be involved in the process of regulating the temperature, air quality, or lighting in the room, if these conditions were initially controlled automatically.	Prefer not to be involved/Prefer to be very involved
	WILL	If involvement means giving your feedback (comfort preferences, complaints) by using an interface (e.g. A mobile app), to what extent are you willing to participate?	Not willing at all /Very willing
Automation scale	AP	Would you prefer your lighting, heating, cooling, and ventilation systems to be more manual or more automated?	More manual/More automated
Comfort aspect preference	COMF	How important are these comfort aspects to you?	-Thermal comfort (indoor temperature) -Visual comfort (lighting) -Indoor Air Quality (fresh air) Not at all important/ important
User-trust	UT1	To what extent would you trust an automated control system with your location data, given all safety measures were ensured:	Not trust at all/ Completely trust
	UT2	To what extent do you think it would be beneficial to provide your feedback (comfort preferences, complaints) to the automated control system?	Not at all beneficial/ Very beneficial
Frequency of feedback	FREQ	How many times per day would you be willing to give feedback on your comfort level for the indoor conditions?	Each hour/Every few hours/ Only when feeling uncomfortable. Not willing to give my feedback
	REM	How would you like to report your feedback?	I would like to report whenever I feel like it. I would like to be reminded to give my feedback. I don't want to give my feedback at all

Manner of feedback	INTF	What interface would you prefer to use to report your feedback?	Smartphone application Web-based Smartwatch or Wristband Other please specify…
	EN	If you could impact the energy consumption of your school by reporting your feedback (comfort preferences, complaints), would you participate in reporting your feedback?	I do not think this is very important, so I would not participate. Maybe, I am available to listen how it works and decide if I want to participate. Yes, I care a lot about energy saving and I would like to actively contribute
	FLEX WILL	If I was notified that the energy grid is overloaded, I would use less energy and accept slightly less comfortable temperatures and dim the lights, if I had personal financial gains	Strongly disagree – Strongly agree
	FIN	If I was notified that the energy grid is overloaded, I would consider using less energy and accepting less comfortable conditions, if:	(1) I had no financial gains. (2) The financial gain for me is small (3) The financial gain for me is moderate, (4) The financial gain for me is high, (5) I don't care about financial gains, I want maximum comfort.
	TIME	The amount of time during the day when I would accept to use less energy and have less comfortable conditions if the grid is overloaded is:	(0) no time at all – (2) for a short period of time only (1 – 2 hours) – (3) for longer periods (over 2 hours per day) (4) All the time when needed.

Table A.2. TPB questionnaire

Construct name	Subconstruct	Question name	Questions
Attitude	Behavioural beliefs	BB1	For me, reporting my feedback to the control system during the day would be pleasant.
		BB2	If I give my feedback to the control system, I can save more energy
		BB3	If I give my feedback to the control system, I can protect the environment
		BB6	The energy problem concerns the whole society and everyone is responsible to save energy
		BB7	I am aware of how control systems can save energy in buildings
	Outcome evaluation	OE8	If I communicate with the automated control system through my feedback, I would feel more satisfied with the comfort conditions
		OE9	If I was notified of how much energy I saved, I would be more committed to reporting my feedback
		OE10	If I would have personal gains due to energy savings, I would be more willing to provide my feedback
		OE11	I would be more committed to reporting my feedback if I was notified of how my comfort preference affects the environment
Subjective Norms	Normative beliefs	NB12	Most people whose opinions I value would agree with me reporting my feedback to adjust indoor conditions
		NB13	If I participate by giving my feedback to adjust indoor conditions, this would set a good example for my peers
	Motivation to comply	MC14	In general, I care greatly about how my friends or colleagues act, and I will do the same as them
		MC15	I will do what my teachers/superiors ask me to do in regards to giving my feedback to adjust indoor conditions.
Perceived Behavioural Control	Control beliefs	CB16	I am confident that I can provide my feedback several times during the day
	Influence of control beliefs	ICB18	The type of user interface to report my feedback will affect my willingness to participate
		ICB19	The requested frequency to report my feedback will affect my willingness to give my feedback
Generalized Intention		GI20	I am willing to participate/communicate with the user-centered control system (a system that takes into account my feedback when controlling temperatures, air quality, and lights).
		GI21	I intend to report my feedback whenever I feel uncomfortable
		GI22	I am willing to encourage my friends or colleagues to participate in reporting their feedback to the control system.

Annex B

B1. Statistical analysis of the survey data with Structural Equation Modelling (SEM)

This Annex shows the detailed statistical analysis for Chapter II. The results from the measurement model are presented in Table B.1.The CV shows how well the questions measure the constructs. Although some constructs have lower AVE than the recommended threshold, they are still acceptable considering that the Cronbach's alpha and the CR meet the criteria. Furthermore, the factor loadings for some questions are lower than the recommended values between 0.4 and 0.7 [83], or as other state the factor loadings need to be at least 0.7 according to [83], larger than 0.5 [78], etc. In this study, some loadings did not reach the desired 0.7. However, the items with factor loadings of less than 0.7 were still retained, according to [67], as it was tested that their deletion did not significantly improve the reliability of the model. AVE reached the acceptable levels for all constructs as suggested by [278]. Lastly, the $CR > 0.7$ was reached, showing that the chosen questions are reliable. The Cronbach's alpha $\alpha > 0.6$ was reached for all constructs, meaning the questionnaire is consistent.

The divergent validity enables us to evaluate the diversity among questions so that each one measures something else or differs from one another. The metrics used to establish divergent validity is either through Fornell-Larcker criterion (FL criterion) or through HTMT ratio [78]. The results for the FL criterion for all three models were presented in Table B.2, B.3, and B.4, respectively, which show good DV values since each set of questions performs best on their mother construct (e.g., Attitude questions have a higher value in the Attitude construct than the others.

In conclusion, the measurement model confirms that this questionnaire is a valid and reliable measuring instrument to predict occupant behaviour for feedback-reporting behaviour in human-centered control systems.

The proposed hypotheses to establish relationships between influencing factors and the target (the willingness of occupants to interact with HCC by reporting feedback) are formulated as shown below. The hypotheses for models M2 and M3 are formulated based on Figure 2.5 in Chapter II, which also represents the proposed framework to predict the willingness of users to engage in grid flexibility actions (M3). The descriptions of the proposed hypotheses, are as follows:

H1: The fundamental constructs of TPB (the Attitude, Subjective norms, and Perceived Behavioural Control) significantly impact user willingness to share data with HCC for indoor environmental control.

H2: The demographic characteristics significantly impact user willingness:

a. To share data with HCC for indoor environmental control.
b. To engage in grid flexibility actions.

H3: Notifications or nudges sent to users significantly impact:

a. User willingness to share data with HCC for indoor environmental control.
b. User willingness to engage in grid flexibility actions.
c. The Perceived Behavioral Control (perceived capability of users) to share data with HCC for indoor control or to engage in grid flexibility actions.

H4: User preferences for control systems (control access, automation level, using HCC) significantly impact:

a. User willingness to share data with HCC for indoor environmental control.
b. User willingness to engage in grid flexibility actions.
c. User attitudes toward sharing data with HCC for indoor control and engaging in grid flexibility actions.

H5: User trust significantly impacts:

a. User willingness to share data with HCC for indoor environmental control.
b. User willingness to engage in grid flexibility actions.
c. User attitudes to share data with HCC and engage in grid flexibility actions.
d. The Perceived Behavioral Control (perceived user capability) to share data with HCC and engage in grid flexibility actions.

H6: Personal gains significantly impact user willingness to engage in grid flexibility actions.

H7: Time duration significantly impacts user willingness to engage in grid flexibility actions.

H8: User willingness to share data with HCC for indoor climate control significantly impacts user willingness to engage in grid flexibility actions.

Table B.1. Results of the measurement model of models M1, M2, and M3

			Model M1				Model M2 & M3			
			β	α	CR	AVE	β	α	CR	AVE
Attitude (ATT)	Behavioural beliefs	BB1	0.72	0.87	0.90	0.51	0.74	0.83	0.88	0.51
		BB2	0.82				0.84			
		BB3	0.79				0.80			
		BB6	0.67				0.68			
		BB7	0.52				0.57			
	Outcome evaluation	OE8	0.75				0.78			
		OE9	0.76							
		OE10	0.54				0.52			
		OE11	0.77							
Subjective Norms (SN)	Normative Beliefs	NB12	0.86	0.75	0.86	0.66	0.86	0.70	0.80	0.52
		NB13	0.88				0.88			
	Motivation to Comply	MC14	0.45				0.45			
		MC15	0.60				0.60			
Perceived Behavioural Control (PBC)	Control Beliefs	CB16	0.70	0.54	0.76	0.51	0.69	0.54	0.76	0.51
	Influence of control beliefs	ICB18	0.79				0.80			
		ICB19	0.64				0.66			
Intention (INT)		GI20	0.87	0.70	0.80	0.52	0.87	0.75	0.86	0.66
		GI21	0.78				0.78			
		GI22	0.79				0.79			
User preferences (UP)		AP					0.29	0.60	0.77	0.48
		CA					0.67			
		ICA					0.81			
		WILL					0.86			
User trust (UT)		UT1					0.82	0.61	0.84	0.72
		UT2					0.87			
Notifications received (NOT)		OE9					0.92	0.81	0.91	0.84
		OE11					0.91			
Demographics (DM)		SEX					0.72	0.44	0.78	0.64
		AGE					0.87			
Duration (DUR)		TIME					1.00			
Financial Gains (FG)		FIN					1.00			
Willingness to engage in Grid Flexibility actions (GR)		FLEX WILL					0.80	0.51	0.80	0.67
		EN					0.84			

Table B.2. FL criterion for model M1

	ATT	INT	PBC	SN
Attitude	**0.73***			
Behavioral Intention	0.71	**0.82**		
Perceived Control	0.62	0.63	**0.72**	
Social Norms	0.67	0.64	0.49	**0.72**

*The top value in a column should be the highest.

Table B.3. FL criterion for model M2

	ATT	DM	BI	NOT	PBC	SN	UP	UT
Attitude	**0.72***							
Demographics	0.18	**0.80**						
Intention to Report Feedback	0.71	0.18	**0.82**					
Notifications	0.69	0.21	0.60	**0.92**				
Perceived Control	0.60	0.14	0.63	0.50	**0.72**			
Social Norms	0.65	0.07	0.64	0.58	0.49	**0.72**		
User preference	0.50	0.25	0.49	0.38	0.37	0.41	**0.70**	
User trust	0.63	0.15	0.60	0.48	0.49	0.48	0.54	**0.85**

*The top value in a column should be the highest.

Table B.4. FL criterion for model M3

	ATT	DM	DUR	INT	NOT	PBC	FG	SN	UP	UT	GR
ATT	**0.72**										
DM	0.18	**0.80**									
DUR	0.27	0.04	**1.00**								
INT	0.71	0.18	0.19	**0.82**							
NOT	0.69	0.21	0.25	0.60	**0.92**						
PBC	0.60	0.14	0.14	0.63	0.50	**0.72**					
FG	-0.18	-0.15	-0.26	-0.13	-0.22	-0.06	**1.00**				
SN	0.65	0.07	0.24	0.64	0.58	0.49	-0.11	**0.72**			
UP	0.50	0.25	0.07	0.49	0.37	0.37	0.01	0.40	**0.70**		
UT	0.63	0.15	0.15	0.60	0.48	0.49	-0.08	0.48	0.53	**0.85**	
GR	0.60	0.27	0.38	0.51	0.55	0.41	-0.26	0.48	0.37	0.42	**0.82**

*The top value in a column needs to be the highest.

Table B.5. Structural modeling results, hypothesis testing, and path coefficients of model M2

	Relationship	Path weight β	T statistic	P value	Confidence interval 2.50%	97.50%	Hypothesis
H1	Attitude → Intention to Report Feedback	0.264	6.667	0.000	0.185	0.339	Supported
	Social Norms→Intention to Report Feedback	0.216	7.54	0.000	0.156	0.270	Supported
	Perceived Control → Intention to Report Feedback	0.23	7.764	0.000	0.171	0.288	Supported
H2a	Demographics → Intention to Report Feedback	0.028	1.428	0.153	-0.011	0.066	Rejected
H3a	Notifications → Intention to Report Feedback	0.079	2.427	0.015	0.018	0.146	Supported
H3c	Notifications → Perceived Control	0.343	9.425	0.000	0.271	0.414	Supported
H4a	User preference → Intention to Report Feedback	0.079	2.969	0.003	0.027	0.131	Supported
H4c	User preference → Attitude	0.228	7.356	0.000	0.166	0.288	Supported
H5a	User trust → Intention to Report Feedback	0.126	4.358	0.000	0.07	0.184	Supported
H5c	User trust → Attitude	0.511	16.45	0.000	0.447	0.569	Supported
H5d	User trust → Perceived Control	0.327	9.543	0.000	0.257	0.391	Supported

Table B.6. Structural modeling results, hypothesis testing, and path coefficients of model M3

	Relationship	Path weight β	T statistic	P value	Confidence interval 2.50%	97.50%	Hypothesis
H1	Attitude → Intention to Report Feedback	0.263	6.667	0.000	0.185	0.339	Supported
	Social Norms → Intention to Report Feedback	0.216	7.626	0.000	0.158	0.270	Supported

	Perceived Control → Intention to Report Feedback	0.231	7.807	0.000	0.172	0.288	Supported
H2a	Demographics → Intention to Report Feedback	0.028	1.381	0.167	-0.012	0.066	Rejected
H2b	Demographics → Willingness to Engage in Grid Flexibility	0.121	4.9	0.000	0.072	0.169	Supported
H3a	Notifications → Intention to Report Feedback	0.079	2.425	0.015	0.017	0.146	Supported
H3b	Notifications → Willingness to Engage in Grid Flexibility	0.272	7.722	0.000	0.203	0.341	Supported
H3c	Notifications → Perceived Control	0.342	9.386	0.000	0.270	0.414	Supported
H4a	User preference → Intention to Report Feedback	0.079	3.008	0.003	0.028	0.132	Supported
H4b	User preference → Willingness to Engage in Grid Flexibility	0.098	3.025	0.002	0.036	0.161	Supported
H4c	User preference → Attitude	0.226	7.283	0.000	0.164	0.286	Supported
H5a	User trust → Intention to Report Feedback	0.127	4.382	0.000	0.071	0.184	Supported
H5b	User trust → Willingness to Engage in Grid Flexibility	0.07	1.964	0.040	0.001	0.139	Supported
H5c	User trust → Attitude	0.513	16.559	0.000	0.450	0.571	Supported
H5d	User trust → Perceived Control	0.327	9.509	0.000	0.257	0.391	Supported
H6	Personal gains→ Willingness to Engage in Grid Flexibility	-0.096	3.444	0.001	-0.151	-0.042	Supported
H7	Duration → Willingness to Engage in Grid Flexibility	0.234	9.093	0.000	0.182	0.282	Supported
H8	Intention to Report Feedback → Willingness to Engage in Grid Flexibility	0.175	4.644	0.000	0.102	0.248	Supported

The predictive potential of the model measured using the explained variance R^2, the model fit through the SRMR factor, and the Q^2, computed through Smart PLS. These are presented in Table B.8. The acceptable results of SRMS range in values that are less than 0.1 [83] and for a more conservative threshold, it is 0.08 [84].). The yielded values satisfy the conditions according to [83] and are at a boundary value with [84]. Q^2 presents the predictive relevance that needs to be greater than zero to be relevant according to [279]. The results show that all models have predictive relevance. Since the R^2 of the intention to engage in grid flexibility action is lower than 0.5 but considering the novel concept of grid flexibility to the respondents and the fact that the Q^2 and SRMR have acceptable levels, an almost moderate predictive potential of R^2 can be accepted.

Table B.8. The predictive power of the models measured with R^2 (the explained variance), SRMR (the model fit), and Q^2 (the predictive relevance of the model)

Prediction metrics	**Model M1**	**Model M2**	**Model M3**	
	A*	A	A	B
R^2	0.619	0.639	0.639	0.452
SRMR	0.086	0.081	0.077	0.077
Q^2	0.615	0.54	0.541	0.434

*A-Willingness to share data with HCC, B-Willingness to engage in grid flexibility actions

Annex C

Table C.1 The questions used in the HComfort smartphone application to collect user feedback on multiple comfort aspects

	Measured parameter	Question	Answer
Indoor Air Quality	Air quality sensation	How does the air quality feel to you?	Just right Slightly stuffy Stuffy Very stuffy
	Air quality preference	How would you prefer the air to be?	No change More fresh air
	Humidity sensation	How does the air humidity feel to you?	Dry Slightly dry Just right Slightly humid Very humid
	IAQ Comfort	In terms of air quality only, how would you describe your current comfort level?	Comfortable Uncomfortable
Thermal Comfort	Thermal preference [28]	How would you prefer the room temperature?	Cooler No change Warmer
	Thermal sensation [280]	How do you currently feel?	Hot Warm Slightly warm Neutral Slightly cool Cool Cold
	Air movement preference *	How would you like the air movement to be?	Less No change More
	Thermal comfort	In terms of Thermal comfort, how would you describe your current comfort level?	Comfortable Uncomfortable
Visual Comfort	Illuminance sensation [280]	Describe the current lighting	Too dark Dark Just right Bright Too bright
	Lighting preference	How would you like the brightness level to be?	Dimmer No change Brighter
	Glare sensation [162]	What degree of glare are you experiencing?	Imperceptible (no glare) Perceptible (little glare) Disturbing (significant glare)

			Intolerable (Extreme glare)
	Shading use*	Do you need to use the blinds?	Yes No
	Visual comfort	In terms of Visual comfort only, how would you describe your current comfort level?	Comfortable Uncomfortable
Health & Wellbeing	General Comfort	In general, including all comfort aspects, are you comfortable at the moment?	Comfortable Uncomfortable
	Comfort aspect impact *	Which aspect is affecting your comfort the most currently?	IAQ Thermal Visual Acoustic None of the above
	IEQ satisfaction	Overall, how satisfied are you with the indoor environment?	Very dissatisfied Dissatisfied Somewhat dissatisfied Neutral Somewhat satisfied Satisfied Very satisfied
	Productivity *	How would you rate your current productivity level?	Very productive Productive Neutral Unproductive Very unproductive
	Health symptoms *	Have you experienced any health symptoms related to the indoor environment?	No Headache Respiratory issues Allergies Dry eyes or skin Other
	Mood *	What is your current mood?	Happy Content Calm & relaxed Bored Annoyed Stressed Angry Sad
	State/Condition *	Describe your current state	Hungry Thirsty Tired Sleepy Energetic Neutral

* The questions with the (*) sign, were removed in the field experiment, to shorten the length of the survey and to avoid survey fatigue considering that the contribution of these features was minor as assessed in the lab experiment.

Annex D

This annex shows some more findings from the lab experiment including comfort-related results, how different comfort aspects correlate, why it is important to measure comforts separately (e.g., thermal comfort, IAQ, visual comfort) and not as a unit, how user satisfaction correlates to comfort and exploring the relationship between comfort, productivity, mood and health conditions.

The distribution of user-reported comfort varied significantly on a day-to-day basis during the lab experiment. Figure D.1., shows the changes in perceived comfort for all participants for different days for IAQ, thermal and visual comfort. Furthermore, how the perceived overall comfort differs depending on varying levels of CO_2 and air temperature, is shown in Figure D.2.

Figure. D.1.a) Distribution of comfort votes by for IAQ (upper) and thermal (lower) and daily measurements. Left: Distribution plots show data spread. Right: Bar plots highlight detailed distribution

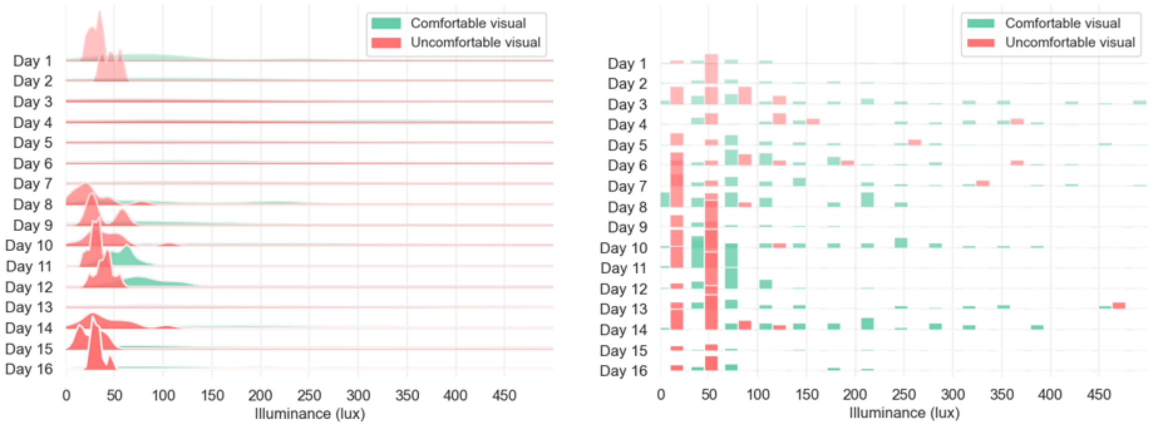

Figure. D.1.b) Distribution of comfort votes by aspect for visual comfort and daily measurements. Left: Distribution plots show data spread. Right: Bar plots highlight detailed distribution

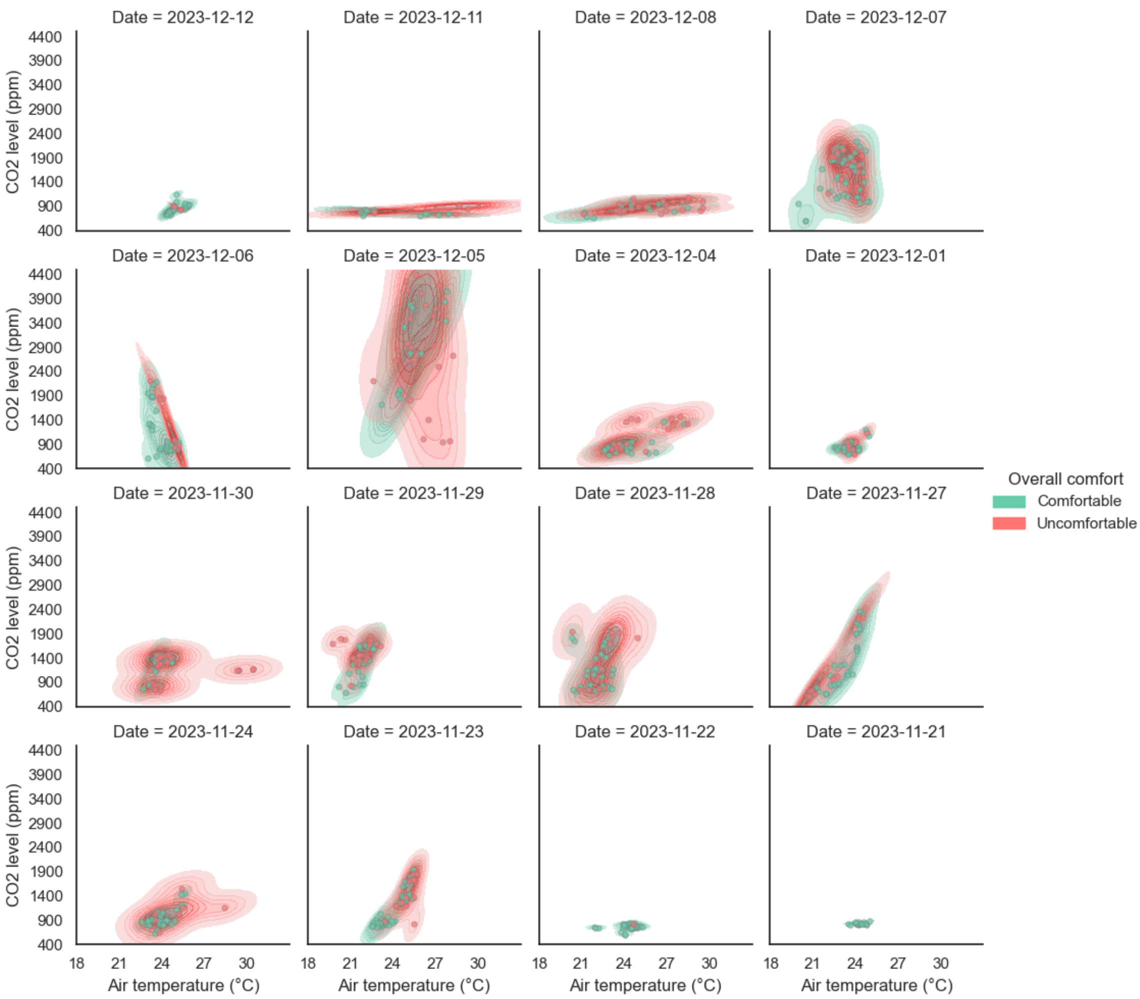

Figure D.2. Distribution of perceived overall comfort based on air temperature and CO_2 level

The correlation between CO_2 levels and air temperature, and their impact on IAQ comfort, thermal comfort and the overall reported comfort are shown in Figure D.3. This figure shows the aggregated data for all days for different users for the lab experiment. The significant difference among users is clearly depicted emphasizing the variety of preferences within the same indoor conditions. It is interesting to notice that overall comfort resembles IAQ and thermal comfort votes but is not exactly like either of them. Therefore, it is important to clearly distinguish the comfort aspects when collecting occupant feedback.

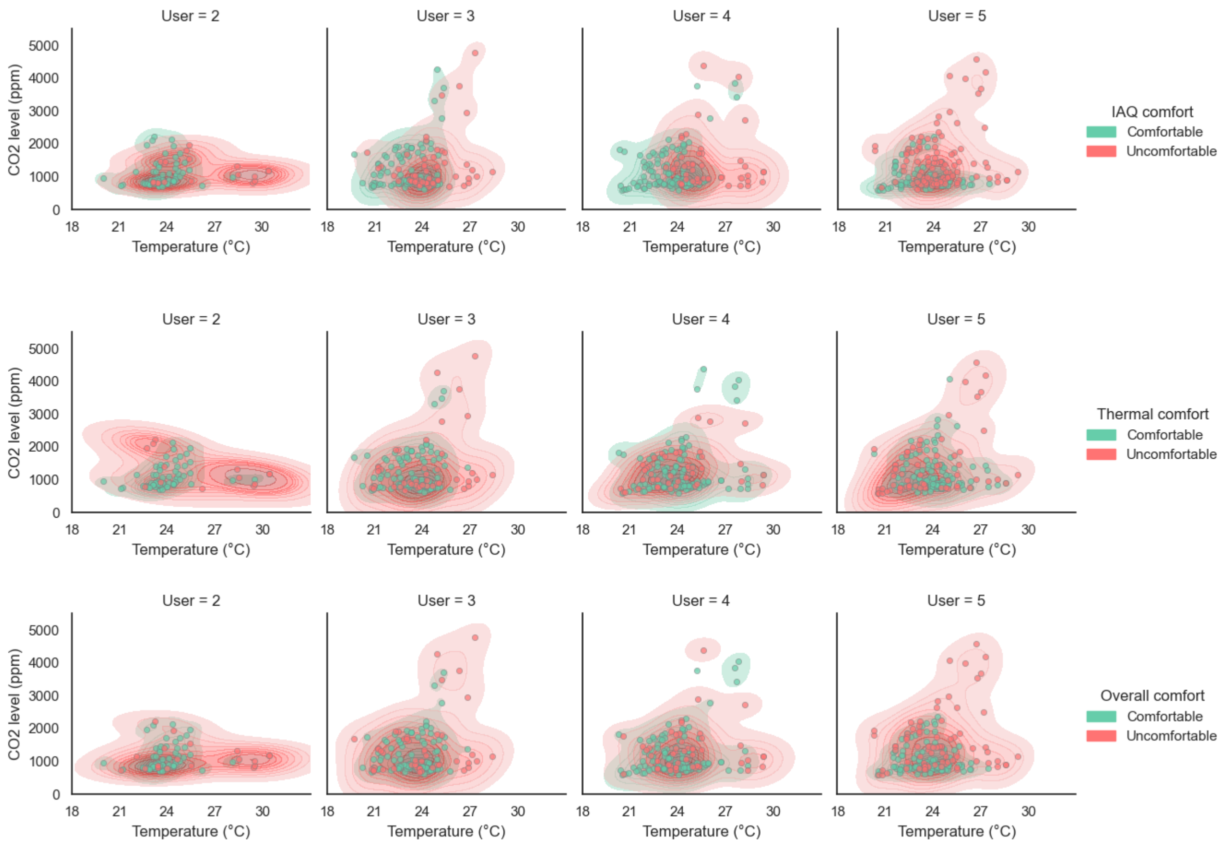

Figure D.3. Comparison of how different reported perceived comfort (IAQ, thermal and overall comfort) changes depending on CO_2 level and air temperature. Upper row: IAQ comfort, middle: Thermal comfort, lower row: Overall comfort

To have a clearer vision of the change in IAQ, thermal and overall comfort reported by users in terms of CO_2 and air temperature, Figure D.4. shows the data for only one day among the 3 weeks of experiment, as an example of how the occupant perceptions change for some of the users in the experiment.

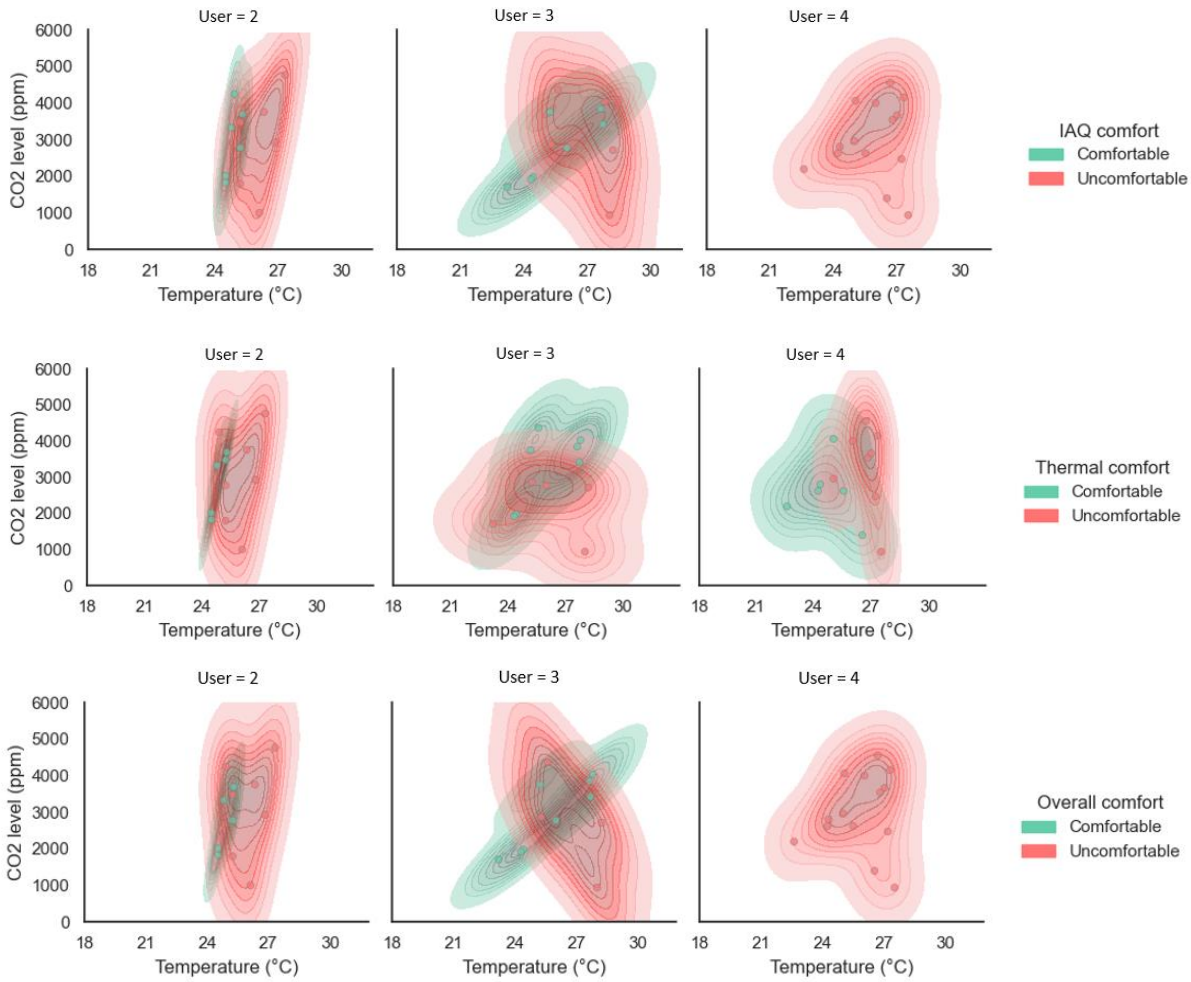

Figure D.4. Comparison of how different reported perceived comfort (IAQ, thermal and overall comfort), for different users (2,3,4) change depending on CO_2 level and air temperature. Upper row: IAQ comfort, middle: Thermal comfort, lower row: Overall comfort

Achieving higher occupant satisfaction is one of the fundamental aims of HCC, alongside a higher comfort level for occupants. The correlation between occupant satisfaction and perceived comfort was investigated in Figure D.5. with data collected in the lab experiment. The findings show that the participants might be dissatisfied with the indoor conditions but still report being comfortable. However, when they are satisfied, they rarely report discomfort for IAQ and thermal, but for visual there are some cases considering the high impact seating or position have in visual comfort.

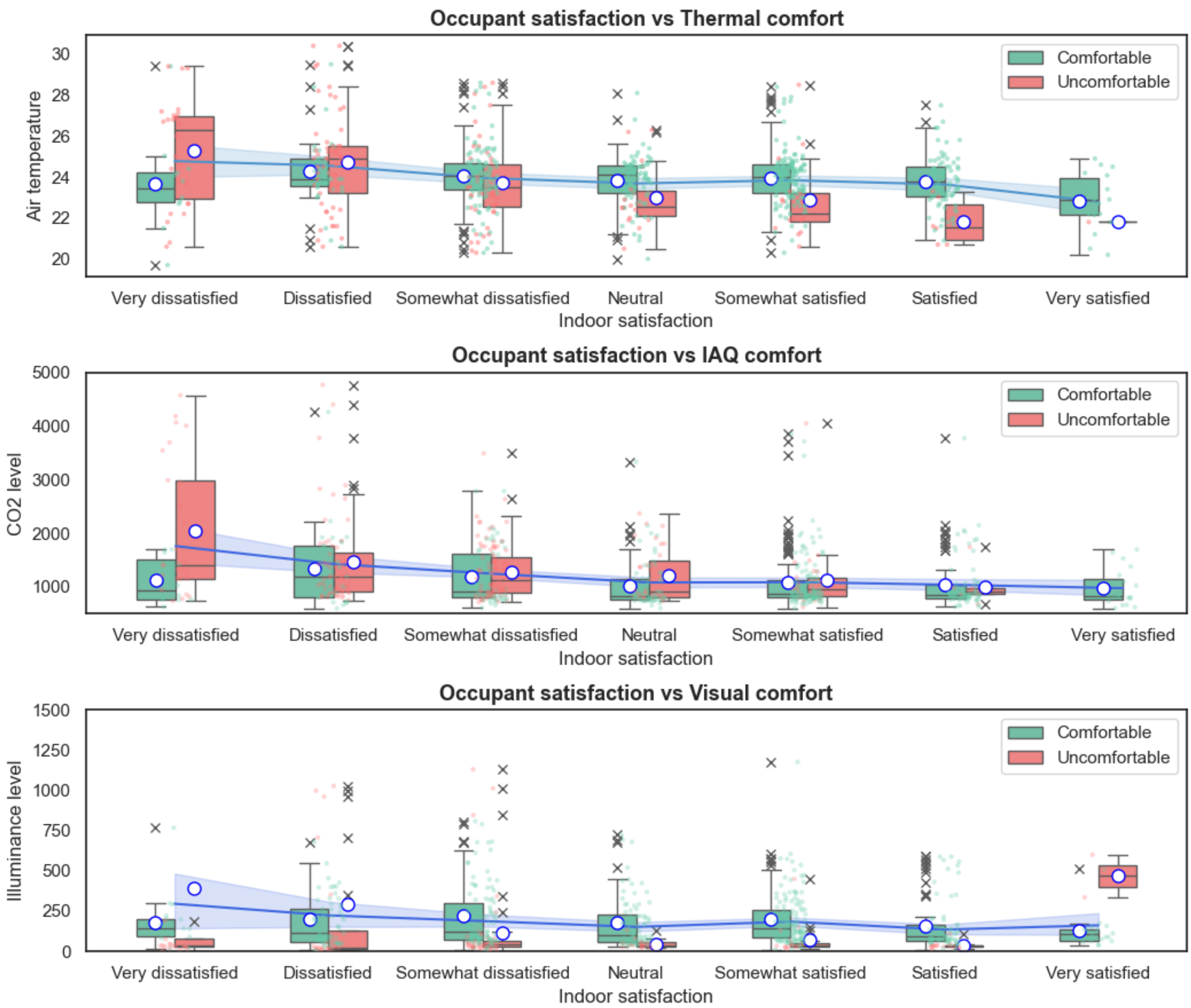

Figure D.5. Correlation between occupant satisfaction and comfort for IAQ, thermal and visual comfort

Figure D.6 shows the correlation of the responses of perceived comfort, productivity, mood, condition, and health symptoms of participants using a Sankey diagram. The findings show that most occupants reported being productive when they were comfortable, whereas when unproductive was reported, most of the time the occupants were uncomfortable. Furthermore, self-reported votes of productive, and very productive are more related to positive moods like happiness, content, calm and relaxed whereas uncomfortable and unproductiveness is more related to negative feelings like annoyed, bored, stressed. Moreover, based on the state or conditions of the participants, the majority had neutral feelings, followed by sleepy then energetic. Lastly, in terms of reported health symptoms, the majority showed no health symptoms, but sometimes headache, dry eyes or skin, and respiratory issues were reported. However, the cause-and-effect relationship of these correlations needs to be studied more to extract generalizable statements.

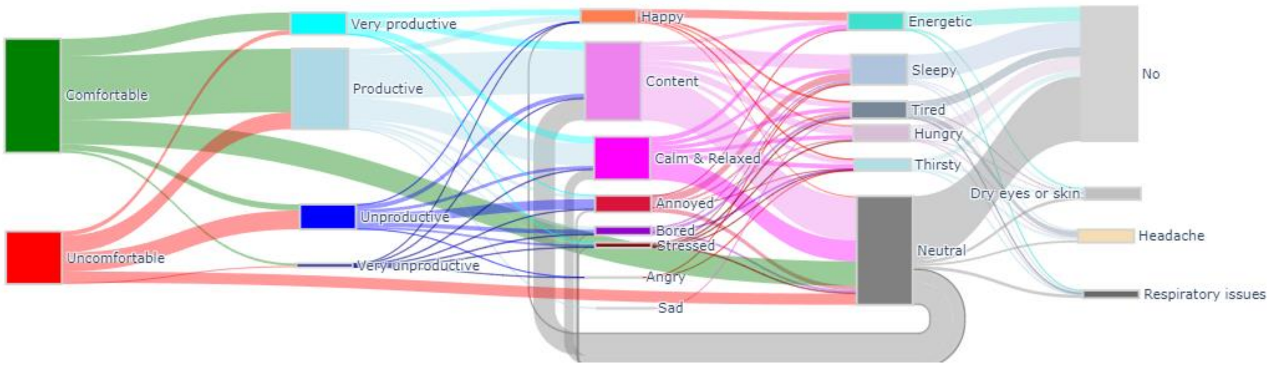

Figure D.6. Sankey diagram of the relationship between comfort, productivity, mood, condition, and health symptoms for all users of the lab experiment

D.1. Analysis on the amount of datapoints needed for PCMs with reduced inputs

Figure D.7. shows how the model performance (F1 score) stabilizes with the increase of available data points for models that are built upon a reduced number of inputs. Furthermore, the change and stability of specificity is also depicted for all-inputs PCMs (Figure D.8.) and reduced inputs PCMs (Figure D.9).

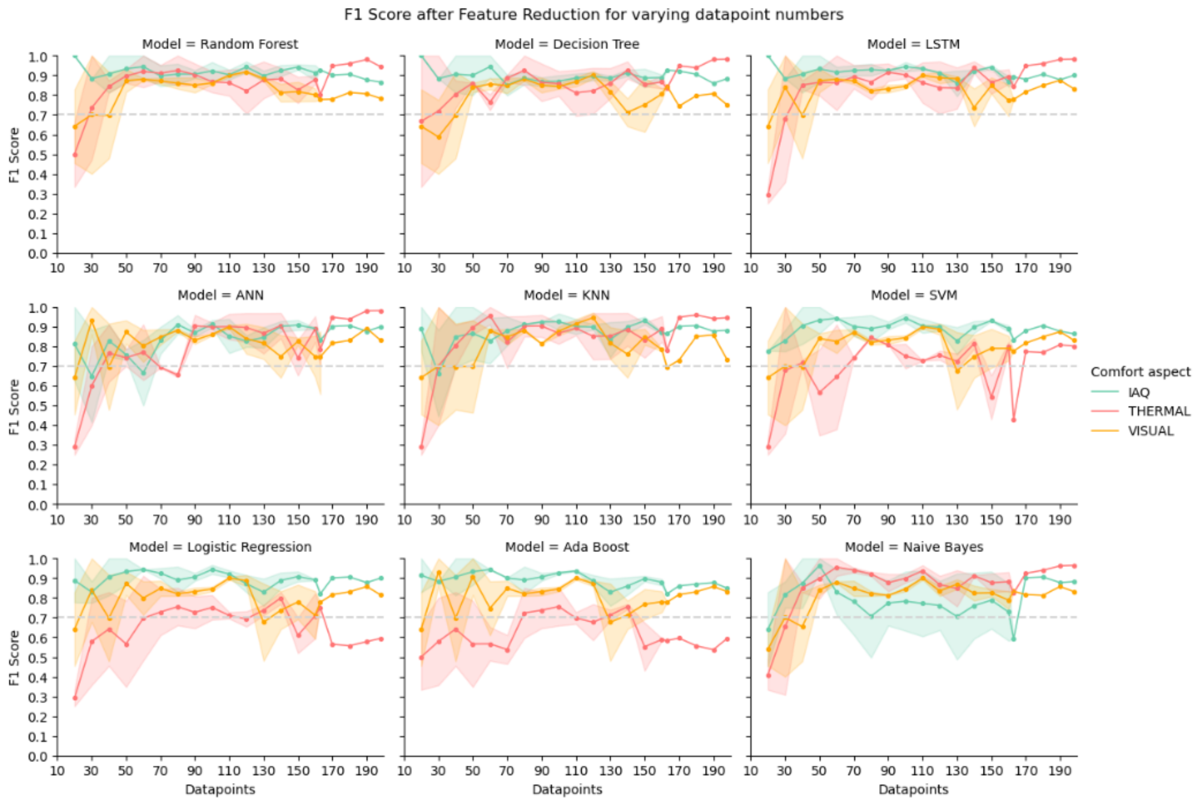

Figure D.7. Comparison of prediction accuracy (F1 score) of PCMs depending on the number of data points for all comfort aspects. Data are shown for the models with reduced inputs

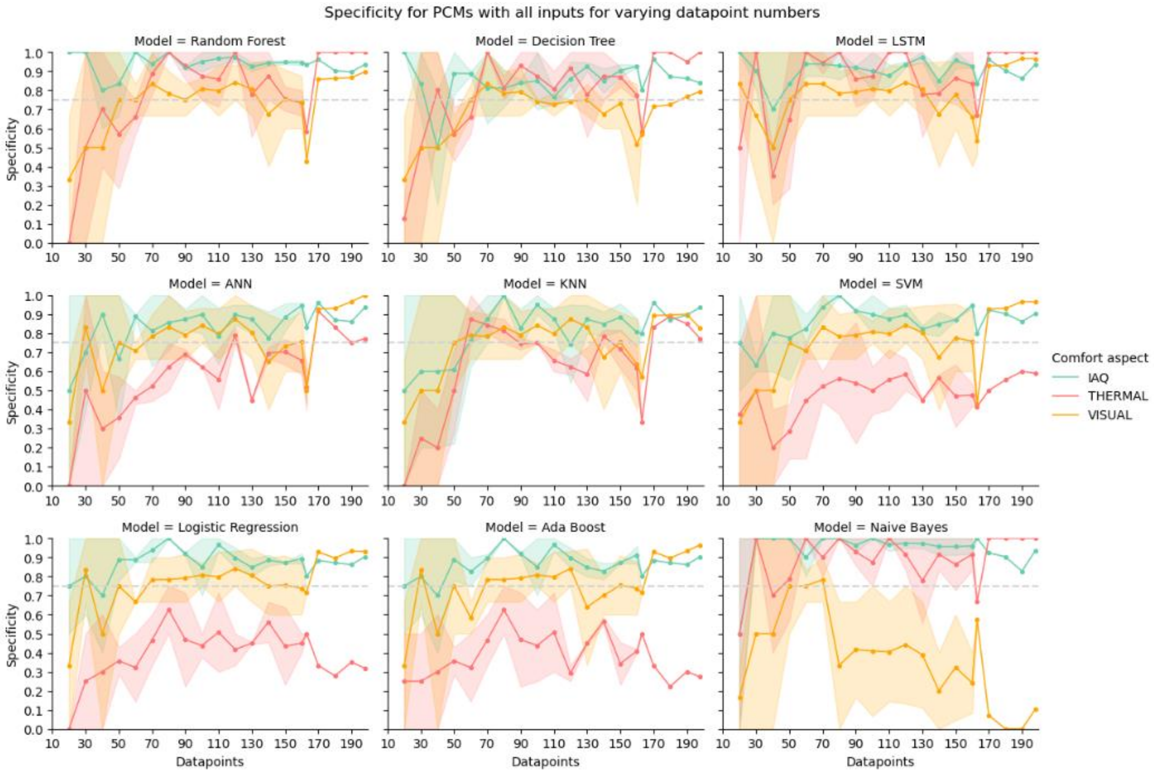

Figure D.8. Comparison of prediction accuracy (Specificity) of PCMs depending on the number of datapoints for all comfort aspects. Data are shown for the models with all initial inputs

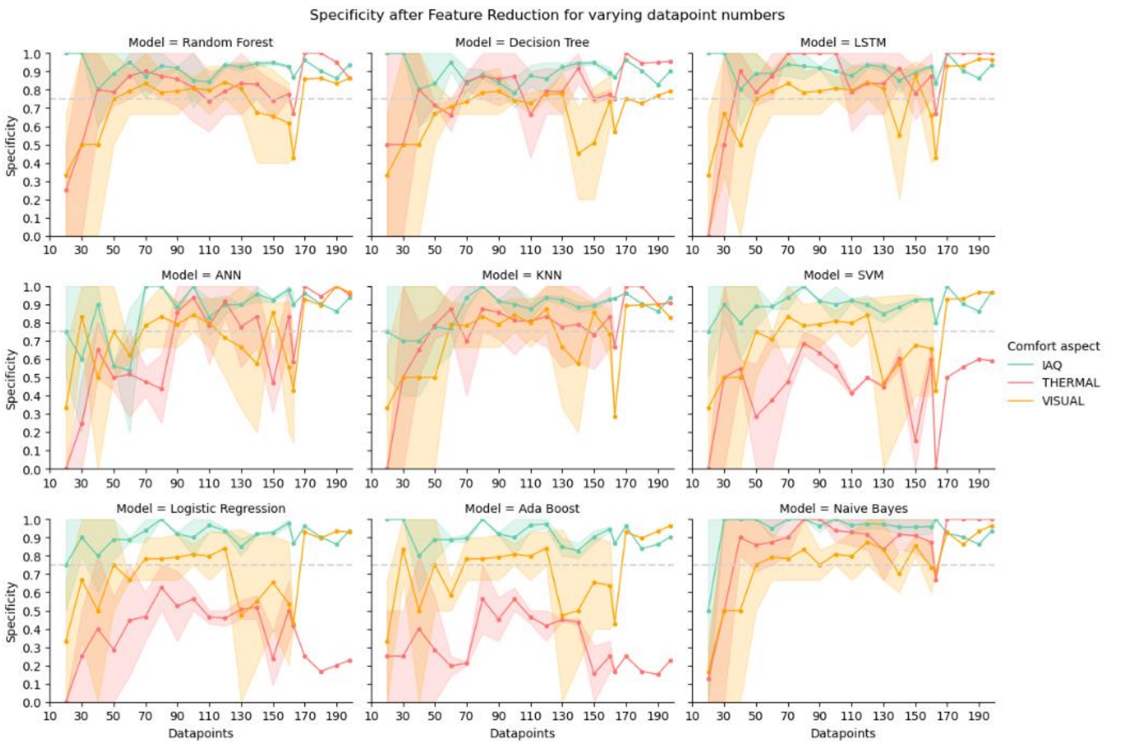

Figure D.9. Comparison of prediction accuracy (Specificity) of PCMs depending on the number of datapoints for all comfort aspects. Data are shown for the models with reduced inputs

Annex E

Figure E.1. shows the depiction of the model performance for PCMs of Group I – "High engagement" occupants when using preference-based models. Due to the small number of data points, the model performance is lower than the models of the lab experiment.

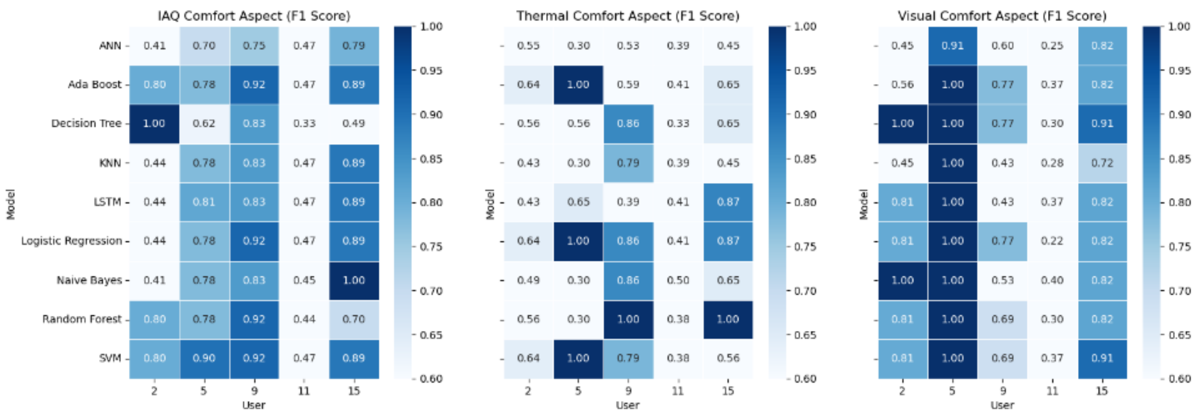

Figure E.1. The comparison of model performance measured with F1 score for each user for Group I – "High engagement" occupants. Results are shown for IAQ PCMs (left), thermal PCMs (middle), and visual PCMs (right). Preference-based models are tested for Group I.

Figure E.2 compares the effectiveness of comfort-based PCMs and preference-based PCMs for different comfort aspects. The average F1 scores for all users in Group I – "High Engagement" show that while comfort-based PCMs occasionally outperform preference-based PCMs for thermal and IAQ comfort, the overall average difference across all users and comfort aspects is minimal. This suggests that comfort-based binary classification models can be effectively used. If integrating comfort-based models into control systems, it is crucial to provide clear instructions to occupants on reporting their feedback: "uncomfortable" should indicate a need for change in indoor conditions, and "comfortable" should mean no changes are needed.

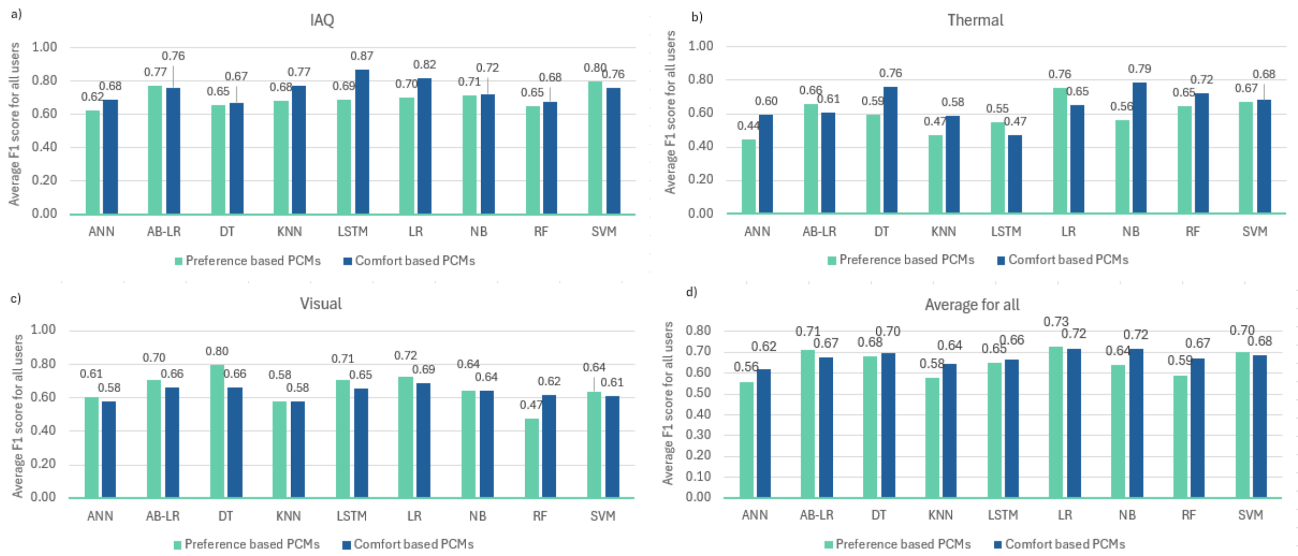

Figure E.2. Comparison of the performance preference-based models and comfort-based models for Group I

Annex F

F.1. Comparison of energy consumption, costs, load shifting, and comfort for different control strategies

In the following sections, the detailed simulation results to evaluate the performance of different control strategies under different conditions are presented. First the results for peak hours are presented and then for the entire day.

Results on energy consumption, costs, load shifting, and comfort for peak hours. Figure F.1. presents detailed results for different scenarios during peak hours, showing energy consumption in kWh for both summer and winter. It also includes energy savings in kWh and percentage, as well as the load shifting ability. The results show that while MPC saves the most energy during heating season, the DR-HC-MPC saves the most energy in both heating and cooling season compared to the baseline scenario which is standard PID. Unsurprisingly, the DR-HC-MPC has the highest load shifting ability during both heating and cooling season.

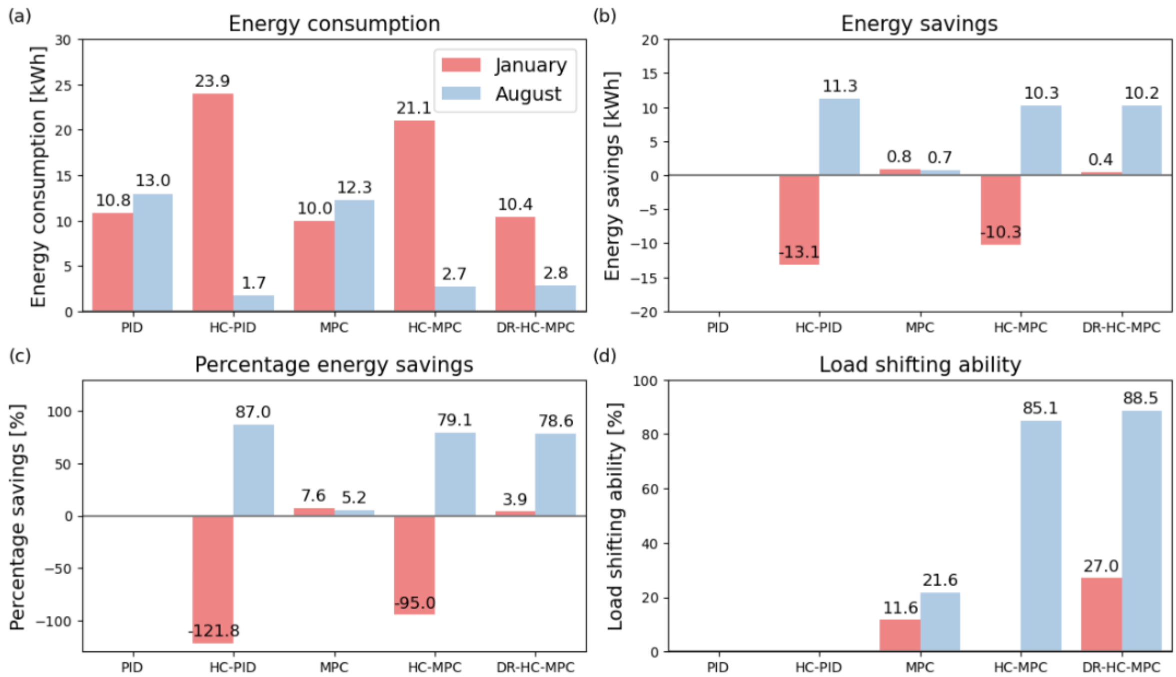

Figure F.1. KPIs during peak hours for energy consumption (a), energy savings (b), percentage of energy savings (c), and load shifting ability (d) are presented separately for the winter season (heating periods, in red) and summer season (cooling periods, in blue)

Figure F.2. shows the total costs (EUR), cost savings (EUR), cost savings in percentage and the thermal discomfort. The results show that integrating user preferences into conventional controllers like PID during heating season causes a significant increase in costs. A cost increase during the heating season is also caused when integrating user preferences into the MPC controller, but only in heating season, as during cooling season there are significant cost savings. The DR-HC-MPC enables cost savings in both heating and cooling season while adhering to occupant preferences, although the savings during heating season are only 4.6% but during cooling season they reach up to 97.9%. As per the thermal comfort, the highest comfort is achieved when integrating user preferences into PID or MPC, but these are accompanied with higher cost. The DR-HC-MPC enables higher comfort than standard PID (the baseline) but lower than the HC-PID or HC-MPC. But this is the trade-off between cost savings and comfort, where this dicomfort occurs only for two hours during peak times and not the whole day.

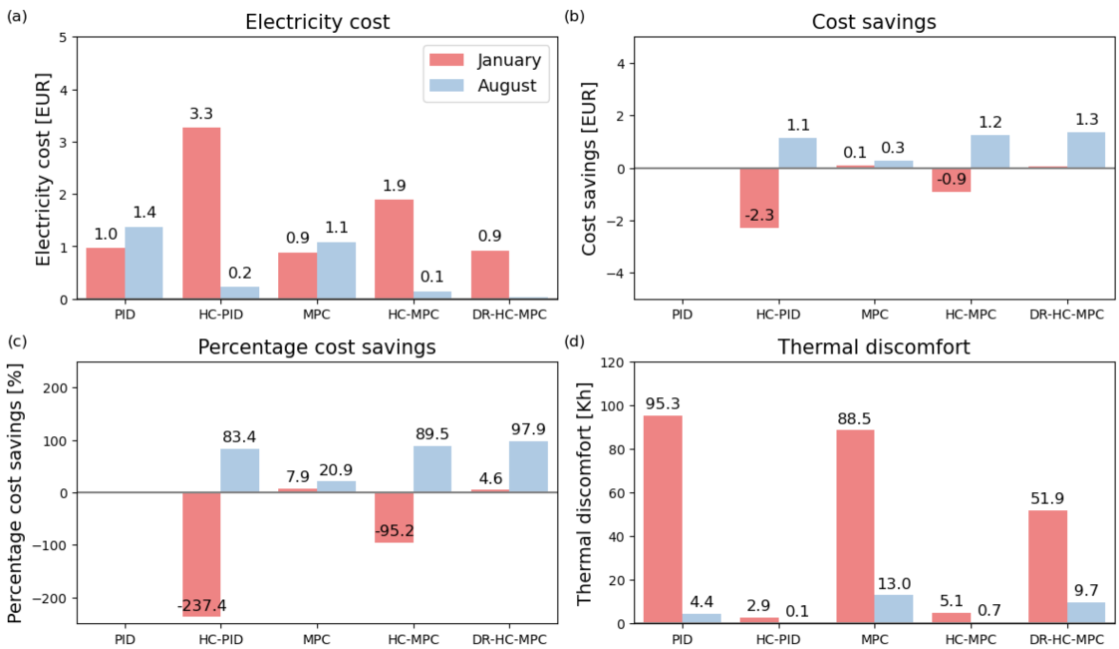

Figure F.2. KPIs during peak hours for electricity cost (a), cost savings (b), percentage of cost savings (c), and thermal discomfort (d) are presented separately for the winter season (heating periods, in red) and summer season (cooling periods, in blue)

The energy pricing model significantly impacts the energy costs of the PID scenario even if PID doesn't consider electricity prices. In Figure F.3. The impact of the fixed and dynamic electricity prices used for the reference PID scenario significantly changes the yielded costs for all scenarios since the reference point changes, indicating that, in general, static costs cause lower costs than dynamic prices.

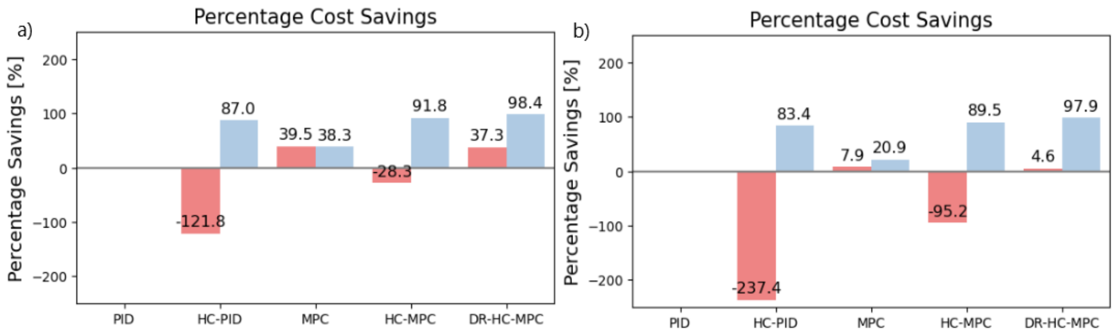

Figure F.3. Comparison of cost savings during peak hours in heating and cooling seasons, contrasting (a) fixed electricity prices with two tariffs (left) and (b) dynamic electricity pricing (right)

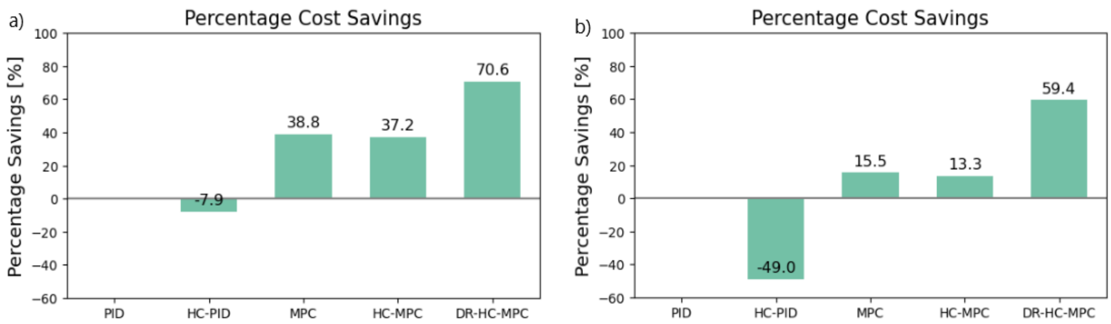

Figure F.4. Comparison of peak hour cost savings, aggregating heating and cooling seasons, under (a) fixed electricity prices with two tariffs (left) and (b) dynamic electricity pricing (right)

Results on energy consumption, costs, load shifting, and comfort for the entire day. To understand the implications of different scenarios throughout the entire day, not just during peak hours, results are also presented for the entire period when the building is occupied, from 06:00 to 20:00. Figure F.5. shows the results for heating and cooling season, separately, and Figure F.6. for both seasons, cumulatively. The results indicate similar outcomes to the analysis of the peak hours. Figure F.6 highlights the significant impact of integrating user preferences and engaging occupants in demand response: increased comfort compared to the standard PID baseline (86.1 Kh compared to 591.7 Kh), a 7.1% increase in cost savings, and a higher load-shifting ability of 39.7%.

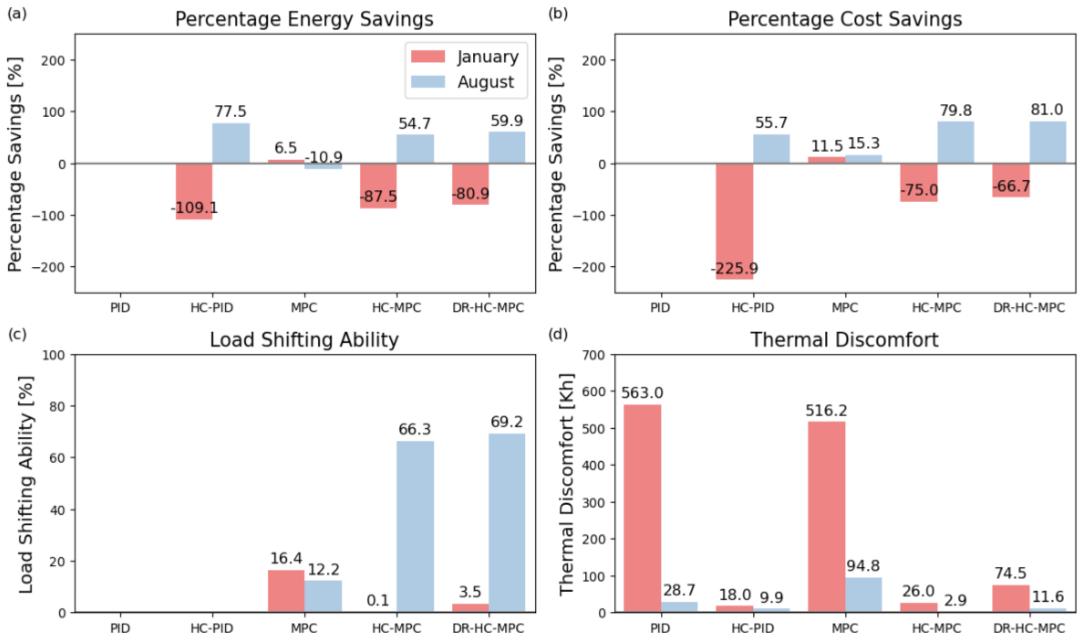

Figure F.5. KPIs for the entire day while occupied (06:00 – 20:00) for percentage energy savings (a), percentage cost savings (b), load shifting (c), and thermal discomfort (d) are presented separately for the winter season (heating periods, in red) and summer season (cooling periods, in blue)

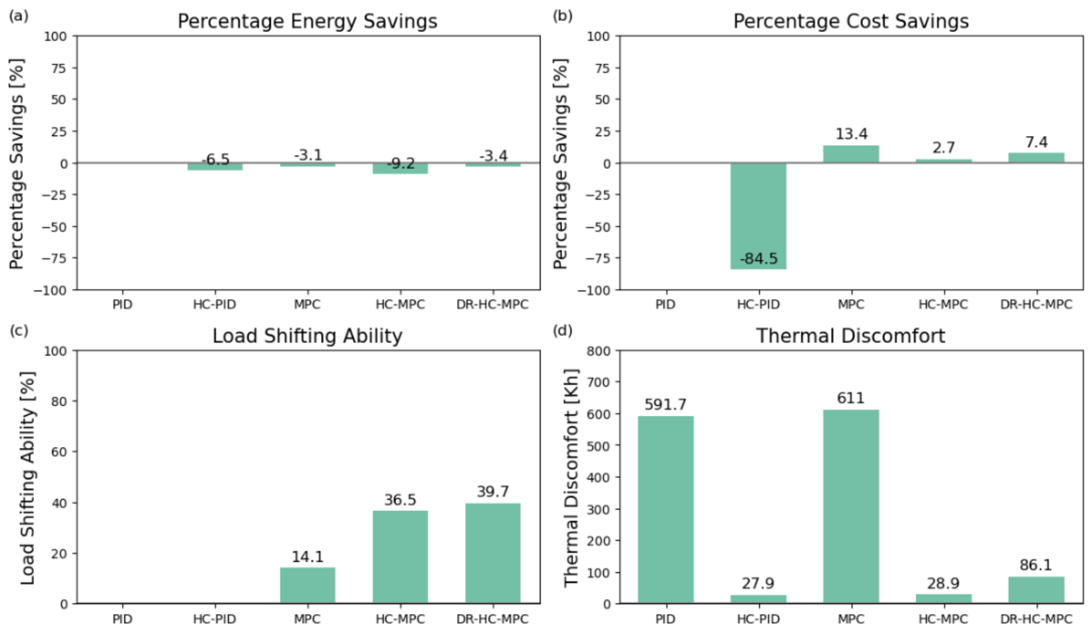

Figure F.6. KPIs for the entire day while occupied (06:00 – 20:00) for percentage energy savings (a), percentage cost savings (b), load shifting (c), and thermal discomfort (d) are presented for aggregated heating and cooling seasons

Figure F.7 and Figure F.8 show that energy cost savings throughout the entire day vary depending on whether PID control is used with fixed or dynamic electricity price models. When using dynamic electricity prices, the PID control that integrates user preferences incurs approximately twice the costs compared to when fixed electricity prices are used.

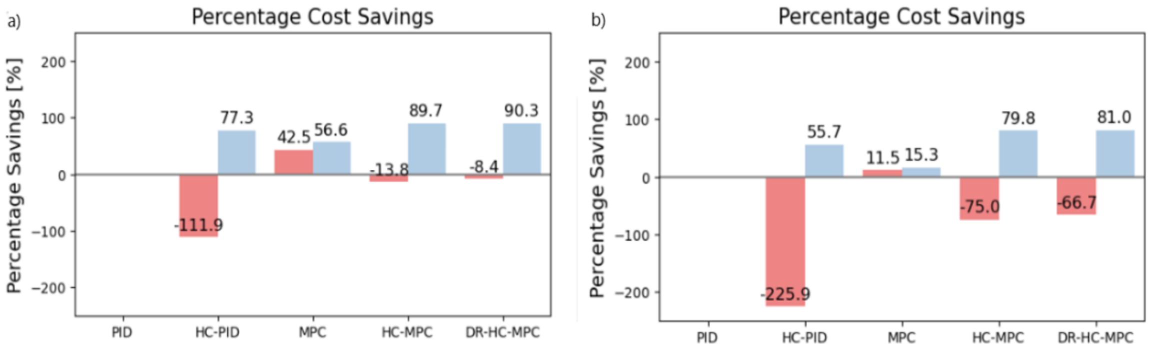

Figure F.7. Comparison of cost savings for PID control in heating and cooling seasons, contrasting (a) fixed electricity prices with two tariffs (left) and (b) dynamic electricity pricing (right), for the entire day when occupied (06:00-20:00)

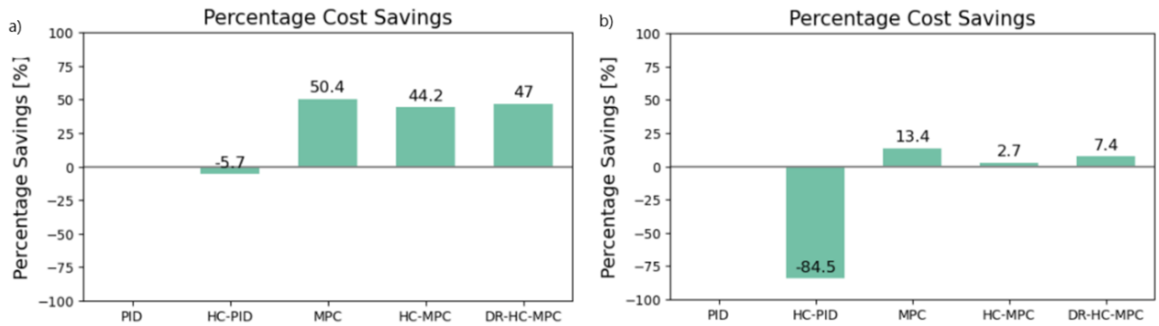

Figure F.8. Comparison of cost savings for PID control, aggregating heating and cooling seasons, under (a) fixed electricity prices with two tariffs (left) and (b) dynamic electricity pricing (right), for the entire day when occupied (06:00 to 20:00)

Biography

Arlinda Bresa was born in Unna, Germany, on January 24, 1994. She completed her education in her homeland, Republic of Kosovo, where she earned her Bachelor and Master's degrees in Thermal Energy and Thermotechnics from the Faculty of Mechanical Engineering, University of Prishtina. She graduated with honors for her outstanding academic performance.

During her studies, she developed a keen interest in smart buildings and sustainable energy, which led her to pursue doctoral studies at the University of Zagreb. She conducted her research under the mentorship of Prof. dr. sc. Tea Žakula within the Laboratory of Energy Efficiency. In addition to her doctoral studies, Arlinda has been a Teaching Assistant at the University of Prishtina for the past seven years. Before that, she worked as an Operation Control Center Officer at Prishtina International Airport. Near the end of her PhD, she spent a month as an invited postdoctoral research visitor at Aalto University, Finland, in the Electrical Engineering and Automation department researching indoor air quality in built environments.

Arlinda is highly dedicated to her professional development. She has participated in summer schools focused on green and sustainable technology at the Technical University of Vienna and BOKU University in Austria, and at Radboud University in the Netherlands. She has also completed various training courses in Python programming, machine learning, project management, and teaching for higher education, as well as earlier training in operation management at Boğaziçi University in Istanbul, Turkey. She has published several papers in high-impact journals and conferences and is a prestigious journal reviewer. Her research and professional activities reflect her commitment to advancing the field of energy efficiency and sustainable building technologies towards more human friendly solutions.

List of publications

Journal publications

I. A. Bresa, T. Zakula, and D. Ajdukovic, "Occupant-centric control in buildings: Investigating occupant intentions and preferences for indoor environment and grid flexibility interactions," *Energy and Buildings (Q1 journal)*, p. 114393, Jun. 2024, doi: 10.1016/j.enbuild.2024.114393.

II. A. Bresa, T. Zakula, and D. Ajdukovic, “A framework to predict the willingness and influencing factors of building occupants to interact with advanced control systems in buildings,” *Energy Reports (Q2 journal)*, vol. 10, pp. 4078–4086, Nov. 2023, doi: 10.1016/j.egyr.2023.10.071.

III. A. Bresa, T. Zakula, and D. Ajdukovic, “Occupant preferences on the interaction with human-centered control systems in school buildings,” *Journal of Building Engineering (Q1 journal)*, p. 105489, Nov. 2022, doi: 10.1016/j.jobe.2022.105489

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- **Conference presentations - Extended abstracts**

IV. A. Bresa and T. Zakula, “Humanizing Human-Centered Control Systems in Buildings and Occupant Comfort Prediction Using Machine Learning,” presented at the AI in AEC - Artificial Intelligence in Architecture, Engineering and Construction, Helsinki, Finland, Mar. 2024.

V. A. Bresa and R. Selimaj, “Investigating the Impact of Occupant-related Characteristics on Thermal Comfort in Buildings using Machine Learning,” presented at the International Conference on New Achievements in Science, Technology and Arts” – ICNA-STA, 04-05 May 2023, Prishtina, Kosovo.

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