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APPLICATION OF SMART TECHNOLOGIES IN ANALYSIS OF PERSONAL THERMAL COMFORT

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PRIMJENA PAMETNIH TEHNOLOGIJA KOD ANALIZE PERSONALIZIRANE TOPLINSKE UGODNOSTI

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1. INTRODUCTION

The building sector is subjected to continuous progress and constant advancements are being implemented in the buildings to improve the comfort of the occupants. In recent times, awareness was raised regarding energy consumption within the buildings. Due to the increasing number of buildings and improving energy access in developing countries, European Union (EU) frameworks for boosting building's energy performance recognized building sector as crucial for achieving environmental goals [1]. Domestic hot water and space heating are the major energy consumers in buildings, followed by appliances, space cooling, and lighting systems [2]. Novel approaches in building design and management are reflected through the application of advanced technologies within the Smart Building concept [3] and are based on Internet of Things (IoT) principles, using sensors and user-friendly applications. Smart management of the systems in buildings implies intelligent control of the connected sensor-embedded devices to provide both efficient energy consumption and a comfortable environment for the occupants [4]. To achieve the integration of smart technologies in the buildings, the IoT framework is fundamental for data collection and communication. In their paper [5], the authors provided a review of general IoT applications in buildings, both residential and commercial, through specific IoT-based solutions. It can be summarized from their work that numerous recent studies deal with implementing IoT technologies in buildings through various building systems. However, from all considered studies, the key elements extracted are crucial for distinguishing smart buildings from conventional ones. The indicators are divided into smart design, smart action, smart control, smart planning, smart monitoring, smart mobility, smart energy, smart waste, and smart water. The latter elements require diverse data types, and the main challenge is processing the large-scale data gathered from IoT devices and sensors. An important step forward in smart building development is the building's "learning" ability through machine learning applications that enable autonomous building decisions based on the collected data [6]. The impact of the users (occupants) in the buildings has a key role in building energy performance, i.e., review study regarding the occupant impacts [7], analysis of occupant's impact in high performance buildings [8] and the role of the occupants in building energy performance [9]. Research study [10] indicated that half of the most significant factors of energy performance in buildings are human-influenced: maintenance, occupant activities, building operation and occupants behavior as well as the indoor environmental quality. Therefore, apart from developing technologies focused on energy management, it is important to consider the user impact as well, which can deliver energy savings in buildings [11]. Since the lighting, heating, ventilation, and air-conditioning are the greatest energy-consuming systems in the buildings [4], the biggest energy-saving potential can be accomplished by upgrading these systems with energy-efficient technologies and solutions for advanced energy management [12]. Improved and more efficient buildings can upgrade the life quality of occupants, and mitigate energy poverty while also providing additional benefits, i.e., better health and indoor comfort, opportunities for green jobs, and general economic and social wellbeing [1]. The user comfort in buildings can be regulated through four basic comfort parameters, such as: visual comfort, acoustic comfort, thermal comfort and air quality [13]. Currently, the thermal comfort (TC) criteria are regulated through standards based on the Predicted Mean Vote (PMV) such as ISO 7730 [14], ANSI/ASHRAE Standard 55 [15], as well as adaptive models [16]. When compared with the subjective thermal sensation votes of the occupants, limitations regarding the proposed models have been discovered pointing out that the PMV approach could either overestimate or underestimate thermal sensation [17], and consequently a disproportion between the designed and actual energy consumption in buildings occurs resulting in the waste of energy due to overcooling/overheating [18]. In work [19], the authors have pointed out that a “one size fit all” approach in designing the thermal comfort conditions in buildings is insufficient to cover all the possible cases. Namely, it does not consider the variations in thermal preferences of building occupants or the diversity in their metabolic activity, clothing level, expectations, physiology etc. In study [9], the authors discussed the impact of occupants in the buildings through the energy saving potential. They have estimated the potential in energy savings due to the user behavior, where savings were from 10% to 25% for residential buildings and from 5% to 30% for commercial buildings. The occupants are the ones responsible for the controlling of energy-consuming systems in buildings, and adjusting them in accordance to their own preferences rather than focusing on the energy efficiency. Therefore, it is reasonable to develop such technologies, which can balance the minimization of energy consumption with a maximization of user comfort at the same time. A better understanding of individual human thermal comfort requirements could fulfill both occupant preferences and Nearly zero-emission building (NZEB) requirements, resulting in improved occupant satisfaction and decreased energy consumption [20].

The smart building topic is well addressed within the literature. There is a plenty of research work that deal with upgrading the heating and cooling system management in buildings and including the thermal comfort of the users. Trying to assure the satisfaction of occupants with thermal conditions, studies are describing local heating/cooling systems focusing on adjusting suitable thermal conditions in small areas only, or targeting certain regions of the human body with locally installed fans, heaters, or other devices [21] such as heated/cooled chairs proposed by [22], cooling robot Roving Comforter (RoCo) [23], Thermal clothing [24] etc. On the other hand, data-driven approach relies on streaming data collection through a network of connected sensors, gathering user and environmental related information with the aim to optimize energy consumption and user thermal comfort. The latter approach can improve the overall thermal comfort of occupants as well as the energy efficiency of heating and cooling systems [25].

Data-driven thermal comfort approach will be discussed into more details in this work through a condensed overview of the proposed solutions as an important foundation for further scientific work in the smart building area. Therefore, the main novelty of this work is to provide a review of the novel approach in buildings and application of smart technologies, with emphasis on the personal thermal comfort in order to provide current state-of-the-art and identifying the research gap for the future work.

2. DESCRIPTION OF REVIEW METHODOLOGY

Thermal comfort issue is a hot research topic in the recent years (2017. - September 2022.) with a growth trend, resulting with overall of 12.685 published papers dealing with “thermal comfort” and 7.187 published papers considering “thermal comfort” AND “buildings” as reported in the Scopus database in the given timeframe. The distribution of the published papers through the years is presented in Figure 2.1. [26]. With the aim to simultaneously optimize energy consumption and user thermal comfort in the smart building paradigm, various technical solutions have been proposed and will be discussed in this work in detail.

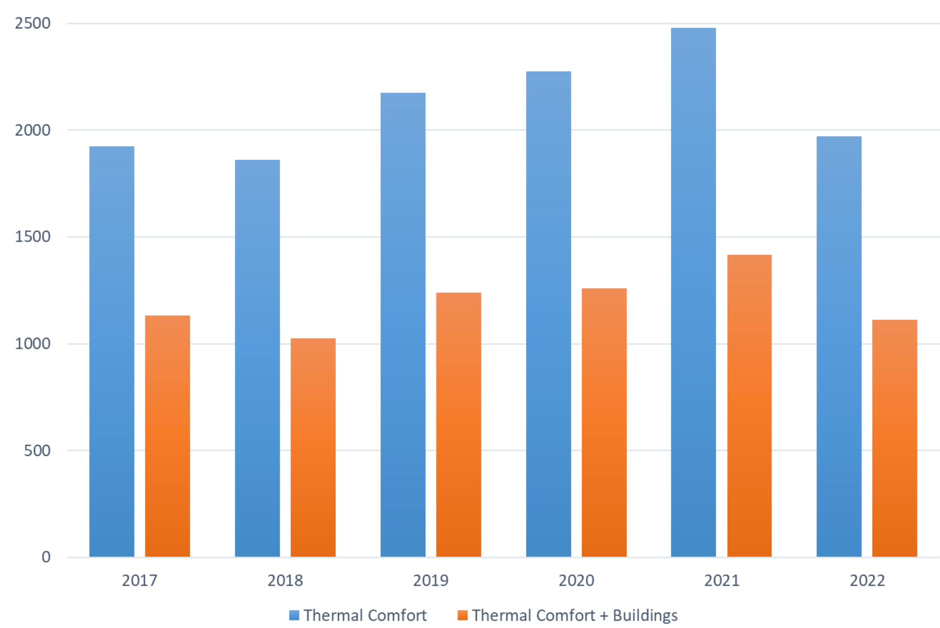

Figure 2.1. Published papers from the Scopus database, referring to “thermal comfort” and “thermal comfort” + “buildings”

To be distinguished from the existing literature, this paper addresses the following open research questions:

- identification of the parameters which were considered as inputs in personalized thermal comfort modelling,
- review of the technologies and methods used to collect the information on the defined parameters,
- contributions and limitations of the existing technologies,
- questioning the perspective for further integration of the proposed solutions with the smart building management system.

The main sources of the reviewed articles, i.e., existing research findings in Elsevier's Scopus [26] and Web of science [27]. The primary selection was obtained with respect to the following keywords: ("thermal comfort" AND ("sensor-s/ing" OR "wearables" OR "metabolic rate"). Studies that have these specific terms in the title, abstract or list of key words were searched for, since these were relevant for the herein conducted study. The considered articles are written in English with the years of publication being between 2017 and September 2022. After the primary selection, considering the research objectives, articles proposing data-driven personalized thermal comfort exploration were selected to the secondary examination, where the main goal was to systematize the research works offering smart technologies and methods which investigate personal thermal comfort for indoor conditions. The papers, which analyzed an insight into the individual's reaction to indoor environmental conditions, were considered to give novelty in this research area. The selection criteria are presented in Figure 2.2. Each paper was studied considering the predefined questions (research goals). The factors that affected personalized thermal comfort accuracy were divided in three levels as they were chronologically determined through experiments. The first level refers to the examination and selection of crucial parameters that affect the thermal comfort of the individuals, and which are therefore used as input information in the model development. The second level includes smart technologies used to retrieve relevant information about defined input parameters. Finally, the processing of the collected information (statistical analysis, machine learning) can be considered as the third level in the development of the personal thermal comfort models. The aim of data-driven approach in the development of thermal comfort modelling is the application in smart buildings, through intelligent management of heating and cooling systems. Division of influential factors in thermal comfort modelling is presented in Figure 2.3. [28]. The paper was structured accordingly. As a result, this paper provides further contributions: (I) systematization of inputs that are found to affect personal thermal comfort, (II) critical review of the smart technologies and methods used for sensing and detection of the defined inputs proposed in the available literature and (III) a brief insight into approaches of processing the collected data. The thermal comfort solutions in the domain of personalized comfort systems (local warming/cooling) were not included in this paper since it was above the main scope of this work.

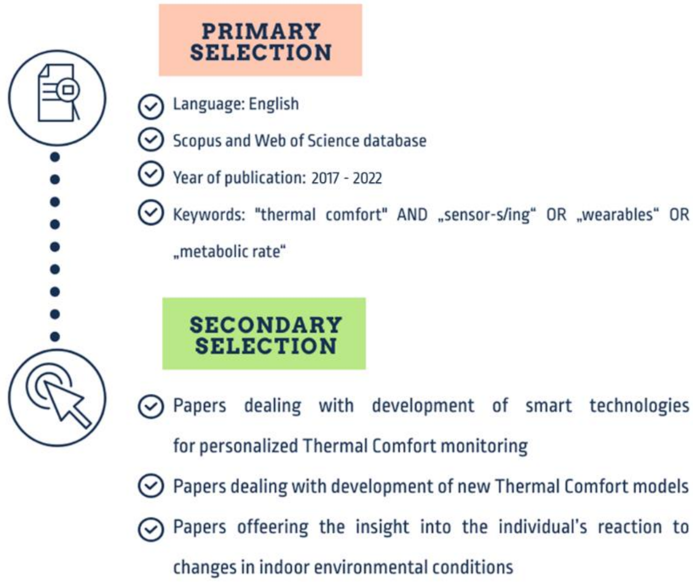

Figure 2.2. Paper selection criteria [28]

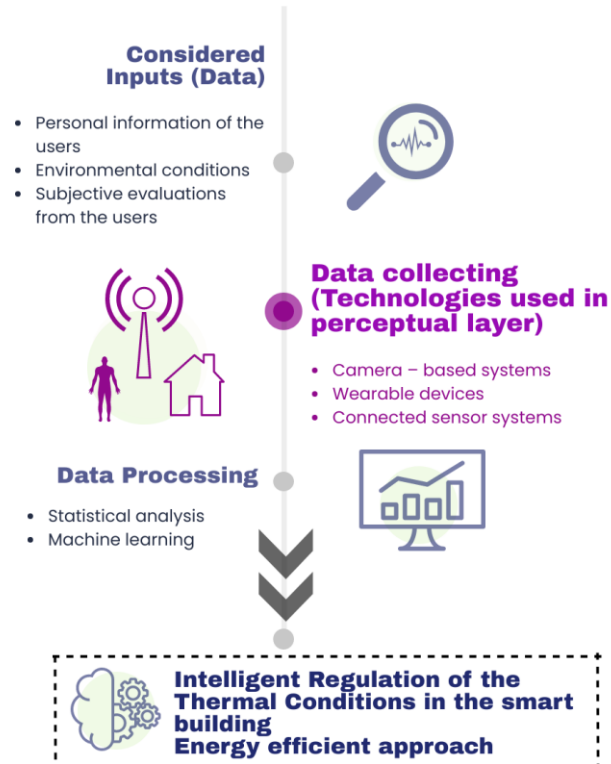

Figure 2.3. Division of influential factors in thermal comfort modelling [28]

3. OVERVIEW OF INPUTS THAT AFFECT PERSONAL THERMAL COMFORT

The selection of influential parameters for thermal comfort evaluation is partially determined by specific standards, while some additional parameters were used in experimental approaches that could have impact on thermal comfort. Regarding the standards, thermal comfort is affected by four environmental variables and two occupant-related, and the PMV model is the prevailing TC indicator. When designing the personalized thermal comfort models, researchers are prone to rely on the findings from the standards, but some additional parameters may be included in the evaluations if they are brought into relationship with TC. The examined studies propose diverse solutions to specify the inputs for the models more precisely. They mainly consider pre-defined parameters, trying to understand the best approach to determine MET and CLO values and the overall thermal comfort of occupants in building facilities. The inputs which were considered for the personal thermal comfort models in the examined studies are summarized in the upcoming section. In their research [18], the authors expressed MET as the function of room air temperature together with air velocity, taking into consideration the physiological adaptation effect. It was assumed in their work that the mean radiant temperature is equal to the room air temperature and the relative humidity is set to be a fixed value - 50% while the CLO was obtained from tables in the standards. They also considered the feedback from the participants through conducted subjective surveys. The assumption for the mentioned approach was a sensitivity analysis conducted by [29] and supported by [30], who revealed that personal parameter such as MET is found to have the highest impact in determining the PMV among all the variables. Similar to the previous [25], also presumed the MET to be the most influential parameter affecting personal thermal comfort. In order to develop a valid method, the experimental conditions were defined: the CO_2 concentration was kept below 1000 PPM, air temperature, MRT, air relative humidity, air velocity were measured as the conditions in the experiment room. The heart rate data were collected together with the invariable information (age, gender and weight) of the subjects and used for the calculation of the MET value in accordance with the international standard for metabolism, ISO 8996. Ultimately, the difference in metabolic rate was analyzed based on gender and body mass index (BMI).

In [31] the authors limited their study to TC in the cooling mode. The influence of all six PMV variables was analyzed with respect to the energy consumption of the cooling systems, in order to develop a controller based on thermal comfort inputs. The analysis indicated that the indoor air temperature is the most influential factor for PMV > 0 and followed by MRT, MET, and indoor air velocity. The previous is important to notice when setting the target temperature in summer period. In cases when PMV < 0, MET is determined as most influential, followed by temperature of the air, CLO and MRT. Previous directs that metabolic rate can be considered as the most influential factor for winter conditions when setting required temperature. In work [32], the authors demonstrated that the change in MET and CLO values have a great effect on the personal TC. For developed IoT-based personal TC, suitable for an accommodating environment, i.e., mean radiant temp, room air temp, air velocity, relative humidity, CLO and MET were combined to facilitate the individuality of the developed model. However, their experiment was restricted to three activities: sitting, standing with little walks, and sleeping, and the metabolic rate values were taken from the table for the given activities.

Study [33] considered the development of a dynamic monitoring system regarding thermal state of the occupants under two activity levels, i.e., low (rest) and high (cycling) level and three temperature levels (5°C -low, 24°C-normal and 37°C-high). The MET, average skin temperature (including locations on the body: scapula, chest, and arm), heart rate, heat flux and aural temperature were measured during the experiments. It is indicative from the provided results that a "multi-input-single-output (MISC) discrete-time transfer function", is best to estimate personal metabolic rates for the considered activities, as MET was inferred to be not-easily/invasively measured. Aural temperature, average skin heat flux and heart rate, were considered as input variables for MET prediction. In the same work, personal thermal sensation votes were included through questionnaires based on the ASHRAE seven-point questionnaire.

Study [34] considered ankle and wrist skin temperature, heart rate, and wrist accelerometer, together with meteorological data and surveys, when developing a personal thermal comfort model. Parameters were selected based on the findings from the previous conducted studies which reported that heart rate [35], skin temperature [36] and physical activity [37] have an impact on the thermal comfort. However, the indoor room conditions were not considered, which could be valuable information as the subjects spent most of their time indoors. The results imply that skin temperature on the ankle is more important parameter to thermal preference when compared with the temperature on the wrist, or heart rate (intermediate ranges), while the heart rate could be a good indicator at a high value for cooler conditions.

The study in [38] collected information on air temperature, relative humidity, CLO, wrist skin temperature, wrist skin relative humidity, heart rate and thermal sensation vote (TSV) in multi-occupant offices. The parameters were selected based on the conclusions from the literature review and measuring device settings. The collected data was used to build a model for prediction of the TSV based on the indoor environmental and physiological data. The study relied on the hypothesis based on the insight in the collected data relations and literature review. The temperature difference of skin on was nearly linearly related to the difference in the air temperature. The skin relative humidity variation was assumed to be the same as the air relative humidity variation. Metabolic rate was estimated from the heart rate according to the ISO 8996 methodology [39] and guidelines in literature [40]. The TSV prediction with the collected data resulted with R2 = 0.89. However, the conducted study hasn't considered the influence on heart rate by other factors (age, physical fitness etc.).

Human subjective evaluation is essential in modeling TC conditions and was discussed in [41], and the ASHRAE 55 questionnaire was used to ponder the difference between occupant subjective TC and system TC levels. Indoor temperature, air relative humidity, air velocity and participant heart rate were included as parameters through the experiment and selected based on the previous research findings in [42] study about the applicability of the heart rate as a predictor for thermal comfort and [43] experimental study on thermal comfort. Heart rate was also selected as input since there are various commercially developed technologies for heart rate data acquisition (i.e. smart watches, wristbands, chest straps etc.). The results revealed close correlation of heart rate with respect to the environmental parameters in personal thermal comfort.

The authors in [44] observed influential parameters as for instance: hand skin temperature, pulse rate, ambient air velocity and temperature, mean radiant temperature and air humidity. The developed method included normalized skin temperature, spectral characteristics, pulse rate, and air temperature as inputs. A significant relation of pulse rate was revealed when predicting thermal state, subject to the user's BMI and gender. Warmer sensations cause raised pulse rate within females and occupants with low BMIs, while a pulse rate of high BMI occupants increases in warmer environments. However, these findings are based on an experiment with a young population in a controlled environment, only considering cool-discomfort cases. While developing „Robust non-intrusive interpretation“ [45], a room temperature, wrist skin temperature and facial skin temperature track was ensured. The results indicated importance of the facial skin temperature since it can be effective indicator regarding occupant thermal comfort. What is left to investigate is how to distinguish and detect different facial regions, and the impact of temperature gradients in these regions on the thermal comfort of individuals.

Heart rate variability was the main user - related input in the study [46] trying to establish whether a user is experiencing thermal discomfort. The experiments were conducted on max. of 13 participants. Simultaneously with the heart rate information, the environmental conditions were measured as well, i.e., air temperature (measured with thermocouples at 1.1. m height), air velocity (anemometer placed at 1.25 m from the window and 1.10 m from the ground), relative air humidity (0.7 m from the floor and 1.25 m from the window) and the globe temperature (1.10 m from the ground). The experiments covered cold – induced comfort, warm – induced comfort and transient air temperature. The authors highlighted that environmental parameters are important for prediction of thermal comfort and physiological information from the smart watch could be used as support for personal models development. In [47] skin heat exchange rates were explored on the face and wrist by coupling it with variations in skin temperature, air temperature and relative humidity. The correlation between heat exchange between human and environment, thermophysiological responses, ambient environment and thermal preference of the occupants were investigated. According to the main results, it was found that the considering heat ex-change rates have a better performance when predicting the thermal comfort of occupants in comparison with the case when employing ambient temperature and skin temperature as features. Their experiments were performed under controlled conditions, and it is still necessary to investigate these findings in field studies, where the parameters are generally less controlled. Similar to the previous study, [48] indicate that the wrist skin temperature and its time differential, together with the heart rate, can be used for estimating human thermal sensation accurately in different activity states. The experiment observed environmental parameters (indoor temperature, the concentration of CO_2, air velocity, and relative humidity), thermal characteristics, skin temperature, activity state and heart rate.

The study [49] collected temperature data of the user’s face, body skin, and the thermal sensation vote due to exposure to the environmental conditions in the thermal chamber for fixed MET (~1) and CLO (~0.15). The facial skin temperature measured on chin, nose, cheeks, and forehead was selected to represent the mean skin temperature (MST) since the ANOVA test result demonstrated that MST could distinguish thermal sensation with a 95% significance level. However, this approach isn’t without the limitations and facial region should be better explored for the thermal comfort investigation. It was reported in the paper that the nose and chin skin temperature cannot express thermal sensations for “slightly warm” and “warm”. Furthermore, the forehead and cheek skin temperature cannot accurately distinguish thermal sensation in the range between “cool“and “warm” and therefore cannot be used as representatives for MST. In the study [50] authors discussed TC for an indoor environment, considering average radiant temperature, ambient temperature, air relative humidity, wind velocity (indoor), CLO and MET. According to the conducted analysis, the ambient temperature has the highest influence on PMV (which was chosen as the TC standard in their study), while wind velocity and relative humidity have a low impact on the PMV. Research [51] analyzed variables which affect the PMV for the TC assessment such as energy metabolism, effective mechanical power, thermal insulation of clothing, indoor air temperature, average radiant temperature, CLO, indoor air temperature, relative air velocity, partial water vapor pressure (air), convective coefficient of heat transfer, and surface temperature of clothing in accordance with the non-linear PMV index formulation.

In the [52] the feasibility of detecting electroencephalogram (EEG) signals with an electroencephalogram was examined for determining if a person has reached thermal comfort, which may lay a foundation for some future research in this direction. This approach was based on the study (Yao et al., 2008) which reported the connection of the EEG signal variation in thermally uncomfortable state. Authors considered thermal comfort and hot discomfort cases, and the developed model almost had 90% accuracy in the discrimination between these two states, while the subjects were performed reading tasks. For perspective in thermal comfort modelling, cool discomfort cases should be investigated, as well as different types of activities. Also, the impact of other thermal comfort parameters should be considered such as air humidity, air velocity, etc. The potential change in user mental state was also not included in their investigation. EEG signal acquisition was also applied in [53] together with other physiological signals, i.e., photoplethysmogram (PPG), electrodermal activity (EDA), skin temperature and the body movement (3-axis acceleration). The experimental campaign took place in a controlled climate chamber, with pre-defined ambient temperatures, i.e., cold (16 ± 0.6°C), neutral (24 ± 0.9 °C), and hot (31 ± 2.4 °C).

Authors in [54] explored the effect of evaporation on the user's thermal state and thermal comfort when users are exposed to heat stress. The pro-posed approach aimed to predict evaporative heat loss was and to investigated if it would be suitable to determine thermal state and comfort. All variables according to their model could be calculated by direct measurements of air temperature, radiation amounts (solar radiation as well as infrared radiation), and skin temperature, except for evaporative heat loss which could be estimated from skin and environment approximations for humidity. The main limitation of their proposed work is directed on considering only one measuring point, assessing evaporation on human body anatomical regions.

The model for individual thermal comfort was proposed in [55], considering the human and environmental parameters. Air temperature, speed and humidity, position of the user, type of the user activity and clothing as well as personal information of the user (age, gender, height, and weight) were selected as the inputs for the thermal comfort model in their investigation. The activity type was taken from the corresponding activity table, and only four cases were considered (lying, sitting relaxed, sitting and working and standing relaxed). In study [56], the authors were keeping track of the air temperature and relative humidity, clothing temperature and exposed skin temperature. The analysis showed that skin and clothing temperatures, at different body locations, are crucial for the thermal comfort level of the occupant. As the clothing insulation was kept constant during the experiment, it is reasonable to examine the effect of different clothing insulation on the clothing temperature measurements. The results indicated that it is promising to include some additional parameters in their model (such as BMI).

Furthermore, in [57], the authors introduced skin conductance as a feature in the personal comfort modelling. The personal thermal comfort was investigated in various combinations along with skin temperature, clothing, heart rate, MET, air temperature and humidity. This way, individual variables could be separated and individually evaluated. Indoor air temperature and skin temperature were found to be the most prominent to capture the occupant thermal comfort followed by MET. Using clothing resistance, it is found to result in less accurate predictions of thermal comfort. Heart rate is reported as a relatively accurate predictor of thermal comfort. Other data were also collected and provided by the wearable devices, such as user acceleration and angular velocity, number of steps, ultraviolet radiation exposure intensity and total number of calories burned by the wearer. The work did not report the importance of the mentioned data in the personal thermal comfort modelling. The authors in study [58] also investigated skin conductance together with skin temperature and heart rate as physiological data. Also, motion-based activity was captured to calculate the user's MET, based on usual office activities (e.g., walking, sitting, climbing, standing, stairs, descending stairs, etc.). Ambient temperature and relative humidity data were collected as environmental inputs. It was noted that skin conductance, heart rate, and metabolic rate can be considered as strong predictors for "cool" and "warm" dis-comfort cases regarding one user. For a different user, ambient temperature was found to be a good predictor regarding discomfort cases. It was also presented through con-ducted experiments that activity-based metabolic rates can be considered as a strong predictor of personal thermal state for most users (9 out of 10). An exceptional case was noted with one subject for whom activity-based metabolic rates did not make any significant impact in predicting thermal states. The authors concluded that the impact of the considered inputs on thermal comfort can differ between subjects. In experiment [59] authors have included the facial movement data (facial expressions) as a feature in thermal comfort modelling examining it in relation to the galvanic skin response and heart rate changes as well as the subjective response. Air velocity, relative humidity, black globe temperature and air temperature were chosen as indicators of the room environmental conditions. However, any significant results for thermal comfort detection were not reported and this approach requires further investigation for the application in mentioned context.

The parameters which were considered as inputs for personal thermal comfort models in the reviewed literature are grouped as follows and summarized in Table 3.1.:

- Environmental conditions,
- Personal information of users,
- Subjective evaluations from users.

Table 3.1. Inputs considered for personal thermal comfort modelling

Reference	Environmental data	Personal data	Subjective response
[18]	MRT, Room air temp, relative humidity, Air velocity	MET, CLO	Y
[25]	Air temperature, MRT, air velocity, relative humidity	MET, heart rate	NA
[31]	MRT, Room air temp, relative humidity, air velocity	MET, CLO	N
[32]	MRT, Room air temp, air velocity, relative humidity	MET, CLO	N
[33]	Ambient air temperature	Heart rate, aural temperature, average skin temperature, skin heat flux, core temperature, metabolic rate	Y
[34]	Meteorological information (outdoor conditions), temperature near the user (on the outside of the pants)	Skin temperature at wrist and ankle, heart rate, and wrist accelerometry	Y
[41]	Indoor temp, relative humidity, air velocity	Heart rate	NA
[44]	Air temperature and air velocity, relative humidity, and MRT	Hand skin temperature and pulse rate	Y
[45]	Room temp. and humidity	Wrist skin temp., facial skin temperature	Y
[47]	Air temperature and relative humidity	Heat exchange rate, wrist skin temp., facial skin temperature	Y
[48]	Indoor temp., CO2, Air velocity, Rel. humidity	Skin temp., Active state, Heart rate,	Y
[50]	Ambient temperature, MRT, relative humidity, indoor wind speed	CLO, and MET	NA
[51]	Indoor air temperature, MRT, relative air velocity, partial pressure (water vapour)	MET, CLO, Surface temperature of clothing, coefficient of clothing, coefficient of heat exchange by convection	NA
[52]	Indoor temp	MET, CLO, brain activity	Y
[54]	Global solar radiation, ground-sourced and atmospheric infrared radiation, ground-reflected solar radiation, the air humidity and temperature	metabolic heat generation and skin temperature	Y

[55]	Air temperature, air humidity, wind speed around the person	MET, CLO, the body position and user personal information (gender, age, height, and weight)	Y
[56]	Office temperature, relative humidity	Exposed skin temperature and clothing temperature	Y
[57]	Air temperature, air humidity	Skin conductance, skin temperature, clothing, heart rate, MET	Y
[58]	Ambient temperature and relative humidity (RH)	Heart rate, skin temperature, electro-dermal activity, motion-based activity	Y
[59]	Air velocity, relative humidity, black globe temperature, air temperature	CLO, fat percentage, height, weight, age, gender, period of residence in the observed geographical area, galvanic skin response, heart rate, facial muscle movement (facial expression)	Y
[38]	Air temperature, relative air humidity	CLO, wrist skin temperature, wrist skin relative humidity, heart rate	Y
[49]	Air temperature	Age, BMI, face skin temperature from 4 points; forehead, nose, cheek, and the chin	Y
[17]	Air temperature, relative humidity and CO_2 level	MET, gender, age	Y
[53]	Air temperature	Heart rate, skin conductance, EEG, skin temperature	Y
[46]	Air temperature, air velocity, relative air humidity, globe temperature	Heart rate	Y

From the results of the conducted review, that are presented in the Table 3.1., it can be concluded that room air temperature is the main indicator for the indoor environmental conditions. Relative air humidity, air velocity and mean radiant temperature are also frequently used environmental parameters in thermal comfort modelling, following the well-known Fanger's logic developed through the standards. Additionally, outdoor meteorological conditions, CO_2 level, black globe temperature and partial water vapor pressure in the observed environment where included some studies. The carbon dioxide level is reported to be crucial factor in thermal comfort modelling in the conducted study [17]. The frequency of the environmental inputs inclusion in the considered literature is presented in the Figure 3.1. (based on the literature review presented in the Table 3.1).

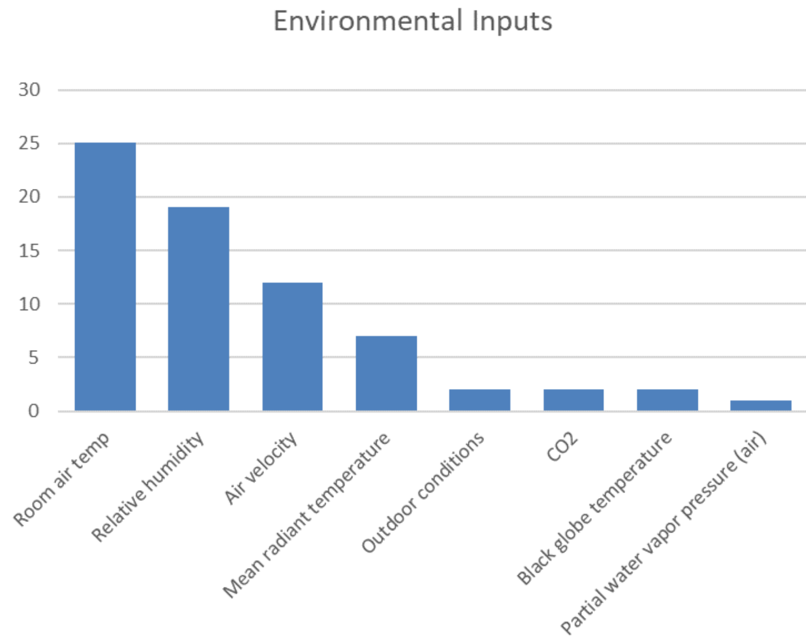

Figure 3.1. Environmental inputs in the thermal comfort modelling

When considering the user – related parameters, MET and CLO are frequently included in the evaluation. In order to gain a better insight into the response of users to changes in environmental conditions that can be indicators of thermal comfort, additional parameters were considered in the reviewed studies. Skin temperature was used the most commonly on different body regions i.e., face, wrist, ankle, scapula. Skin temperature has been shown to be applicable as predictor for MET [34], thermal sensation [49] and thermal comfort [57], depending on the approach which was used in the experiment. Heart rate was also frequently used as parameter in the considered literature. Moreover, heart rate was reported to be indicator for thermal comfort in studies [41] and [57], thermal sensation in [48] and for thermal preference of the user in cooler conditions [34]. Also, heart rate data was used for calculating MET in accordance with ISO 8996 standard methodology [39] and guidelines in literature [38]. Skin conductance was introduced as feature in the personal comfort modelling [57]. In combination with MET value and heart rate, skin conductance was found to be a strong predictor for “cool” and “warm discomfort cases” [58]. The application of the user – related inputs in the considered literature is presented in the Figure 3.2. (based on the literature review presented in the Table 3.1.). Other user – related parameters such as skin heat flux, activity of the user, aural temperature etc., were included in the reviewed literature, but additional research is necessary in this regard to draw relevant conclusion, since there is a quite low number of conducted studies.

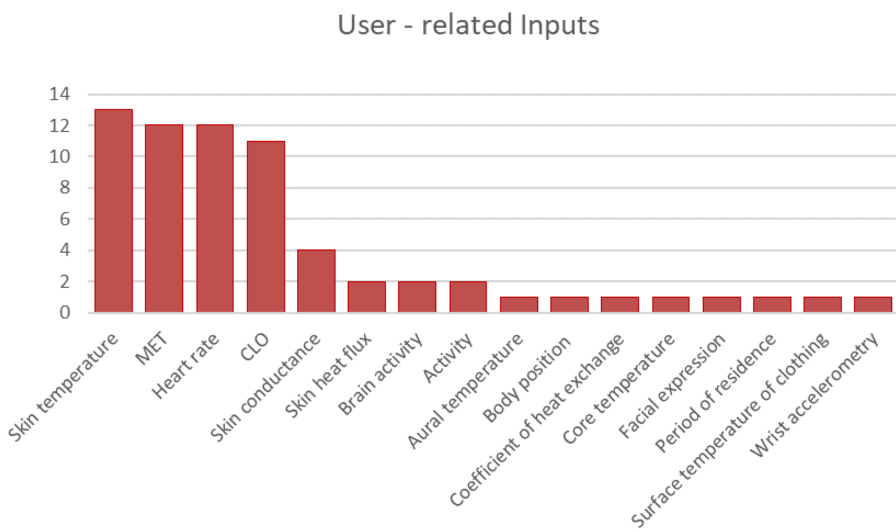

Figure 3.2. User - related inputs in the thermal comfort modelling

4. SMART TECHNOLOGIES AND METHODS FOR INVESTIGATION OF PERSONAL THERMAL COMFORT

When approaching personal thermal comfort modelling, various researchers have offered their contributions by proposing innovative smart technologies and methods for detecting thermal comfort parameters in the perceptual layer. As the importance of defining relevant inputs for the model is well known, another crucial factor, which affects the model's accuracy, is the technology that is being used in the proposed evaluation methodology, as it has a direct impact on the data provided to the model.

While the environmental variables are suitable to be measured by different commercial sensors, the personal variables (MET and CLO) usually remain being estimated roughly from the tables defined in the standard [31]. The method for reading off the MET and CLO values from the table (or the activity journal) belongs to the category of "observation", and can have an error of up to 20% [30]. According to the methodologies from the ISO 8996 standard, there are four different levels of accuracy when measuring metabolic heat production in the body [60]. Level I and II methods (screening and observation) consider the approximate value of the metabolic rate value and do not take into consideration the individual characteristics of the users. Estimations, tables as well as other input data provided in the standard refer to the "average" individual. The method of measuring the metabolic rate on level III calculates MET on the basis of measuring the heart rate (real time). The main drawback of the level III method is that it neglects psychological factors, but the error rate is less than 10%, while the accuracy is better than that of methods on levels I and II. Direct calorimetry measures the heat transfer from the body into the surroundings in a certain amount of time. It is usually measured by using complex and demanding technology, and for this reason, direct calorimetry is rarely used in thermal comfort investigations. Level IV methods account for being the most accurate methods but require more complex technologies and sensors of very high resolution and are not suitable for continuous on-site measurements. They are shown in Table 4.1. [39].

Table 4.1. Levels for determining metabolic rate [39]

Level	Method	Accuracy
I Verification	Classification with regard to occupation Classification with regard to activity	Rough information Very high risk of error
II Observation	Tables for group classification Tables given for specific activities	High risk of error Accuracy ± 20%
III Analysis	Measuring the heart rate in determined conditions	Medium risk of error Accuracy ± 10%

IV Expertise	Measuring oxygen consumption Direct calorimetry	Low risk of error Accuracy ± 5%

In the existing literature, different approaches were also considered and mostly rely on the principles of method II, III and partially IV regarding ISO standards. The applied technologies vary among studies to provide accurate data to the developed data-driven models and will be discussed in the upcoming sections. Technological solutions can be categorized according to their data acquisition principle. In this regard they are divided on connected sensor systems, camera-based technologies, and wearable devices.

4.1.Connected sensors systems

In work [33], the climate chamber experiment was conducted, with a premise that the best way to estimate individual MET is by continuously measuring heart rate, aural temperature, and average heat flux. Individual thermal sensation then can be predicted by using the classification model and estimate the MET as well as the core body temperature. An individualized thermal sensation prediction can be used for adjusting the indoor conditions to be compliant with the thermal comfort of the users, and thus prevent possible overcooling or overheating. The suggested approach provides both real-time data and individual user data. To gather important user-centric data, the temperature sensor (Shimmer-Sensing, Dublin, Ireland) was used for skin temperature measurements together with two patches for body temperature (greenTEG, Zurich, Switzerland) and two heat flux patches. A wireless ear Bluetooth temperature sensor (Cossinus One) was used to estimate core temperature. Heart rate was monitored by using a polar H7 ECG (Polar, Kempele, Finland) strap, which was placed under the chest of the subject, at a sampling frequency of 128 Hz. In order to reckon the correlation of the metabolic rate with the measured variables, the MetaMAX 3B (CORTEX-Medical, Leipzig, Germany) spiroergometer was used to calculate the metabolic rate (indirect calorimetry principle). The environmental conditions were predefined, as the experiment was performed in a climate chamber for three different temperatures from 5°C - low, 24°C - normal and 37°C - high, and two activity levels; low (seated) and high (cycling). For the further improvement of the proposed system, the main request would be to examine the performances in dynamic environmental conditions and for different activity levels.

Work [34] proposed fourteen personal thermal comfort models with various machine-learning algorithms in order to predict the thermal preference of the subjects. Based on the insight from the previous studies, the authors decided to consider wrist and ankle skin temperature, heart rate, and wrist accelerometry. The sensors for monitoring the occupants were selected based on their convenience to wear during the day. The iButton device (DS1923, Maxim Integrated Products, U.S.) was used for wrist and ankle skin temperature measuring every 60 seconds. The polar H7 chest-strap (Polar Electro, Ltd., Finland) was applied for heart rate measurements in second intervals. A small cellphone (POSH Mobile, Ltd., U.S.) was set in a wrist pocket, which detected the activity level of the subjects. The developed models have the best prediction outside the thermal neutrality zone which can be useful in practice because it is of interest to avoid people feeling over-cooled or over-heated. The developed models lead 78% accuracy, and it is greater than in the conventional models; PMV and adaptive. The proposed approach enables real-time and individual subject data, which is an important advantage when compared to conventional models. However, their approach is lacking indoor environmental data, which might be a limitation for further possible implementation into HVAC systems.

A structure for the automatic HVAC control in smart buildings was elaborated in [51]. The system architecture aimed to optimize the energy efficiency and thermal comfort for the indoor environment in smart buildings. The proposed solution relies on non-linear PMV formulation updated with the data collected from the sensors. Data on air velocity, air temperature and humidity values were collected by sensors. Occupant activity and clothing insulation were left to be estimated with the given tables from standard. For the sake of the model, simplified assumptions were provided: the MET was considered to be a fixed value at 70 W/m^2 (sedentary activities), CLO was considered for working clothes at 0.14 $(m^2K)/W$, together with the thermal insulation of a chair 0.016 $(m^2K)/W$. The air velocity was kept in the interval from 0.15 (m/s) to 0.25 (m/s), and it was thus considered as a constant and equal to 0.1 (m/s). An experiment implementing the proposed system was deployed in a real environment in the campus building as proof regarding the concept and demonstration of control algorithm effectiveness. Particularly, significant energy savings were obtained in comparison to standard regulation, based on convectional thermostats. Thermal comfort was obtained despite the present disturbances by occupant's variations and the windows / doors opening. A similar approach was found in [50] and the application of the technology is described in [61] by the same authors where "Thermal Comfort Environmental Monitoring System Based on IoT Architecture" was proposed. The thermal comfort PMV index was determined in accordance with the ISO 7730 standard [62]. Environmental variables were updated in the model with actual sensing data while clothing insulation is considered as a fixed value (0.6 clo), as well as the metabolic rate (1.2 met, 70 W/m^2). Sensors for air temperature and humidity and wind velocity collected the relevant data, while CO_2 and particulate matter were only used for reference. If the system operated in energy-saving mode, it could provide additional 11.3% of energy savings. As much as these systems seem to be effective on the side of HVAC control, the input data might suffer from estimation uncertainties in terms of thermal comfort. It is recommended to try to provide real-time occupant information (MET, CLO) to get a better insight into user feedback and consider the individual differences among them.

A machine learning thermal comfort method was presented in [44], which predicts a personalized Thermal sensation index by sensing hand skin temperature, pulse rate and ambient air parameters with a set of connected sensors. The sensor network consisted of a Velocicalc 9545 sensor (TSI Inc., USA) to measure air velocity air temperature and relative humidity, Transducer 845 (TSI Inc., USA) to measure air velocity, LM3 (TSI Inc., USA) for Black Globe Temperature measurements. The skin temperature measurements were performed with an Exacon D-S18J (Libelium Co., Spain) sensor and pulse rate was detected by using a Pulsioximeter (Libelium Co., Spain). The proposed method is data-driven and can be considered as adaptive and provide real – time data. Due to the popularity and availability of wearable sensing technology, it can be applied individually to the users. Also, by including air temperature as a parameter to the model, it opens the opportunity to further model development considering the integration of HVAC control via the Internet-of-Things to meet energy-efficient and comfortable building requirements. On the other hand, to provide more reliable data, future improvements regarding the model should be directed towards more dynamic environmental conditions since cool-discomfort was the only one considered until now. As a younger population was exclusively examined, it is recommended to investigate a larger group of subjects, with different ages in various activity levels. A thermal comfort evaluation model developed in [55], proposed an artificial neural network, based on PMV model parameters with updated data from environmental sensors. Personal parameter data (MET, CLO) were entered from the tables. They also considered age, gender, height, and subject weight, which were reported through a questionnaire in two parts. The first part included basic information regarding the subjects such as height, age, gender, weight. The second part considered the thermal comfort parameters, i.e., type of clothes, type of the activity performed by occupants, and their thermal comfort perception on a 7-point scale. The accuracy of the proposed model is reported to be better than the PMV. The mean squared error (MSE) of the developed model was about 0.39, while for the traditional PMV model MSE was about 2.1. This approach does not consider the individual differences among users, which might be a cause for uncertainties in a wider use. The proposed system has the possibility for the integration of thermal information in a building model in order to realize energy savings by optimizing the HVAC system, with regards to user thermal comfort.

Furthermore, in study [47], a connection between the heat flux of facial and wrist skin as well as personal thermal comfort was examined under transient environmental conditions. The heat flux sensor consisted of many thermocouple junction pairs across the heat flux gauge and thermocouple. The developed methodology was applied when detecting both the heat exchange rate from the skin, and skin temperature. A DHT-22 sensor was connected with an Arduino microprocessor, for the air temperature and humidity measurements at 0.5 Hz in a temperature range from 20°C to 30°C. The heat exchange rate is found to have high positive correlations with thermal preferences and a high negative correlation with air temperature and skin temperature (median -0.87 and -0.95). When compared to the skin temperature as well as surrounding temperature as features, the skin heat exchange rate had better performance results regarding the thermal comfort preference inferring of subjects. In further experiments, the authors suggest the integration of heat flux sensors with wearable devices to provide the users a more comfortable experience. A s skin surface and sensor contact are needed, which could be considered as a restriction when designing prototype devices. The impact of other environmental factors should also be examined, as they can affect user experience as well.

A slightly different adaptive approach was presented in work [63], where the authors bypassed personal parameter detection from the subjects, relying on the subjective responses from the users in combination with the environmental air temperature and ambient light level monitoring. The app was designed to collect factors such as age, gender, and type of the user (student/staff/faculty designation) and subject thermal sensation for the possible future manipulation of the HVAC system. The interface of the app was designed as a “virtual thermostat” to give the possibility to anonymously report the subjective experience of the room temperature conditions by virtually lowering or raising the temperature (± 0,5°C). During the examined study, the app was only of informative nature, and it did not provide any connection with the HVAC system in order to actually change the room temperature, but instead was recorded as feedback for future adjustments. The system integrated wireless Bluetooth low energy (BLE) proximity beacons to trigger the app on mobile phones when the user passes in the vicinity of the beacon. Temperature sensors were embedded in the beacons used in the study to provide the environmental data as well. The proposed solution presents a flexible, low-cost participatory sensing approach, which is non-invasive to the users. In case of further development, it has the potential to reduce the carbon emissions of the HVAC system electricity consumption. However, prior to this, the system should be updated with more accurate sensing devices and include user-related parameters (clothing and metabolic rate). Another aspect worth investigating would be the dynamical thermal sensation change of the occupants, to provide queries at the right moment to register discomfort triggers as much as possible, and simultaneously avoid subject fatigue caused by reporting the query [13].

4.2.Camera-based technologies

A thermal comfort detection approach was proposed in [25] through a non-invasive system using a Kinect camera (contactless sensor), which registers the behavior of the user and thus the activity of the users can be extracted. During the "learning" process of the model, subject heartbeat data (using the Fitbit™ bracelet) was collected together with the environmental parameters in controlled conditions using sensors. Artificial intelligence (AI) was able to learn image information and MET for certain behaviors. The MET value was calculated in accordance with level III ISO 8996 standards [39]. Using MET values and kinect camera images, deep learning was achieved to estimate the thermal comfort of the users. The model was formed to predict the metabolic rate using a kinect camera so that it could be applied without the further use of sensors which is illustrated on the Figure 4.1. Their approach resulted with a non-invasive and contactless method, while on the other hand, the individuals may feel discomfort due to being recorded. Moreover, the available data are limited with the camera angles.

Figure 4.1. Illustrative representation of using Kinect-camera for thermal comfort detection [25]

An IoT based thermal comfort control system was elaborated in [32]. A temperature sensor, air velocity sensor and a humidity sensor were used to provide the indoor environment information. A video camera was applied to detect the metabolic rate, as well as the clothing insulation by observing occupant behavior. Occupant activity was captured by video camera and fed into a pose detector – OpenPose to extract the pose-based key points. Human activity was determined based on the extracted features. Possible indoor activities were divided on sitting, standing with little walks, and sleeping. The collected images were divided accordingly to be assigned with the corresponding tabular metabolic rate values. Clothing insulation was obtained by extracting the color histogram, Gabor filter and Hu invariant moment (captured individual images used for classification). Four typical clothing classes were employed in their system, together with clothing insulation values; short-sleeved shirts, long-sleeved shirts, jackets or sweaters, and cotton coats. The given system can provide real-time information on indoor thermal comfort conditions. On the other hand, it does not consider the personal differences in metabolic rates among the individuals, as it assigns the same MET value to all users, relying just on their activity. Furthermore, the system is limited by considering only three MET and four CLO values. Additionally, the users may feel discomfort due to video camera recording and the available data can be restricted by the camera angles as an already noted issue in the previous study.

Another camera – based approach was described in [45] with a thermal and kinect dual camera system aiming to extract skin temperature and predict user thermal preferences at different angles and positions. The proposed system implements human detection (RGB camera) and provides distance information with depth sensors. Temperature measurements are taken with a thermal camera. The system was verified through the monitoring of skin temperature on the face for 16 subjects in a multi-occupancy experiment with two subjects at a room temperature range between 20°C and 27 °C. The room temperature and humidity sensors collected the information of the environmental conditions. The results showed that the facial skin temperature increased in all subjects along with an increase in room temperature. It was also found that skin temperature variations are linked to the comfort states delivered by the occupants through the provided questionnaire. Still, the facial region should be investigated more thoroughly because the cheeks and nose seem to be more indicative to the thermoregulatory process of an individual. The proposed approach was positively evaluated by the subjects in terms of privacy issues, usefulness, and non-intrusiveness. The system should be tested on a larger population, and in more dynamic environmental conditions, which indicates the limitation of the work. Also, as noticed by the authors, additional challenges may arise in larger space examination including more subjects simultaneously, for instance increased viewing distance, occlusions, and occupant registration.

The facial temperature was also investigated in [49] with low-cost thermal camera in environmental chamber. The experiment was planned as initial step for HVAC control systems based on thermal comfort detection. The thermal camera temperature readings were compared with data from thermocouples for the same facial regions. It was reported in the paper that thermal camera is less sensitive than thermocouples and has more diffused measurements of the face skin temperature. It was then concluded that the thermal camera readings of the face skin temperature result with low accuracy of the thermal comfort prediction. Another limitation of the proposed study is that it used data from only 17 male respondents and females are reported to have a higher thermal sensitivity. Furthermore, thermal comfort model was explored in [56] for transient conditions using a three-camera system (color, depth and thermal). The system was designed using off-the-shelf components: a combination of depth sensors and a color camera (kinect), to identify and observe the occupants. The thermographic camera (flir lepton) was used to detect the temperature of the occupants and a point infrared sensor (MLX90614) was used for thermographic camera calibration. During the experiment, two parallel measurement sets were obtained. The user's skin temperature and clothing temperature were recorded continuously from different locations on the body (e.g. arms, chest and head) during the experiment, using the above-mentioned sensing platform, which was placed facing the subject. The thermal profiles were extracted for each body part. Room temperature as well as relative humidity were recorded in a one-minute period, using a sensor placed near the subject. MET (1.1 met) and CLO (0.54 clo) values were kept constant during the experiment. The results revealed that the difference in temperature on the human body was correlated with thermal comfort. The collected data also showed that the skin temperature variance over a small surface was highly correlated with thermal comfort. The authors suggested that the proposed approach could lead to a smart heating and cooling system operation which can avoid unnecessary contact with occupants. Further research should be directed towards system evaluation with different building types (residential, commercial, and industrial), followed by different occupant activity levels and different clothing insulation levels. Privacy concerns should also be investigated more thoroughly.

Experimental setup for the camera-based system was proposed in the reasearch [59] for facial muscle movement (facial expressions) detection through the iMotions software using Logitech C925e Webcam high-definition camera. Additionally, shimmer wearable sensor platform - Consensys GSR Kit GSR was used containing optical pulse sensor (earlobe and finger), galvanic skin response (GSR) finger electrodes, biophysical leads and a wrist strap for biometrical data collection. The experiment was conducted in the environmental chamber where air and black globe temperatures were measured near the participants by Pt 100 sensors. The authors have presented the framework for extraction of the facial movement data through the iMotions software, and synchronization with the biometrical data from the shimmer sensing platform. On the other hand, the implementation of the air temperature data form the other sensor isn't enabled in the proposed system. Although the latter system has provided relevant data, it hasn't been validated in terms of thermal comfort detection property in the considered paper.

4.3. Wearable devices

In [48], the authors discussed smart wristband devices for detecting the personal parameters of the users, i.e., wrist skin temperature and also heart rate by integrating the skin temperature sensor HES-S3 and heart rate sensor HXM-08L. The developed system continuously kept track of environmental conditions with the air temperature sensor (TS-FTD04), air humidity sensor (TS-FTD04) and CO_2 sensor (C7232A5810). The experiment was performed during the summer, considering the indoor temperatures from 22 °C to 30°C in step of 2°C. The potential use of skin temperature at the wrist and its time differential was examined. The heart rate was considered in thermal sensation detection with a high degree of accuracy for different activities. The conducted research indicated that thermal sensation is affected by the indoor temperature and the degree of thermal sensation is determined by the activity state of the subject. The estimation model in strenuous exercise is found to have the highest accuracy between the examined models. The thermal sensation model correlation coefficient based on the skin temperature at the wrist and heart rate is determined in the amount of 0.941, which implies high accuracy in thermal sensation estimation. The wrist skin temperature was not significantly correlated with thermal sensation of female subjects, which might be due to a small sample size (10 human subjects). Additional tests with a wider number of subjects would increase the accuracy of the results, which should be enabled. Winter season should be investigated as well to get more credible data. The proposed system has perspective to be further used for the automatic control of building heating and cooling systems towards an improvement in energy efficiency.

Another thermal comfort study with wearable device was conducted in [41] for the Cyber–Physical human centric system in the smart house. A hot-wire anemometer was used to register the air velocity, an SHT75 digital sensor was used for indoor temperature measurements and relative humidity, while an Apple watch series 4 collected the user data regarding heart rate. The results revealed that there is a linkage related to the environmental factors and heart rate in thermal comfort, which might be examined easily with commercially available sensors. Also, the connection between the thermal comfort and heart rate is correlated. The proposed approach has the perspective to be further used in an automatized regulation of heating/cooling systems. However, the system is unable to predict precisely enough the thermal comfort of subjects with respect to their preferences. The previous claim raises questions regarding the understanding of the thermal sensation questionnaire among subjects. It opens a new direction in TC research to explore if a revision is needed in the feedback collection to provide more accurate subjective responses from the users. In the literature [64] authors are proposing smart and less intrusive approach for feedback collection and in the [65] consider that it is necessary to reduce the number of questions in the thermal comfort questionnaires. To provide more in-depth answers, research would be necessary with respect to the raised issue.

Another application of wearable devices in the thermal comfort domain was examined in study [17] on four examined subjects during cooling season. Move 3, was used in the study, a specialized sensor for measuring the dynamics of the metabolic rate, which is based on user activity. Along with the wearable device, the data logger TROTEC BZ 30 was used for an indoor environment (relative humidity, air temperature and CO_2 level). Compared to the tabular metabolic rate values, the authors provided an insight into personal MET detection with regards to gender, age and daily individual dynamics. A machine learning model for MET prediction was developed and compared with measured MET values. It was concluded that the current tabular MET values do not provide precise enough results as they do not cover the dynamic changes in user behavior. However, the authors did not provide personal comfort models to predict the thermal preference of the users, which could be beneficial for further progress, possibly in the controlling of heating and cooling systems. Also, the experiment should be repeated on a larger sample to confirm the findings. The authors in [58] used the medical-grade Empatica E4 wristband as a wearable device which offers real-time acquisition of human-related data. It has specialized sensors for detecting physiological data; a photo plethysmography sensor (provides blood volume pulse, from which cardiovascular features such as heart rate may be derived), an electro dermal activity sensor (for skin conductivity), infrared thermopile (for skin temperature) and 3-axis accelerometer (captures motion-based activity). Data on environmental conditions (air temperature and humidity) were collected using a digital psychrometer thermo-hygrometer. A survey on subject thermal comfort was conducted every 5 min. The focus of the experiment was to study the feasibility of activity-based MET as a predictor for personal thermal comfort using a wearable device and environmental sensors. Predictive performances were noted to rise up to 8.5% with activity-based metabolic rates as a predictor. The conducted experiment also found to have weak prediction power for neutral thermal sensation. The previously mentioned findings cannot be observed without limitations. The conducted experiment was limited to 10 subjects, a predominantly younger population. Also, the experiment was conducted for only 4 weeks during summer, which leads to the conclusion that different weather conditions still need to be taken into account. Empatica E4 wristband was also used in [53] together with headband for EEG signal acquisition - Interaxon MUSE for user data acquisition. The authors applied wearable devices to evaluate the user's thermal comfort in the workplace conditions. The whole experiment took place in climate chamber. The machine learning classification accuracy of approximately 76% was reported by the authors. However, the study was limited with the number of respondents which should be widened. Also, real environmental conditions should be applied in order to overcome laboratory controlled environment and the sources of measurement uncertainty. The wearable device Microsoft Band 2 application in personal thermal comfort modelling was conducted in [57] together with a Hobo Data Logger UX100 and temperature and humidity sensors. Additionally, the mobile application was developed to collect the data from the wearable device and to enable the participants to report their feedback through the survey. Machine learning algorithms were successfully applied to pre-processed data to predict the comfort level of each subject, without the further necessity for a subjective response. Both the personalized and general model as well as the accuracy of the personalized models seems to be higher than the general model, which is the main finding of the work. In addition, the use of a galvanic skin resistance sensor (for skin conductance) improves the accuracy of the proposed models. An intelligent thermal comfort control of the building's HVAC system is proposed in the same work. Simulation results show a superior performance when compared to the average thermostat set-point use. The proposed controller should also be evaluated experimentally for a more reliable conclusion. The accuracy of the used sensors, application usability, and the small data size can be considered as limitations regarding the proposed thermal comfort model work.

Furthermore, in [38] Hesvit S3 wristband was used for biometrical data acquisition (wrist skin temperature, wrist skin relative humidity and HR). Environmental data was managed through the thermostat (Siemens 544–760A) and recorded via data logger (Sper Scientific 800,049). HVAC system control strategy was developed to calculate indoor parameters using the using the wristband collected physiological data and predicted TSV. This approach is more difficult to apply in multi-occupant offices since it is practically impossible for all occupants to feel neutral at the same time. Another limitation of the proposed system is in the wristband sensors readings. Sometimes the data might be measured inaccurately e.g., if the wristband isn't worn properly (too tight or too loose).

Another commercially available wearable device, Samsung Galaxy Watch was applied in [46] for heart rate information and the participants were asked to wear the device on the non-dominant hand while different environmental conditions. In their work, heart rate information was acquired from the photopletysmographic (PPG) sensor on the watch. This type of technology can be deeply influenced by movements of the arm or loose connection of the sensor and the skin.

The above-described smart technologies used for detecting the inputs in personalized thermal comfort models are summarized in Table 4.2. with respect to the technological approach, type of parameter they are monitoring, type of building they were designed for and the number of subjects that were examined in the reviewed study.

Table 4.2. Technologies used for detecting inputs in personalized thermal comfort models

Ref	**Environmental sensors**	**Sensors for occupant-related information**	**Type of building**	**Number of subjects**
Camera-based systems				
[25]	/	Kinect camera, Fitbit	office room	31
[32]	Air Temperature, air velocity and humidity sensors	Video camera	/	/
[45]	Room temperature and humidity sensors	Fusion of thermal and RGB-D cameras, wristband temperature sensor	office	16
[56]	Temperature, humidity sensor	Thermographic camera, depth sensor and color camera	office	30
[59]	Pt 100 air temperature sensor, pt 100 black globe temperature sensor, air humidity sensor	high-definition Logitech C925e Webcam, shimmer sensor platform - Consensys GSR Kit GSR	environmental chamber	29
[49]	/	Thermal camera (flir one)	environmental chamber	17
Wearable devices				
[17]	Data logger TROTEC BZ 30 for indoor environment (temperature, relative humidity and CO_2 level).	Move 3	office	4
[48]	Air temperature sensor (TS-FTD04), air humidity sensor (TS-FTD04), CO_2 sensor (C7232A5810)	Skin temperature sensor (HES-S3), heart rate sensor (HXM-08L)	environment chamber	10
[41]	Hot-wire anemometer sensor, SHT75 digital sensor	Apple watch series 4	residential building	6

[57]	Hobo Data Logger UX100, humidity and temperature sensors	Microsoft Band 2	/	3
[58]	Digital psychrometer thermo-hygrometer	Empatica E4 wristband	office	10
[38]	Siemens thermostat, sper scientific data logger	Hesvit S3 wristband	office	24
[53]	Climate chamber	Empatica E4 wristband	Climate chamber	14
[46]	Thermocouples, anemomometer, RH sensor, globe thermometer	Samsung Galaxy Watch	Experimental infrastructure	10 / 10 /13
Connected sensor systems				
[33]	Climate chamber	Polar H7 ECG strap, MetaMAX 3B spiroergometer sensor, Shimmer temperature sensor, gSKIN® bodyTEMP patches, in - ear Bluetooth temp. Sensor (Cosinuss)	three climate-controlled chambers	25
[34]	iButton for air temperature near subject	iButton device (skin temperature), Polar H7 strap (heart rate), small-size cell-phone for accelerometer data (activity levels)	/	14
[44]	Air temperature sensor (Velocicalc 9545, TSI Inc.), black globe temperature sensor (LM35, TI Inc.), air relative humidity sensor (Velocicalc 9545, TSI Inc.), air velocity sensor (Velocicalc 9545, TSI Inc.)	Skin temperature senor (Exacon D-S18JK, Libelium Co.), Pulsioximeter (heart rate sensor, Libelium Co.)	office room	20
[47]	DHT-22 sensor	Heat flux sensor, thermocouple	/	18

[50]	Various sensing devices (Arduino mega 2560), temperature, wind velocity, air humidity, PM and CO_2 sensors	/ (MET and CLO values are used as constants from the tables)	office	12
[51]	Net of sensors that perceives environmental conditions	/ (MET and CLO values are used as constants from the tables)	campus building	/
[55]	Wind speed, humidity and temperature sensor	For personal parameters, data entered from the tables	university research room	30
[61]	Air volume sensor, carbon dioxide sensor, fine aerosol sensor, temperature sensor and humidity sensor	/ (MET and CLO values are used as constants from the tables)	/	/
[63]	Air temperature, ambient light level sensors	BLE proximity beacon (Estimote proximity beacons), motion sensor	business (library, public or study gathering space, lecture hall, classroom, large open-plan studio)	52

From the conducted analysis, it can be concluded that in the considered thermal comfort studies, the technologies for data acquisition are based on the network of connected sensors. The principle for environmental data collection is similar through the literature and is based on the air temperature sensors in combination with various sensing devices that perceive environmental conditions i.e., relative humidity, CO_2, light level and wind speed sensors. Also, some experiments are conducted in the climate chamber with controlled environmental conditions regulated through the thermostat. User-related data acquisition is more complex and technologies in this regard are divided on the connected sensor systems, camera-based systems and wearable devices. Figure 4.2. shows the frequency of thermal comfort technologies application through the considered literature (the analysis was obtained mainly based on the references from the Table 4.2.).

Connected sensor systems are the most common technological approach in the thermal comfort experiments since it is the most flexible in terms of sensor application. This approach is found in the proof-of-concept experiments, to investigate the importance of particular inputs in thermal comfort modelling. It enables the application of various sensors for data collection and is not limited by the sensor positioning. It enabled the application of chest strap sensor for heart rate data, spiroergometer sensor, temperature sensors, temperature sensor patches, in - ear Bluetooth temperature sensor, pulsioximeter, heat flux sensor, thermocouples, proximity beacon and motion sensor to acquire user-related data combined with environmental sensors. However, this approach is restricted for the application within experiments since it is based on the raw sensors setup which is rather unpractical for real-scenario in the buildings.

Camera-based systems are established on contactless principle. Various recording technologies have been reported through the literature to capture different inputs for thermal comfort modelling. Thermal cameras capturing skin temperature recordings are most commonly used. Kinect camera and video camera were used for MET and CLO values determination through image recognition and pose detection. Additionally, experimental setup was proposed for facial muscle movement (facial expressions) detection through the iMotions software using high-definition web camera. However, the latter approach wasn't validated in the considered paper. As much as the camera based systems are non-intrusive to the users, their application might raise privacy concerns since the users might feel uncomfortable due to the fact that they are being recorded. Also, data collection is limited by the camera angle and the number of the people in recording frame. Another aspect worth reconsidering is the accuracy of the data collected through the cameras. It was concluded in the [49] that thermal camera readings of the face skin temperature result with lower accuracy when compared to the thermocouples. On the other hand, when determining the MET values from the user's behavior, the individual differences between the users are still not properly included. Further developments could be directed to the privacy issue, reading accuracy and more efficient detection in the circumstances when a large sample of occupants is involved.

Wearable devices represent integration of the sensors for the user-related inputs in one compact device which is non-invasive and practical for users to carry during the day. Through the literature, commercial wearable devices were used most frequently in form of the wristband and belt attachment. Authors in [48] have designed their own wristband device. By using wearable devices, the data on the user's heart rate, wrist skin temperature, activity-based metabolic rate, electro-dermal activity, and wrist skin relative humidity can be collected in various combinations, depending on the device selected. This approach seems to be promising for the users in the buildings since it is practical, non-intrusive and this kind of devices is already commercially available. However, wearable technologies are not without limitations. The data readings might be inaccurate if the device isn't worn properly (i.e., too tight, or too loose). In some situations, the accuracy of the sensors should be additionally investigated.

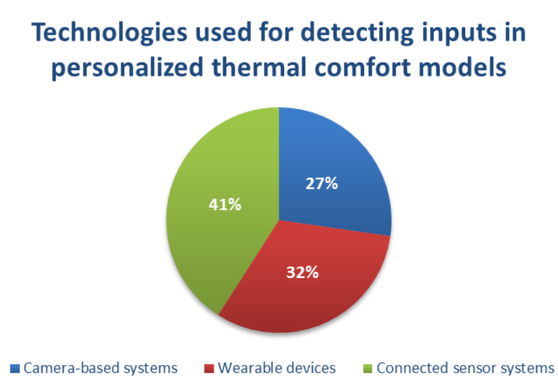

Figure 4.2. Technologies used for detecting inputs in personalized thermal comfort models

5. DATA PROCESSING

The personal comfort models differ from the conventional ones because they are developed individually for the users. Unlike conventional systems, personal comfort models are considered as data-driven because they rely on continuous collection of relevant data with appropriate techniques or sensing devices which are discussed and categorized in the previous section. Data-driven approach results with a huge amount of data used as input to the models aiming to predict the future thermal comfort of the individual. Along with accurately defined inputs and technological sensing devices, appropriate data processing is crucial in the personalized thermal comfort approach. Different machine learning (ML) and statistical modeling techniques are applied when creating personalized thermal comfort models [47]. Statistical analysis is used for defining the relationship between the parameters, while ML algorithms are applied for learning from the collected data and predicting the values of the thermal comfort indicators.

Through the literature a great variety of machine learning methods are used for classification and prediction of the thermal comfort indicators, based on the inputs selected for the experiment. Some studies also considered more than one algorithm to evaluate which one has the best performance. Most commonly used algorithms are extracted in the Figure 5.1., using references from the Table 4.2. According to the Figure 5.1., Support Vector Machine (SVM) is the most represented machine learning technique in the processed literature, with 8 studies applying it for the thermal comfort prediction, followed by Random Forest (6 studies) and Artificial Neural Network (ANN) (4 studies). SVM is reported to be one of the most popular supervised learning approaches in general. It can perform both linear classification as well as non-linear classification by adopting the kernel approach [57].

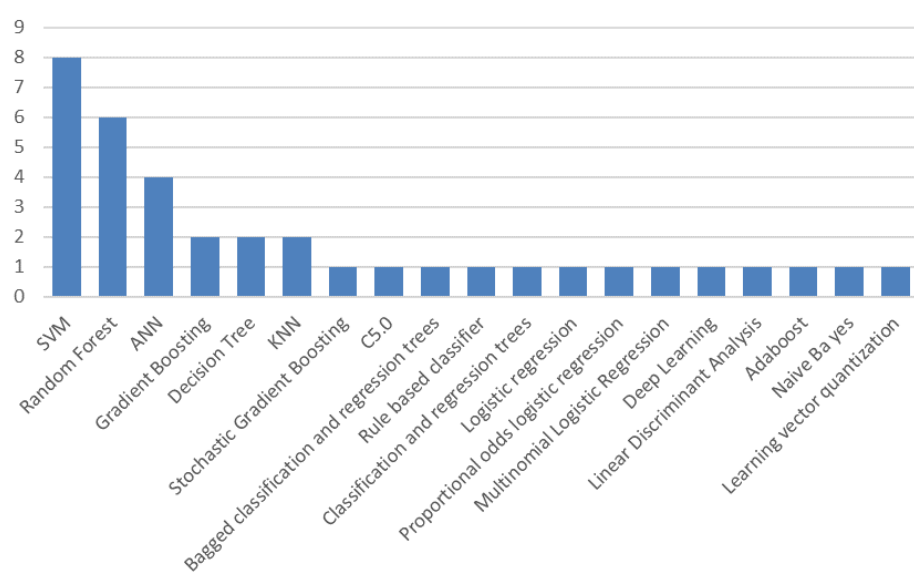

Figure 5.1. Machine learning techniques applied in thermal comfort modelling

In study [34], the authors developed 14 models for each subject with various machine-learning algorithms. Their data processing was conducted with a pack-age of “caret” under R which considers over 200 algorithms. Four groups of algorithms were applied: linear methods (Logistic Regression and Linear Discriminant Analysis), non-linear methods (Support Vector Machine, K-Nearest Neighbors, Neural Network, and Naïve Bayes), trees and rules (Classification and Regression Trees, J48 Decision Tree, and Rule-Based Classifier), and ensembles of trees (Bagged Classification and Regression Trees, C5.0, Stochastic Gradient Boosting, Random Forest and Random Forest by Randomization). Each model should be evaluated to assess its individual thermal comfort prediction. In the [34], the “Ensembles of Trees” category is shown to have the best performance in personal comfort model development. In studies [55] and [66], the proposed models were compared to conventional ones. However, a comparative evaluation among alternative, data-driven models or methods should be conducted to provide more significant conclusions. Since the model accuracy is affected by data characteristics, the crucial issue in the model evaluation is in the absence of specified criteria for model validation and comparison [67]. A detailed analysis of machine learning and statistical modelling is above the scope of this work and the main idea was to emphasize the importance of data processing in the personalized thermal comfort. For sure, more focused analysis is recommended in this area as a part of future research work.

6. NOVEL TRENDS IN SMART MANAGEMENT OF THE HEATING/COOLING SYSTEMS

Generally speaking, novel trends in smart management of the heating/cooling systems in buildings are reflected in the implementation of smart sensing technologies through the detection and decision-making process. The selection of important indicators for conditions in the observed room (e.g. occupant's presence, environmental conditions etc.) and application of sensory devices for data acquisition is a basepoint for efficient heating/cooling adjustment. Based on the acquired information, the regulation logic of the heating/cooling system can be proposed to provide comfort to the occupants while minimizing energy consumption. The smart sensors can be applied to gather information about the parameters that might influence energy consumption and propose a regulation solution to fit the real conditions in the building.

In the paper [68], authors developed an IoT prototype for energy-efficient building management assisted by the room occupancy detection. The premise of the study is that, based on the information about room occupancy, heating and cooling system engagement can increase the energy efficiency and can be optimized to provide comfortable environment to the occupants while being present in the room. The authors have conducted the energy–saving simulation through the Energy Plus simulator, and the results show that described approach can reach the average electricity reduction of 12 % annually (~ 9,600 kWh/y and 480 $/y). The authors have pointed out the importance of the room occupancy information for management in other building segments as well, i.e., lighting control. On the other hand, the described approach has a downside, since it does not provide a good performance for detecting multiple occupants entering a room simultaneously nor their feedback on the provided environmental conditions. Occupancy of the room information and the outdoor temperature conditions for the thermostat–based HVAC system with natural gas furnace and a direct expansion cooling coil and the condensing unit was investigated in [69] for different geographical conditions. The simulation was conducted for five representative cities for distinctive climate zones in the United States (Fairbanks, New York City, San Francisco, Miami, and Phoenix). The authors investigated different HVAC self-coded controlling strategies combining three thermostat types (always on, schedule-based, and occupancy driven) with two control algorithms (fixed setpoint and adaptive control) considering the application of the sensing devices to determine the occupancy of the room and the outdoor temperature conditions. Authors have drawn significant conclusions regarding different applied cases compared to the standard "always-on" thermostat with a fixed setpoint as a reference. For the fixed setpoint scenario, the results were as follows: When using a schedule-based thermostat, the heating system is working at 12 °C (heating) or 32 °C (cooling) during the time between 8 a.m. and 5 p.m. (work/school time). Otherwise, the heating setpoint is 21 °C, and the cooling setpoint is 23°C. This approach can reach energy saving impact from 13 % up to 38 %, depending on the city (max. ~10 MWh in Miami). This approach resulted in an increased discomfort ratio of up to 20 %.

- The occupancy-driven thermostat activates fixed setpoint temperatures (21 °C / 23 °C) when the occupant is in the object, and when the house is vacant 12 °C / 32 °C regime is activated.

This model can save up to 34 % of the consumed with a less significant increase in uncomfortable level.

The authors tried to reach an increased comfort level for the occupants and investigate energy consumption, considering the scenario with adaptive setpoints which change with respect to the sensed outdoor temperature:

- The “always-on” thermostat in this scenario can save up to 54 % of the used energy.
- Schedule based adaptive setpoints can raise the energy saving impact up to 67 %.
- Occupancy detection can provide energy saving of 63 %.

The best comfortable ratio was evaluated [15] for the “Always on” mode with the adaptive setpoints, particularly for the New York city and San Francisco (98,7%). It is important to highlight that the provided results are based on the simulation, without the feedback from the occupants and the real environment conditions together with user evaluation would be useful for more meaningful results. Also, a location of the building and the climate play a significant role for the energy saving potential. In [51], authors have proposed the Model Predictive Control (MPC) architecture for HVAC system smart management, based on the IoT and evaluated it in real environment, an office building (laboratory) at the University of the Polytechnic of Bari. HVAC system in the building is central which provides Fan Coil Units (FCUs) with water (hot / cold). The experimental laboratory was equipped with three FCUs, which can be regulated remotely. Smart sensors for indoor conditions, i.e., air temperature, carbon dioxide (CO_2) level, number of occupants and energy consumption were installed. Actuators were also implemented in the laboratory to provide automatic control of HVAC system. MPC based controller was developed to detect the most efficient HVAC system regime and automatize the system control in order to optimize both thermal comfort and energy savings. The latter approach resulted with the reduced energy consumption of approximately 15 % – 20 % with average daily savings being 18.6 %. The experimental setup was compared with traditional thermostat control system with indoor temperature setpoint of 22 °C during the work hours. The uncertainty in estimation of input parameters, i.e., humidity and occupant number is noticed which could be a possible drawback for the accuracy of the model. Additionally, the occupant’s thermal comfort was derived from linearized Predicted Mean Vote (PMV) index, and the real - time user feedback on the comfort would be significant indicator of the provided system. Further on, authors in [70] have simulated the work of a central heating system with respect to the outside air temperature and humidity, indoor air temperature, and presence as monitored parameters. The proposed approach allows the operation of the heating system based on the specified rules (occupants presence, outside temperature threshold) and could be useful in reducing the energy consumption. The authors have used the energy source (fuel) price simulation as the indicator of the consumption savings. For 50 h of continuous proposed system performance, the fuel cost can be decreased by $10.84 (~36 L, considering fixed fuel price of 0.3002 $/L) for one room. In order to obtain substantial data, a real environment experiment should be worked out.

In the study [71], authors proposed the IoT upgrade for the decentralized Variable air Volume (VAV) HVAC system which is characteristic for the office buildings and the prototype was demonstrated in the University building. The system uses sensor measurements (air temperature, CO_2 level, air humidity) together with forecast on weather, heating load and occupancy. The user comfort is calculated from the [15]. The sensor measurements are implemented in the Model Predictive Control (MPC) which determines the minimal required energy for cooling while maintaining the comfort of the users. With the latter approach, energy savings can be reached up to 20 %. However, similar to the other studies, the authors haven't included the user feedback about the comfort in the office. In [71] a platform for energy management in public buildings was developed for electrical energy reduction through HVAC and lighting system control based on human presence detection. Temperature, humidity, luminosity, and electrical power measurements were implemented and linked with user presence information (through an identification card reader for students and a Bluetooth beacon for external users). This way, unnecessary work of HVAC and lighting systems in unoccupied areas can be avoided and energy consumption can be reduced. The authors included the sociological aspect in their approach as well by trying to affect the behavior of the users through raising their awareness about consumption with planned notifications in the belonging application with rewarding mechanisms. The provided platform resulted in a change in the lighting system work and 40 % savings in energy waste from lighting. Energy savings in the heating system were not evaluated for the proposed approach, and neither was user comfort considered, which could be a critical limitation for the real-case implementation of the described approach. A slightly different work was approached in the study [72], where IoT sensors were implemented for the reconstruction and monitoring of heating pipe networks within community heating systems with gas-fired boilers. The system operation and control of temperature and flow were upgraded with respect to the changes in outdoor temperature. With the decrease in the outdoor temperature, the temperature of the water supply increases, and the circulating hot water flow changes adaptively, which enables the energy-efficient work of the system. Based on the proposed features, the authors evaluated the benefits of the novel approach. The heat source, exchangers, and the system have 33.98 %, 17.93 %, and 7.52 % of power-saving potential. The primary and secondary pipe networks consumed about 24.13 % less power after the upgrade. The provided work, however, focused only on the technical aspect, neglecting the thermal comfort feedback from the users. It can be concluded from the existing studies in the literature that the current operating settings in the heating and cooling systems in the buildings have energy losses which could be reduced following the novel approach of sensing important indicators of energy consumption and modifying the working regime accordingly. The room occupancy information is the most prominent information for the heating / cooling regime setup since the operation strategies were developed to follow the number of occupants in the room(s) and adjust the heating and / or cooling accordingly. When the occupants are not present in the room, the environmental control can be off or at fixed setpoints which potentially consume less energy. As presented in detail through the paper, crucial aspect worth investigating is also the user's subjective evaluation of the thermal environment through the personal thermal comfort investigation. This approach could provide information about the satisfaction of the users with the environment and pave the way for new user-centric approaches in heating and cooling systems.

Table 6.1. Application of the sensing technologies in the heating / cooling systems and energy saving potential

Paper	*Type of system*	*Data collection*	*Thermal comfort*	*Energy savings*
[69]	Thermostat – based HVAC system with natural gas furnace and a direct expansion cooling coil and condensing unit	Occupancy of the room, outdoor temperature conditions	Adaptive (ASHRAE 55)	Fixed thermostat setpoint: schedule based: 13% - 38%, occupancy driven: up to 34 % Adaptive thermostat setpoints: "Always-on": up to 54 %, schedule based: up to 67 %, occupancy driven: up to 63 %
[51]	Central HVAC with Fan Coil Units (FCUs)	Air temperature, CO_2 level, number of occupants and energy consumption	PMV index	15 % – 20 % , average daily 18.6 %
[70]	Central heating system	Outside air temperature and humidity, indoor air temperature and presence sensors	/	During 50 h, fuel cost can be decreased by $10.84 (~36 l, with fixed fuel price of 0.3002 $/l) for one room
[71]	Decentralized Variable air Volume (VAV) HVAC system	Air temperature, CO_2 level, air humidity, weather forecast, heating load and occupancy	ANSI/ASHRAE, 2013	Up to 20 %
[68]	VAV HVAC system	Room occupancy	/	Electricity reduction of 12 % annually (~ 9,600 kWh per year)
[71]	HVAC and lighting system	Temperature, humidity, luminosity, electrical power and user presence	/	40% savings - on lighting
[72]	Community heating system with gas-fired boilers	Outdoor temperature	/	~24.13%

7. CONCLUSIONS AND FUTURE DIRECTIONS IN THE FIELD

Following the Smart City paradigm, trends in the heating and cooling systems in buildings are reflected in the application of smart technologies through different segments, enabling advanced operation and regulation strategies. Through the literature, various studies have investigated the implementation of the sensing devices to detect the crucial indicators of the energy consumption for the heating and cooling systems and develop regulation mechanisms to provide a more comfortable environment for the occupants. This work has provided a critical review of technological solutions used in thermal comfort studies with an emphasis on smart technologies. Additionally, it provided a systematization of inputs considered in thermal comfort modelling, as well as a brief insight into the models used in the studies related to the thermal comfort. According to the herein obtained, review the following main conclusions can be derived as follows:

- environmental inputs considered in provided literature mostly rely on variables defined by P.O. Fanger: air temperature, air relative humidity, air velocity, and mean radiant temperature. On the other side, the outdoor meteorological conditions, CO_2 level, black globe temperature and partial pressure in the observed environment are not included in all research studies related to the thermal comfort modelling. In that sense there is a necessity for additional evaluation of standardized approach,
- correlation between variation of the skin temperature (hands, face) and heart rate with change in thermal comfort of user through literature is well investigated. With respect to the previous findings, the skin temperature has been found as the most common input in thermal comfort studies besides frequently used MET, followed by CLO, heart rate and skin conductance,
- additional parameters are also included as indicators for thermal comfort of individuals such as: EEG signals, skin heat flux, sweat rate, activity rate, aural temperature, body position, core temperature, facial expression. It was also found that further research is necessary in this regard to draw more relevant conclusion,
- technological solutions for thermal comfort detection in data-driven models are based on network of connected sensors. The environmental data collection is acquired through the air temperature sensors in combination with other sensing devices that perceive environmental conditions i.e., relative humidity, CO_2, light level and wind speed sensors.
- user-related data acquisition is found to be more complex and technologies in this regard can be divided into connected sensors systems (which are the most represented in the conducted review), followed by camera-based technologies and wearable devices. Specific technological solutions have certain limitations, such as for instance, wearable devices, which seem to be promising for the users in the indoor conditions since it is practical, non-intrusive and this kind of devices are already commercially available. However, the data readings might be inaccurate if the device isn’t properly worn, so future research studies should consider this fact during experimental investigations,
- certain approaches in data-driven thermal comfort modelling only update classic models with real-time data, while others have developed their own models. When designing the system, solutions can provide real-time information. However, they generally do not

consider individual differences. In most studies, MET and CLO are taken as constants from tabular values, despite the fact that such approach has shown to cause errors of up to 20%. Several experiments addressed this problem by setting sensors on users, most often in form of wearable device or recording them through the camera-based technologies to detect individual response through time. Although mentioned approach contributes to the reduction of the above-specified error, the exact error reduction amount should be determined more accurately. Thus, there is the necessity for the future research work,

- the importance of machine learning in data-driven thermal comfort modelling is found to be crucial. The prediction of personal thermal comfort, based on sensor readings, as well as potential future advanced operation of building systems (with reduced sensor application) are the main benefits of machine learning approach in personal thermal comfort.

It can be concluded that still no technology is mature enough for general application because the conducted experiments have specific limitations. For instance, a limited sample of subjects (occupants), inadequate examined temperature range, or sample of tested activities, etc. Regarding future research work in the field, the following issues are noted:

- many proposed technological solutions are designed to be compatible with heating/cooling management systems in buildings, which is potential path to greener building energy management systems. Future work in this area should be focused on testing and integrating TC models with intelligent HVAC management in smart buildings to improve energy efficiency of buildings. This could be accomplished through development of new personalized models tailored for individual TC and adjusting environmental parameters for purposes of both reducing the energy consumption and increasing indoor environmental quality,
- applicability of TC questionnaire should be investigated more thoroughly. Based on the conducted analysis, it is indicated that compatibility analysis of classical questionnaire with new data-driven models is needed,
- a detailed data processing analysis by using machine learning and statistical modelling is necessary in this area as a part of future research work,
- evaluation among data-driven thermal comfort models should be conducted and somehow standardized to set basis for accurate comparison of various modelling approaches

References

[1] Web source: European Commission, 2018, Energy performance of buildings directive. <https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/energy-performance-buildings-directive_en>, accessed 08.04.2022.

[2] Web source: <iea.org/topics/buildings>, accessed 28.09.2022.

[3] Sinopoli J., 2010. Chapter 1 - What Is a Smart Building? In: Sinopoli J. (Ed), Smart Building Systems for Architects, Owners and Builders, Butterworth-Heinemann, ISBN 9781856176538, Burlington, United States, 1-5.

[4] Zhou K., and Yang S., 2018, Smart energy management, Chapter In: I. Dincer (Ed.), Comprehensive Energy Systems, Elsevier, Oxford, pp. 423–456.

[5] Lawal K., Rafsanjani H.N., 2022. Trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings. Energy and Built Environment, 3, 251–266.

[6] Alanne K., Sierla S., 2022. An overview of machine learning applications for smart buildings. Sustainable Cities and Society, 76, 103445.

[7] Paone Antonio and Bacher Jean-Philippe, The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art,Energies 2018, 11, 953; doi:10.3390/en11040953

[8] Fabi, Valentina & D'Oca, Simona & Buso, Tiziana & Corgnati, Stefano. (2013). The influence of occupant’s behaviour in a high performing building, Proceedings in CLIMAMED 2013 – 7th Mediterranean Congress of ClimatizationAt: Istanbul.

[9] Zhang, Yan & Bai, Xuemei & Mills, Franklin & Pezzey, John ('Jack'). (2018). Rethinking the role of occupant behavior in building energy performance: A review., Energy and Buildings. 172. 10.1016/j.enbuild.2018.05.017

[10] Yoshino H., Hong T., Nord N., IEA EBC annex 53: total energy use in buildings—analysis and evaluation methods, Energy Build. 152 (2017) 124–136, doi: 10.1016/j.enbuild.2017.07.038

[11] Pivac Nikolina, Nižetić Sandro, Zanki Vlasta, Occupant behavior and thermal comfort field analysis in typical educational research institution: A case study, Thermal Science 2018 Volume 22, Issue Suppl. 3, Pages: 785-795 (2018)

[12] Web source: European Commission, 2020. Heating and cooling. <https://energy.ec.europa.eu/topics/energy-efficiency/heating-and-cooling_en>, accessed 11.04.2022.

[13] Pigliautile Ilaria, Casaccia Sara, Morresi Nicole, Arnesano Marco, Pisello Anna Laura, Revel Gian Marco, Assessing occupants’ personal attributes in relation to human perception of environmental comfort: Measurement procedure and data analysis, Building and Environment, Volume 177, 2020, 106901, ISSN 0360-1323, https://doi.org/10.1016/j.buildenv.2020.106901.

[14] International Standard Organization, ISO 7730, Ergonomics of the thermal Environment - Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, 2005

[15] ANSI/ASHRAE Standard 55 - Thermal Environmental Conditions for Human Occupancy, American Society of Heating, 2013
[16] Carlucci S., Bai L., de Dear R., Yang L., Review of adaptive thermal comfort models in built environmental regulatory documents, Building and Environment, Volume 137, 2018, Pages 73-89, ISSN 0360-1323, https://doi.org/10.1016/j.buildenv.2018.03.053
[17] Nižetić, S., Pivac, N., Zanki, V., Papadopoulos, A.M., Application of smart wearable sensors in office buildings for modelling of occupants' metabolic responses (2020) Energy and Buildings, 226, art. no.
[18] Zhang, Sheng & Yong, Cheng & Oladokun, Majeed & Wu, Yuxin & Lin, Zhang. (2019). Improving Predicted Mean Vote with Inversely Determined Metabolic Rate. Sustainable Cities and Society. 101870. 10.1016/j.scs.2019.101870.
[19] Parkinson Thomas & de Dear Richard (2014): Thermal pleasure in built environments: physiology of alliesthesia, Building Research & Information, DOI: 10.1080/09613218.2015.989662
[20] Mishra A., Loomans M. and Kosonen R., "Actimetry for Estimating Occupant Activity Levels in Buildings: A Step Toward Optimal and Energy-Efficient Indoor Conditioning," in IEEE Consumer Electronics Magazine, vol. 8, no. 1, pp. 67-71, Jan. 2019, doi: 10.1109/MCE.2018.2867983.
[21] Rajan Rawal, Marcel Schweiker, Ongun Berk Kazanci, Vishnu Vardhan, Quan Jin, Lin Duanmu, Personal comfort systems: A review on comfort, energy, and economics, Energy and Buildings, Volume 214, 2020, 109858, ISSN 0378-7788, https://doi.org/10.1016/j.enbuild.2020.109858
[22] Pasut Wilmer, Energy-efficient comfort with a heated/cooled chair: Results from human subject tests, Article in Building and Environment 84:10-21 · January 2015 with 167 Reads DOI: 10.1016/j.buildenv.2014.10.026
[23] Dhumane, Rohit & Qiao, Yiyuan & Ling, Jiazhen & Muehlbauer, Jan & Aute, Vikrant & Hwang, Yunho & Radermacher, Reinhard. (2018). Improving System Performance of a Personal Conditioning System integrated with Thermal Storage. Applied Thermal Engineering. 147. 10.1016/j.applthermaleng.2018.10.004.
[24] Itani M., Ghaddar N., Ghali K., Ouahrani D. and Chakroun W., "Cooling vest with optimized PCM arrangement targeting torso sensitive areas that trigger comfort when cooled for improving human comfort in hot conditions," Energy Build., vol. 139, pp. 417–425, Mar. 2017
[25] Na, HooSeung & Choi, Joon-Ho & Kim, Hoseong & Kim, Taeyeon. (2019). Development of a human metabolic rate prediction model based on the use of Kinect-camera generated visual data-driven approaches. Building and Environment. 160. 106216. 10.1016/j.buildenv.2019.106216.
[26] Web source: <scopus.com/search/form.uri?display=basic#basic> accessed 20.09.2022.
[27] Web source: <https://www.webofscience.com/wos/woscc/basic-search> accessed 20.09.2022.
[28] Čulić, Ana; Nižetić, Sandro; Šolić, Petar; Perković, Toni; Čongradac, Velimir Smart monitoring technologies for personal thermal comfort: A review., Journal of cleaner production, 312 (2021), 1-16 doi:10.1016/j.jclepro.2021.127685

[29] Hasan, Mohammmad & Alsaleem, Fadi & Rafaie, Mostafa. (2016). Sensitivity study for the PMV thermal comfort model and the use of wearable devices biometric data for metabolic rate estimation. Building and Environment. 110. 173-183. 10.1016/j.buildenv.2016.10.007.

[30] Luo M, Wang Z, Ke K, Cao B, Zhai Y, Zhou X, Human metabolic rate and thermal comfort in buildings: The problem and challenge, Building and Environment (2018), doi: 10.1016/j.buildenv.2018.01.005

[31] Park, Jaesung & Kim, Taeyeon & Lee, Chul-sung. (2019). Development of Thermal Comfort-Based Controller and Potential Reduction of the Cooling Energy Consumption of a Residential Building in Kuwait. Energies. 12. 3348. 10.3390/en12173348.

[32] Zang, Miao & Xing, Zhiqiang & Tan, Yingqi. (2019). IoT-based personal thermal comfort control for livable environment. International Journal of Distributed Sensor Networks. 15. 155014771986550. 10.1177/1550147719865506.

[33] Youssef, Ali & Caballero, & Aerts, Jean-Marie. (2019). Model-Based Monitoring of Occupant's Thermal State for Adaptive HVAC Predictive Controlling. Processes. 7. 720. 10.3390/pr7100720.

[34] Liu, Shichao & Das, Hari Prasanna & Jin, Ming & Spanos, Costas. (2019). Personal thermal comfort models with wearable sensors. Building and Environment. 162. 106281. 10.1016/j.buildenv.2019.106281.

[35] Nkurikiyeyezu K. N., Suzuki Y., Tobe Y., Lopez G. F. and Itao K., "Heart rate variability as an indicator of thermal comfort state," 2017 56th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), Kanazawa, Japan, 2017, pp. 1510-1512, doi: 10.23919/SICE.2017.8105506.

[36] Choi Joon-Ho, Loftness Vivian, Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations, Building and Environment, Volume 58, 2012, Pages 258-269, ISSN 0360-1323, https://doi.org/10.1016/j.buildenv.2012.07.003.

[37] Mishra, Asit & Loomans, M.G.L.C. & Hensen, Jan. (2016). Thermal comfort of heterogeneous and dynamic indoor conditions — An overview. Building and Environment. 109. 10.1016/j.buildenv.2016.09.016.

[38] Deng, Zhipeng & Chen, Qingyan. (2020). Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband. Energy and Buildings. 214. 109872. 10.1016/j.enbuild.2020.109872

[39] B.J.B. ISO, London, 8996: 2004 Ergonomics of the Thermal Environment–Determination of Metabolic Rate, (2004).

[40] Green J.A., The heart rate method for estimating metabolic rate: review and recommendations, Comp. Biochem. Physiol. Part A 158 (3) (2011) 287–304

[41] Fang, Yuan & Lim, Yuto & Ooi, Sian & Zhou, Chenmian & Tan, Yasuo. (2020). Study of Human Thermal Comfort for Cyber–Physical Human Centric System in Smart Homes. Sensors. 20. 372. 10.3390/s20020372.

[42] Nkurikiyeyezu, K.N.; Suzuki, Y.; Lopez, G.F. Heart rate variability as a predictive biomarker of thermal comfort. J. Ambient Intell. Humaniz. Comput. 2018, 9, 1465–1477

[43] Zhu, H.; Wang, H.; Liu, Z.; Li, D.; Kou, G.; Li, C. Experimental study on the human thermal comfort based on the heart rate variability (HRV) analysis under different environments. Sci. Total Environ. 2018, 616, 1124–1133

[44] Tanaya Chaudhuri, Yeng Chai Soh, Hua Li, Lihua Xie, Machine learning driven personal comfort prediction by wearable sensing of pulse rate and skin temperature, Building and Environment, Volume 170, 2020, 106615, ISSN 0360-1323, https://doi.org/10.1016/j.buildenv.2019.106615.
[45] Li, Da & Menassa, Carol & Kamat, Vineet. (2019). Robust non-intrusive interpretation of occupant thermal comfort in built environments with low-cost networked thermal cameras. Applied Energy. 251. 113336. 10.1016/j.apenergy.2019.113336.
[46] Morresi, Nicole & Casaccia, Sara & Sorcinelli, Matteo & Arnesano, Marco & Uriarte, Amaia & Torrens Galdiz, J. Ignacio & Revel, Gian. (2021). Sensing Physiological and Environmental Quantities to Measure Human Thermal Comfort Through Machine Learning Techniques. IEEE Sensors Journal. PP. 1-1. 10.1109/JSEN.2021.3064707.
[47] Jung, Wooyoung & Jazizadeh, Farrokh & Diller, Thomas. (2019). Heat Flux Sensing for Machine-Learning-Based Personal Thermal Comfort Modeling. Sensors. 19. 10.3390/s19173691.
[48] Li, Wei & Zhang, Jili & Zhao, Tianyi & Liang, Ruobing. (2018). Experimental research of online monitoring and evaluation method of human thermal sensation in different active states based on wristband device. Energy and Buildings. 173. 10.1016/j.enbuild.2018.05.056.
[49] Djoko, Faridah & Memory, Motivanisman & Waruwu, & Wijayanto, Titis & Pratama, Raditya & Prayogi, Septian & Muna, Nur & Yanti, Ressy & Budiarto, Rachmawan. (2021). Feasibility study to detect occupant thermal sensation using a low-cost thermal camera for indoor environments in Indonesia. Building Services Engineering Research and Technology. 1-16. 10.1177/0143624421994015
[50] Sung, Wen-Tsai & Hsiao, Sung-Jung & Shih, Jing-An. (2019). Construction of Indoor Thermal Comfort Environmental Monitoring System Based on the IoT Architecture. Journal of Sensors. 2019. 1-16. 10.1155/2019/2639787.
[51] Carli, Raffaele & Cavone, Graziana & Othman, Sarah & Dotoli, Mariagrazia. (2020). IoT Based Architecture for Model Predictive Control of HVAC Systems in Smart Buildings. Sensors. 20. 781. 10.3390/s20030781.
[52] Wu, Meng & Li, Hailong & Qi, Hongzhi. (2020). Using EEG to Continuously Discriminate Feelings of Personal Thermal Comfort between Uncomfortably Hot and Comfortable Environments. Indoor Air. 30. 10.1111/ina.12644.
[53] S. A. Mansi, G. Cosoli, A. L. Pisello, I. Pigliautile, G. M. Revel and M. Arnesano, "Thermal discomfort in the workplace: measurement through the combined use of wearable sensors and machine learning algorithms," 2022 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT), 2022, pp. 54-59, doi: 10.1109/MetroInd4.0IoT54413.2022.9831610.
[54] Yasuhiro Shimazaki, Shunpei Katsuta, Spatiotemporal sweat evaporation and evaporative cooling in thermal environments determined from wearable sensors, Applied Thermal Engineering, Volume 163, 2019, 114422, ISSN 1359-4311, https://doi.org/10.1016/j.applthermaleng.2019.114422.
[55] Ma, & Liu, & Shang,. (2019). A Building Information Model (BIM) and Artificial Neural Network (ANN) Based System for Personal Thermal Comfort Evaluation and Energy Efficient Design of Interior Space. Sustainability. 11. 4972. 10.3390/su11184972.

[56] Cosma, Andrei-Claudiu & Simha, Rahul. (2018). Thermal comfort modeling in transient conditions using real-time local body temperature extraction with a thermographic camera. Building and Environment. 143. 10.1016/j.buildenv.2018.06.052.
[57] Alsaleem F, Tesfay MK, Rafaie M, Sinkar K, Besarla D and Arunasalam P (2020) An IoT Framework for Modeling and Controlling Thermal Comfort in Buildings. Front. Built Environ. 6:87. doi: 10.3389/fbuil.2020.00087
[58] Lee Jeehee & Ham Youngjib (2020): Physiological sensing-driven personal thermal comfort modelling in consideration of human activity variations, Building Research & Information, DOI: 10.1080/09613218.2020.1840328
[59] Marchenko A, Temeljotov-Salaj A, Rizzardi V, Oksavik O. The Study of Facial Muscle Movements for Non-Invasive Thermal Discomfort Detection via Bio-Sensing Technology. Part I: Development of the Experimental Design and Description of the Collected Data. Applied Sciences. 2020; 10(20):7315. https://doi.org/10.3390/app10207315
[60] Luo M., Zhou X., Zhu Y., Sundell J., Revisiting an overlooked parameter in thermal comfort studies, the metabolic rate. Energy and Buildings. 2016, 118: 152-159
[61] Sung, Wen-Tsai & Hsiao, Sung-Jung. (2019). The Application of Thermal Comfort Control Based on Smart House System of IoT. Measurement. 149. 106997. 10.1016/j.measurement.2019.106997.
[62] Fanger P.O., Thermal Comfort: Analysis and applications in environmental engineering, McGraw Hill Book Company, 1970
[63] Konis Kyle, Blessenohl Simon, Kedia Naman, Rahane Vishal, TrojanSense, a participatory sensing framework for occupant-aware management of thermal comfort in campus buildings, Building and Environment, Volume 169, 2020, 106588, ISSN 0360-1323, https://doi.org/10.1016/j.buildenv.2019.106588.
[64] Lee, Seungjae & Karava, Panagiota & Bilionis, Ilias. (2020). A smart and less intrusive feedback request algorithm towards human-centered HVAC operation. Building and Environment. 184. 107190. 10.1016/j.buildenv.2020.107190.
[65] Wang, Zhe & Wang, Jingyi & He, Yueer & Liu, Yanchen & Lin, Borong & Hong, Tianzhen. (2019). Dimension analysis of subjective thermal comfort metrics based on ASHRAE Global Thermal Comfort Database using machine learning. Journal of Building Engineering. 29. 101120. 10.1016/j.jobe.2019.101120.
[66] Kim J., Zhou Y., Schiavon S., Raftery P., Brager G., Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Build. Environ. 129 (2018) 96–106. doi:https://doi.org/10.1016/j.buildenv.2017.12.011
[67] Lee, Seungjae & Karava, Panagiota. (2020). Towards smart buildings with self-tuned indoor thermal environments- A critical review. Energy and Buildings. 224. 110172. 10.1016/j.enbuild.2020.110172.
[68] Huang Q., Rodriguez K., Whetstone N., Habel S., 2019. Rapid Internet of Things (IoT) prototype for accurate people counting towards energy efficient buildings. Journal of Information Technology in Construction, 24. 1-13. DOI: 10.36680/j.itcon.2019.001.

[69] Wang C., Pattawi K., Lee H., 2020. Energy Saving Impact of Occupancy-Driven Thermostat for Residential Building. Energy and Buildings, 109791, DOI: 10.1016/j.enbuild.2020.109791.
[70] Jiménez-Bravo D.M., Lozano Murciego Á., de la Iglesia D.H., De Paz J.F., Villarrubia González G., 2020. Central Heating Cost Optimization for Smart-Homes with Fuzzy Logic and a Multi-Agent Architecture. Applied Sciences, 10(12), 4057.
[71] Ferreira J., Afonso J., Monteiro V., Afonso J.L.M, 2018. An Energy Management Platform for Public Buildings. Electronics, 7, 294, DOI: 10.3390/electronics7110294.
[72] Sun X., Chen F., Pan Z., Bai L., 2021. Research and Evaluation of Energy-Saving Reconstruction of Intelligent Community Heating System Based on the Internet of Things. International Journal of Heat and Technology, 39, 701-710, DOI: 10.18280/ijht.390304.

Abstract

Improving the efficiency of building energy systems is crucial to reach a goal related to the high – performance building, particularly in the space heating and air - cooling domain, which are considered as leading energy consumption systems in buildings. Current trends in the smart building paradigm allowed efficient implementation of user-centric approach in personal thermal comfort modelling. The potential technological solutions in that sense can bring various benefits leading towards improvement of the building energy performance. Existing papers published in the Scopus and Web of Science database have been reviewed in order to investigate a state of the art related to experimental practices in the development and application of monitoring technologies for personal thermal comfort. Consequently, the work brings insights in some of the main research findings in the area focusing on (I) inputs that affect personal thermal comfort, (II) smart technologies and methods used for sensing and the detection of defined inputs and (III) insights into the approaches of collected data processing. Parameters considered in reviewed literature rely on environmental and personal variables. Based on the conducted review, it can be indicated that room air temperature, relative humidity, air velocity and mean radiant temperature (MRT) are frequently used environmental parameters in thermal comfort modelling. Among user – related indicators in the considered literature, skin temperature (hands, face) and metabolic rate (MET) are found to be the most common, followed by clothing insulation (CLO) and heart rate data. Some additional parameters are also found to be influenced by thermal comfort of individual (skin conductance, brain activity, heat flux, sweat rate, aural temperature, body core temperature). Subjective response from users is still unavoidable and recorded through questionnaires. The results of review indicated that technological solutions for detection of thermal comfort parameters in data-driven models are mainly based on network of connected sensors, and can be divided into camera-based technologies, wearable devices and connected sensor systems. Finally, open questions and gaps that inquire further research were also detected and discussed in detail.