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Review

A Review of Recent Literature on Systems and Methods for the Control of Thermal Comfort in Buildings

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Abstract: Thermal comfort in indoor environments is perceived as an important factor for the well-being and productivity of the occupants. To practically create a comfortable environment, a combination of models, systems, and procedures must be applied. This systematic review collects recent studies proposing complete thermal-comfort-based control strategies, extracted from a scientific database for the period 2017–2021. The study consists of this paper and of a spreadsheet recording all the 166 reviewed works. After a general introduction, the content of the papers is analyzed in terms of thermal comfort models, indoor environment control strategies, and correlation between these two aspects. Practical considerations on scope, required inputs, level of readiness, and, where available, estimated cost are also given. It was found that the predicted mean vote is the preferred thermal comfort modeling approach, followed by data-driven and adaptive methods. Thermal comfort is controlled mainly through indoor temperature, although a wide range of options are explored, including the comfort-based design of building elements. The most popular field of application of advanced control strategies is office/commercial buildings with air conditioning systems, which can be explained by budget and impact considerations. The analysis showed that few works envisaging practical implementations exist that address the needs of vulnerable people. A section is, therefore, dedicated to this issue.

Keywords: thermal comfort; indoor environment; control system; building; HVAC

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1. Introduction

People spend most of their time indoors. Whether it is at home, at work, at school, in healthcare structures, or in recreational facilities, the demand for a comfortable environment is a key driver in building research. As pointed out by Frontczak and Wargocki [1], among the aspects encompassed by the definition of human comfort (visual, acoustic, thermal, and air-quality-related), the thermal condition of the occupants is decisive in determining their level of satisfaction. The same study also confirmed the complexity of the matter, and highlighted its subjective nature, the concurrence of multiple influencing factors, and quite a few unsolved controversies.

To preserve or improve human thermal comfort in indoor environments, two elements must be considered. The first element concerns modeling—and thermal comfort models are as essential to the purpose as they are difficult to develop, given the fact that they must standardize the outcome of personal perceptions. The pioneering works by Fanger in the 1970s [2] and de Dear and Brager in the late 1990s [3] are shining examples of this effort, and are the foundation of the reference standards in the field (ASHRAE Standard 55 [4] and EN ISO 7730 [5]/EN 16798-1 [6]). However, despite the existence of such recognized frameworks, contributions on new approaches, investigations, and metrics are constantly added to the body of knowledge. For example, Zhao et al. [7] reviewed the existing thermal comfort models and addressed aspects such as sleeping environments and the specific needs of the elderly, while Arakawa Martins et al. [8] focused on methodological issues associated with model development.

The second element to consider in the creation of a thermally comfortable environment is control, which implies answering the question of how to obtain comfort conditions once they have been predicted through an appropriate thermal comfort model. This layered issue involves the definition of control variables and, possibly, calculation, simulation, and field deployment. When it comes to control variables, the most obvious choice are the operating parameters of heating, ventilation, and air conditioning (HVAC) systems, but this is not—nor it should be—the only option. As discussed by Bean in his guide [9], the achievement of thermal comfort is often mistaken for other objectives, such as energy efficiency or mere code compliance, for which solutions as simple as thermostat set-point adjustment may be enough. Indeed, a gap still exists between thermal comfort and building management communities [10]: occupant satisfaction is mostly associated with room temperature, overlooking "the multiple dimensions and psychological aspects identified by thermal comfort researchers". Indeed, "homes are not uncomfortable: people are" [9], and their perception is influenced by building design choices [11] as well as by personal and general factors, which are known to have an influence on expectations [12]. For this reason, it is worth remarking that thermal-comfort-based control of HVAC equipment, which is the predominant option in practice and in the present literature survey, is only a part of a bigger design strategy.

The inclusion of thermal comfort objectives in building management has been considered from different perspectives. For example, Enescu [13] focused on the main thermal comfort indicators for indoor environment control, while Nagele et al. [14] examined the topic from the angle of room temperature adjustment, and quantified the energy-saving potential of modern automated systems over traditional temperature controllers. Recent works have recognized a progressive paradigm shift from traditional group-average approaches towards personal comfort approaches. Wang et al. [15] discussed individual differences in human thermal comfort perceptions and their influencing factors; Kim et al. [16] and Xie et al. [17] explored occupant-centric frameworks and relative methodologies and requirements; Jung and Jazizadeh [18] focused on human-in-the-loop occupancy- and comfort-driven HVAC operations. The diffusion of new technologies and algorithms is playing an important part in this process. In their 2020 survey, Tomat et al. [19] examined Internet of Things (IoT) applications related to thermal comfort; the authors noted how this class of devices, particularly mobile ones, are instrumental in turning people from passive subjects of measurements to active players in defining their own personal comfort level. After rigorous selection processes, Halhoul Merabet et al. [20] isolated and analyzed over one hundred studies from 1992 to 2020 on the application of artificial intelligence to achieve energy-efficient thermal comfort in buildings, while Čulić et al. [21] mainly concentrated on smart devices and technologies such as sensors, cameras, and wearable devices.

The endpoint of control system deployment is the human–building interface. Day et al. [22] presented a review of the most common building interfaces, exploring the motivation that triggers the interaction, the effect of their operation, and the key features that make a device more usable and, therefore, effective. One of the analyzed interfaces is the thermostat, which is also the subject of studies by Ponce and co-authors (see, for example, [23]) in which the importance of concepts such as expectations and user-friendliness were highlighted as one of the keys to successful devices. The automatic control process can also be replaced or complemented by the promotion of behavioral changes through recommendations. The effect of nudging has been explored in recent publications, sometimes with contradictory results: for example, the experiment by Idahosa and Akotey [24] in a hotel and the investigation by Li et al. [25] in individual offices gave a contrasting interpretation of the influence of environmental appeals on the user's actions.

To summarize, literature reviews can be found on either comfort models or control technologies, occasionally giving information about both aspects, but discussing them separately. To the authors' knowledge, no application-oriented survey exists on studies in which findings from the thermal comfort research corpus have been exploited to devise an indoor environment control system—that is, in which a bridge has been created between thermal comfort and building technology communities. This paper aims to fill this gap by providing a systematic guide to solutions combining scientific evaluation of thermal comfort and development of comfort-based control methods. In the authors' view, the survey can be used as a starting point both from researchers willing to contribute to the field with new studies, and from practitioners looking for complete solutions. The studies were classified according to several aspects, including comfort model, control strategy/algorithm, required inputs, control variables, type of environment, and level of readiness. Where available, practical information for each of the analyzed solutions was given, such as hardware and software used, and estimated cost. To make the findings of this work more readily accessible to the interested reader, the database of the reviewed works was also made available as Supplementary Materials.

The paper is organized as follows: Section 2 describes the methodology and criteria employed to select the papers. Section 3 is divided into several subsections: after a statistical and semantical overview of the selected papers, the actual guide to available solutions is presented, mostly in visual and tabular form, followed by a discussion about the most relevant findings and the limits of the review methodology. As most of the reviewed solutions are developed for standard contexts, some unresolved questions are collected in Section 4 to raise attention on the needs of vulnerable groups of people. Conclusions are briefly drawn in the final Section 5.

2. Methods

In this section, source, criteria, and methodologies are presented that were used to select literature papers and extract information from them. The scope of the research is to identify works featuring solutions for the control of indoor environment to improve or preserve thermal comfort. Therefore, the authors searched for papers presenting simultaneously:

- A clearly identifiable thermal comfort model with inputs and outputs;
- A strategy that exploits the outputs of the thermal comfort evaluation to control well-indicated variables connected to the indoor environment.

For example, a paper discussing an innovative control method of indoor temperature, only indicating the set-point value without specifying the origin of this value, would be excluded; a paper explaining that the set-point equates the neutral temperature calculated from predicted mean vote (PMV) model would not be excluded. The search has been performed in the Scopus database, with the query string graphically visualized in Figure 1.

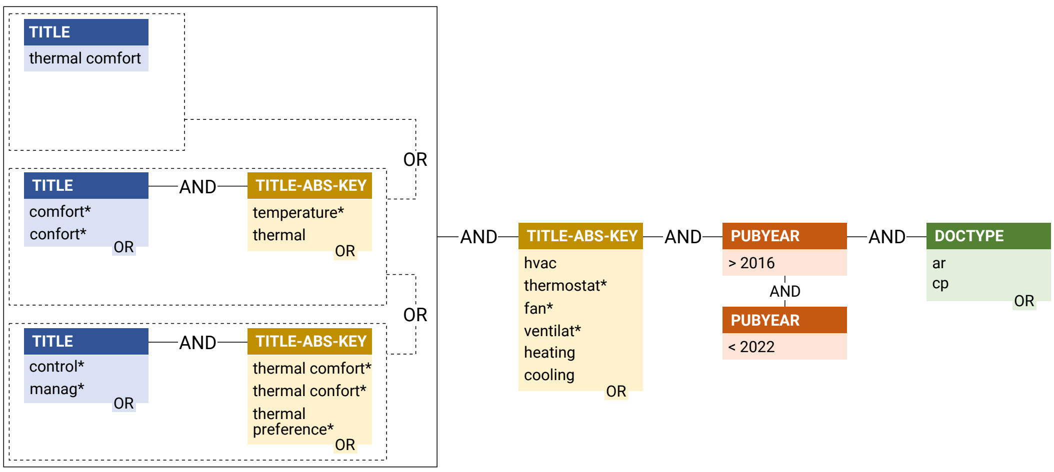

Figure 1. Graphical visualization of query string. Keywords in filled boxes were searched with "OR" logic. Scopus nomenclature: TITLE-ABS-KEY = title, abstract or keyword; PUBYEAR = publication year; DOCTYPE = document type (ar = article; cp = conference proceeding); * = wildcard character.

Thermal comfort- and control-related keywords have been searched in the title and in other informative fields (abstract, keywords), to try and include both comfort-centered (comfort-related words in title) and control-centered (words related to control methods or systems in title) studies. The search has been restricted to the 2017–2021 period. The reason behind this limitation is that the search query includes practical control aspects that are linked to techological evolution. Moreover, a very large number of studies have been published on the investigated topic even in such a small period, indicating rapid progress in the field. This choice, therefore, allowed to consider only the most recent advancements while examining a large number of papers. Since this survey aims to collect primary references, only articles and conference papers have been retained.

The search returned 2472 results. All the following selection processes have been performed manually. Initially, abstracts have been skimmed through to exclude the papers that clearly did not fit the criteria. A total of 244 papers passed this stage, were exported from Scopus in .csv format, and were analyzed. After a final selection based on relevance to the scope and presence of the required information, 166 of them have been included in the present survey and recorded in a reference database. A total of 123 of them are recalled in this paper. Table 1 summarizes the selection steps, tools, and criteria described above.

Table 1. Criteria used for paper selection (TC: thermal comfort).

Selection Stage	Selection Base	Criterion	Process Type	Output	N.
1. Scopus search	Search query	Search query in Figure 1 is satisfied	Automatic	Scopus search results	2472
2. Preliminary screening	Abstract	The study may contain a TC model and a TC-based control strategy	Manual	Raw .csv file	244
3. Database entry definition	Full paper	The study describes a TC model and a TC-based control	Manual	Final .csv file	166
4. Inclusion in main paper	Full paper	The study is relevant for the presentation of the results	Manual	Bibliographic entries	123

The .csv file created at the third stage of the selection process only contained the fields exported from Scopus search, including authors, affiliations, title, year of publication, document type, source title, identifiers, keywords, and open access availability. To make the database more informative and to allow the extraction of statistical figures, the file was cleaned of fields not relevant to this research (e.g., funding details or PubMed ID) and manually completed with new fields based on full paper content, such as

- Monitored quantities (inputs) and control variables;
- Hardware and software;
- Thermal comfort model category and description;
- Control algorithm type and description;
- Application context (season, building type and possible HVAC system);
- Multi-occupancy;
- Validation;
- Strengths and limits;
- Estimated cost of equipment (where specified);
- Level of readiness.

This led to the spreadsheet in the Supplementary Materials, which is the true heart of the work, and the base for all the analysis in Section 3. Here, results are presented in tables and figures; the former summarize information about studies belonging to a given sub-group, whereas the latter provide an overview of the investigated article set. The spreadsheet is made available to the interested readers, to enable them to easily select the most relevant studies for their research or application. For example, information can be filtered based on building or HVAC type, comfort model, or level of readiness.

Python scripts were used to preprocess the Scopus-generated .csv and to extract statistical information, charts, and tables from the database (NumPy, Pandas, Matplotlib, Seaborn, and Geopandas libraries). Keyword relationships were analyzed with VOSviewer tool.

3. Results

3.1. Bibliographic Information

Figure 2 shows the geographical collocation of the examined papers based on the first author's affiliation. US and China display the largest number of contributions. A total of 50% of the documents come from Asian countries, followed by Europe (25%). The South America, Africa, and Oceania component is below 10%. On a methodological note, the first author criterion has been chosen over the corresponding author one because the "Corresponding Address" field in the Scopus-generated file is empty in almost 30% of the cases. However, the countries extracted with the two methods differ in only eight cases.

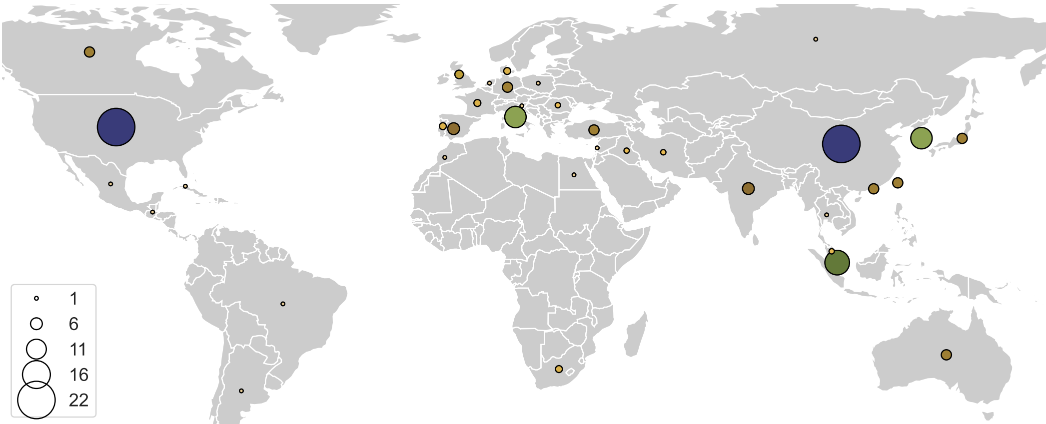

Figure 2. Origin of the examined papers based on first author's affiliation.

The time evolution of the proportion between journal articles and conference papers is reported in Figure 3. It can be noted that the number of documents increased through the years, confirming the trend reported in the literature (see, for instance, Park and Nagy, 2018 [10]). The constant rise in the number of journal articles indicates the growing interest for the subject and a progressive maturation of the studies. According to Scopus details, one third of the papers are published as Gold, Green, Hybrid, or Bronze Open Access, reaching 40% when considering only journal articles.

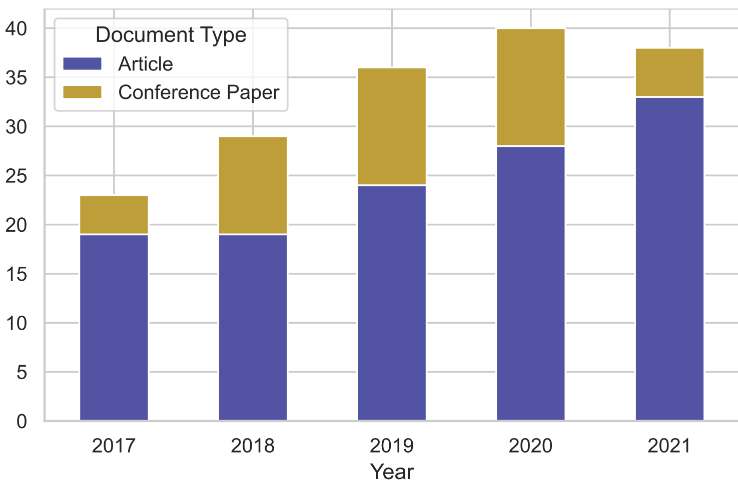

Figure 3. Evolution of investigated papers by document type.

Figure 4 shows the breakdown of the analyzed journal articles by source title, where single occurrences are grouped in slice "Others". A total of 63% of the examined articles were published in 20% of the journals. Of the 123 articles investigated, 40 were published in journals whose titles include the concept of energy, which suggests that the goals of thermal comfort management and energy efficiency are often intertwined. This element will be further discussed in the next subsection.

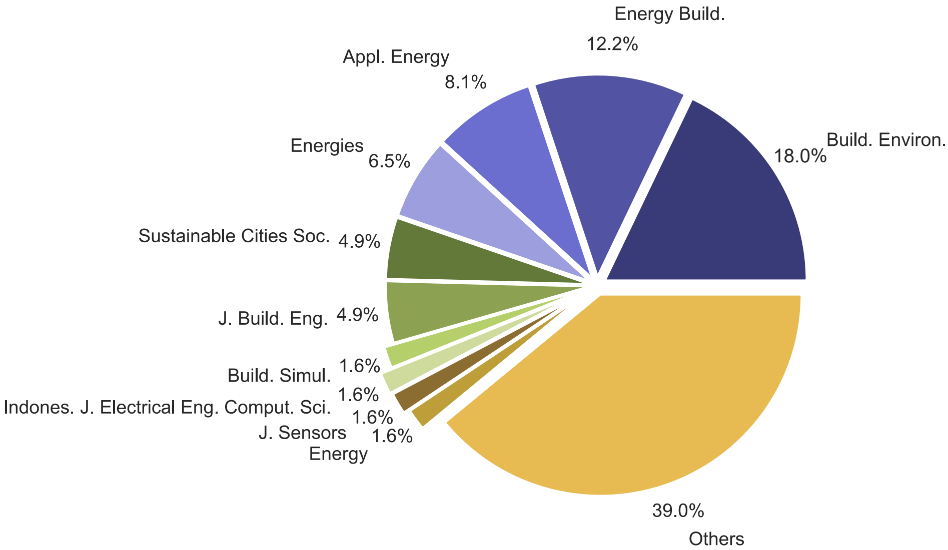

Figure 4. Breakdown of investigated articles by journal.

3.2. Detailed Analysis of Papers

The research query represented in Figure 1 has been designed to incorporate papers featuring both a thermal comfort model and a control system, the latter being expressed with a wide range of methodologies and applications. Figure 5 shows the key blocks of this process: input information is fed to a controller that uses a methodology and the predictions from a thermal comfort model to provide the settings required by a physical indoor environment control system. The same logic was used in keyword analysis, taking the "Author Keywords" field in the Scopus-generated database as reference for 144 out of 166 records (empty field in 22 cases). Initially, all unique keywords were extracted and manually classified in the five categories described in Table 2. Categories "C", "S", and "M" somehow overlap with the rationale behind the query: category "C" is thermal-comfort-related, while categories "S" and "M" are expected to be related mainly to control aspects. On the other hand, category "E" is not directly included in the search query, but it turns out to be an integral part of thermal-comfort-based control literature. After the classification process, the keyword categories of each paper have been determined to return the chart in Figure 6. For example, bar "C+E" indicates the number of papers with at least one keyword "C" and at least one keyword "E", each paper being only counted once. Keywords in category 5 have been ignored.

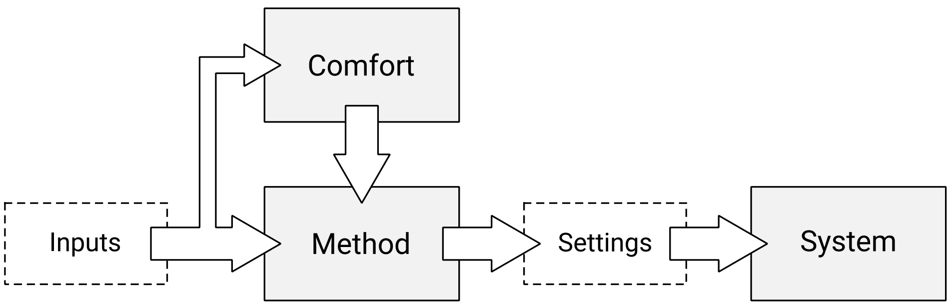

Figure 5. Blocks of thermal-comfort-based control system.

Table 2. Keyword categories for manual classification.

N.	Category	Included Keywords	Real Examples
1	Comfort (C)	Thermal-comfort related	"thermal comfort", "PMV", "thermal preferences"
2	System (S)	Associated with real components or systems	"HVAC", IoT", "thermostat"
3	Method (M)	Describing algorithms, models, and solution approaches	"genetic algorithm", "state-space model", "CFD simulations"
4	Energy (E)	Energy efficiency, saving, and consumption strategies	"efficient energy use", "cooling load", "demand response"
5	Generic/not relevant	Too generic to be classified or out of scope	"man", "electric vehicles"

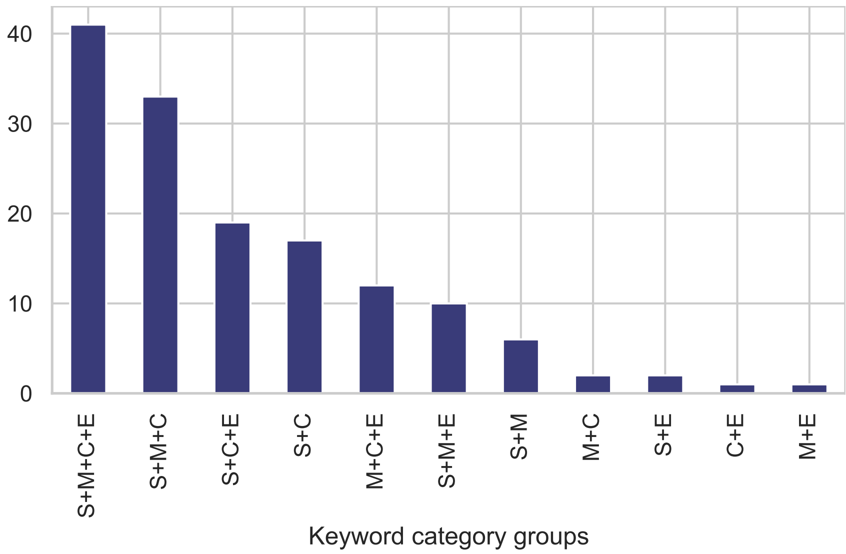

Figure 6. Number of papers containing at least one keyword for the identified semantic categories.

Almost 90% of the papers with reported keywords feature at least a "C" keyword. A similar percentage applies to the "S" category, and method-related keywords are reported for over 70% of the analyzed works. Although energy is not in the search query, 60% of the papers contain "E" keywords, and about 50% have both thermal-comfort- and energy-related keywords. A further confirmation of this bond can be observed in Figure 7, realized in VOSviewer [26]. The size of node items (keywords) is proportional to the number of occurrences, and the link between two items represents the co-occurrence of the two keywords in a document. The distance between groups of keywords (clusters) is the expression of their relatedness. Clusters are automatically identified by the software algorithm, although map creation parameters can be adjusted. In this case, ten clusters were originally returned by VOSviewer, which have been manually reduced to four by changing sub-cluster colors to provide more meaningful information. Three clusters are close to each other and can be associated mainly with HVAC systems and control methods (top-left, in yellow, two sub-clusters merged), to smart buildings and IoT (bottom-left, in olive, four sub-clusters merged), and to thermal comfort and energy (middle, in indigo, three sub-clusters merged). The fourth cluster (right, in cyan, single cluster) describes works focusing on ventilation, which appear to form a cluster on its own.

Keyword clusters do not overlap perfectly with the categories presented in Table 2, but some results are consistent. For example, it is confirmed that thermal comfort studies often include energy considerations, and that control issues can be discussed from the viewpoint of systems and/or methods (HVAC and IoT clusters).

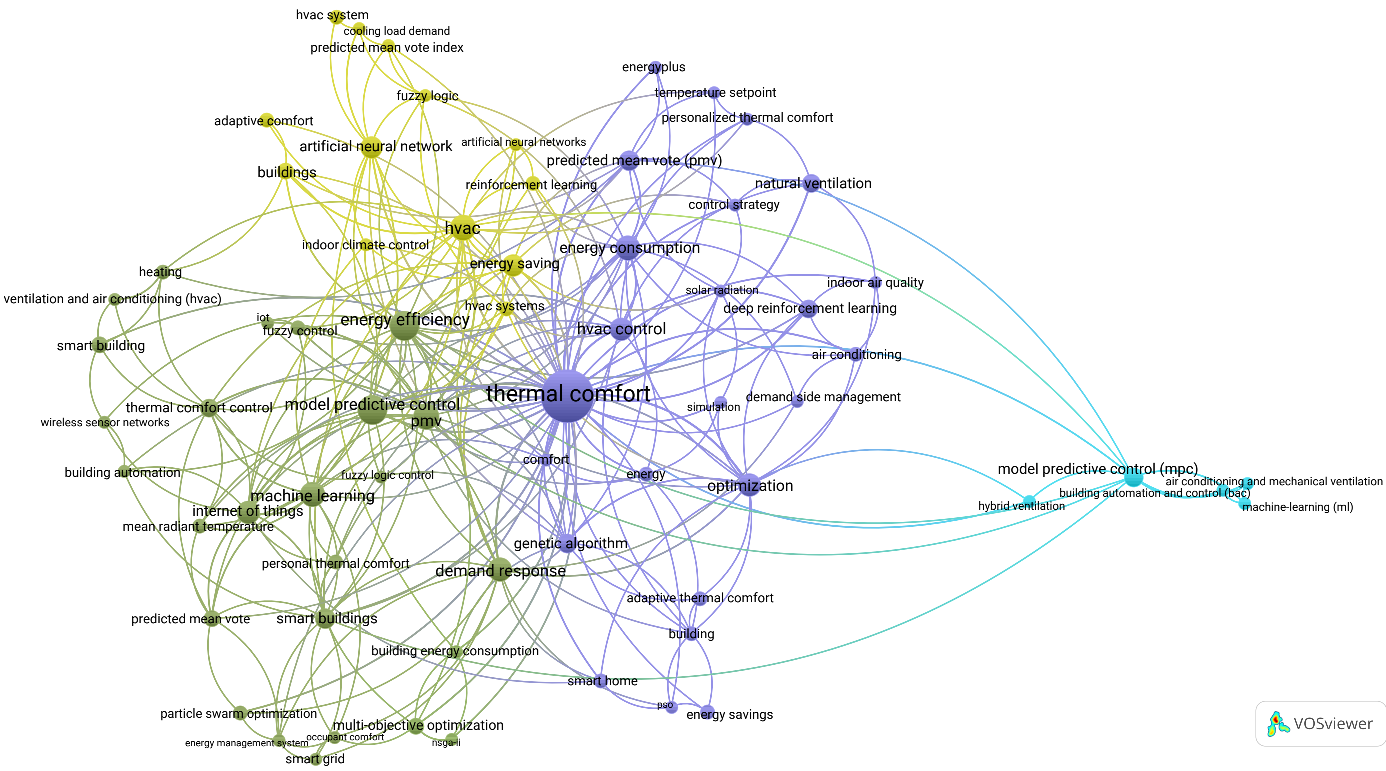

Figure 7. Keyword co-occurrence network.

3.3. Thermal Comfort Models

The PMV model, also known as "static", was developed by Fanger in the 1970s based on the concept that an individual is comfortable when the body is in heat balance, without the need for excessive intervention by physiological thermoregulatory mechanisms (skin temperature and sweat rate within acceptable limits). Based on a large number of experiments, Fanger developed a correlation between the predicted mean vote (PMV) of a group of occupants and the value of some environmental parameters and personal factors—namely, air and mean radiant temperature MRT, relative humidity RH, relative air velocity v_a, metabolic rate M, and clothing insulation I_{cl}. Thermal neutrality is predicted with PMV = 0, with -3 and $+3$ endpoints of the scale indicating a predominantly cold and hot thermal sensation, respectively, within the group of occupants. As a consequence, a certain percentage of people dissatisfied (PPD) can be expected in a range between 0% and 100%, where 0% corresponds to PMV = 0 and 100% corresponds to either of the the thermal sensation scale endpoints.

As noted by Van Hoof's "Forty years of Fanger's model of thermal comfort" [27], the PMV model as developed by Fanger is still the most widespread approach to estimate thermal comfort in buildings, despite some known limitations that Auffenberg et al. [28] described with reference to its practical applications to HVAC control. For example, the model is shaped on statistics over a large population, therefore it represents an average indication that often does not match individual preferences. Moreover, it does not take into account the adaptation mechanisms of the occupants, which are especially important in naturally ventilated contexts. Finally, its predictive accuracy strongly depends on the correct estimation of the model inputs, some of which may be too difficult or too expensive to measure in practical applications. To address such limitations, the response of researchers in the years has been twofold: on the one hand, attempts have been made to modify the original PMV framework by simplification or tailoring actions; on the other hand, completely different models have been introduced that do not stem from PMV, such as adaptive and data-based approaches.

In this work, the subdivision outlined by Li et al. [29] between PMV and non-PMV approaches was adopted to categorize thermal comfort models. PMV models include Fanger formulation and modified models sharing the theoretical foundation with the original study, leaving any other approach to the non-PMV category. Document breakdown according to the thermal comfort model is shown in Figure 8. In most of the studies, PMV is the preferred way of evaluating thermal comfort. The reasons may be that it is mature, standardized, and agreed upon by the scientific community, thus it is adopted also by researchers without long-term expertise in thermal comfort field. Among the non-PMV models, the availability or large amount of measured information makes data-driven approaches attractive. Automatic inference techniques based on occupants' actions are also gaining interest in a user-centric perspective. Adaptive models are a popular choice with natural ventilation, or when simple and flexible formulations are needed.

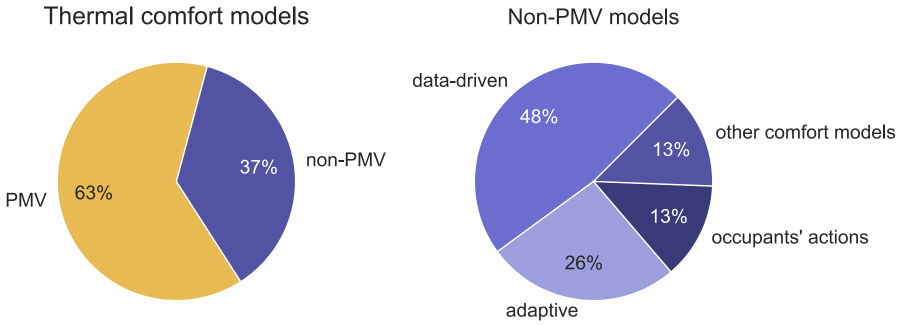

Figure 8. Reviewed documents classified by thermal comfort models: overall (**left**) and breakdown of "non-PMV" sector (**right**).

The boundary between thermal comfort model types is not sharp. To a certain extent, models based on occupants' actions can also be considered data-driven. The same holds for models included into the "other comfort models" group based on regression analysis. Additionally, some studies adopted more than one thermal comfort model to compare performances or to describe comfort in different operation modes (Table 3). Thermal comfort modeling approaches in the reviewed papers are discussed in the following paragraphs.

Table 3. Studies using multiple thermal comfort models.

Reference	Thermal Comfort Models
Menconi et al. (2017) [30]	• PMV • Adaptive
Frătean and Dobra (2018) [31]	• PMV • Adaptive
Chaudhuri et al. (2019) [32]	• PMV, extended PMV, adaptive PMV • Predicted thermal state • Gender-based (male/female) thermal state • Temporal profile thermal state
Fiorentini et al. (2019) [33]	• PMV • Adaptive

PMV models. The majority of the studies reviewed in this survey used PMV models (63%), about one-fourth of which were in modified forms with respect to the Fanger formulation. Examples of simplified PMV models are reported in Table 4. In almost all cases, linearization or linear regression techniques allowed us to simplify PMV model to incorporate it in a complex calculation framework. Input quantities are usually a reduced set of the original model's parameters, but occasionally the simplified function relates PMV with technological variables. It can be observed that personal factors are never part of the simplified models' input set, but they were assumed as constant during the model construction process.

Table 4. Modified PMV models.

Reference	Comfort Model	Input Parameters
Zhang et al. (2017) [34]	Linear PMV model based on regression analysis of experimental measurements; M = 1 met, I_{cl} = 0.57 clo	Room air temperature; supply air flow rate
Hang and Kim (2018) [35]	Linear PMV model based on regression analysis of measured environmental parameters; M = 1.2 met, I_{cl} = 0.5 clo	Indoor air temperature; mean radiant temperature; relative humidity; air velocity
Alizadeh and Sadrameli (2018) [36]	Quadratic PMV model based on regression analysis	Fan blade pitch; fan speed; outdoor air temperature; relative humidity
Chen et al. (2019) [37]	Linear PMV model by Buratti et al. (2013) [38]; coefficients depending on gender and clothing insulation	Ambient temperature; relative humidity
Vallianos et al. (2019) [39]	Adaptive PMV from Yao et al. (2009) [40]	PMV; adaptive coefficient
Kalaimani et al. (2020) [41]	Quadratic PMV models for winter (I_{cl} = 1 clo) and summer (I_{cl} = 0.5 clo); M = 1.1 met, RH = 50%	Indoor temperature; air velocity
Carli et al. (2020) [42]	Linear PMV model from linearization of the original model; M = 1.2 met, I_{cl} = 1 clo	Indoor air temperature; absolute humidity
Fang et al. (2020) [43]	Linearized PMV model based on multi-linear regression; M = 1 met, I_{cl} = 1 clo	Indoor air temperature; air velocity
Li et al. (2021) [44]	PMV model by Deng et al. (2018) [45]; M = 1 met, I_{cl} = 0.57 clo	Mean room temperature; mean airflow velocity
Yang et al. (2021) [46]	Linear PMV model by Yang et al. (2018) [47]; M = 1 met, I_{cl} = 0.57 clo, v_a = 0.136 m/s	Indoor air temperature; mean radiant temperature; absolute humidity

Over half of the PMV-based studies made simplifications on the input parameters, especially clothing insulation and metabolic rate, by assuming them on the basis of standards or public databases (see, for example, the “Compendium of Physical Activities” [48]). Relatively few attempts to estimate these parameters more accurately and in real time can be found among the reviewed papers. Calvaresi et al. [49] obtained M from wearable devices as a function of heartbeat, breathing rate, posture, activity level, and acceleration module. Park and Rhee [50] calculated metabolic heat gain of human body from occupant thermal model. Tanaka et al. [51] evaluated M as a 10 min moving average of metabolic equivalent of task based on walking speed, which is a function of height and body mass. Choi et al. [52] proposed a clothing insulation system recognition based on real-time frames from a camera, relying on a convolutional neural network model built from a large garment image database. Zang et al. [53] used machine learning algorithms to obtain M and I_{cl} from camera images within a discrete range of possible values.

Another frequent assumption is the equivalence of mean radiant temperature with air temperature, which is usually motivated by either sensitivity analyses, as in [54], or simplicity reasons. The estimation of MRT is indeed a complex task, as it can be performed via expensive instrumentation (black globe thermometer) or with one of several calculation procedures exploiting the readings from an adequate number of surface temperature sensors. However, MRT is a key parameter in thermal comfort perception, and simply assuming it equal to air temperature without further validation can compromise the model-predictive capabilities, particularly in old buildings with high window-to-wall ratios [9]. Most of the PMV-based works analyzed in this review made the temperature equivalence assumption without providing a reason. The few that estimated MRT obtained it from calibrated models [55–58], energy simulations [59,60], or measurements [49,61]. Occasionally, assumptions are made also on air velocity and relative humidity, although the latter is generally easy to measure with standard sensors, often in combined temperature/humidity measurement devices.

Non-PMV models. The pie chart on the right in Figure 8 shows that almost half of the 61 papers adopting non-PMV approaches are data-driven. For the sake of brevity, only journal articles are reported in Tables 5 and 6 where inputs, outputs, and data-driven algorithms are summarized. Measured, historical, or literature data have been generally used to build models that can predict thermal comfort subjective indicators (sensation, preference, or satisfaction) or, less frequently, comfort-related parameters such as neutral temperature or mean radiant temperature. For the full list of relevant contributions, which includes the articles in Tables 5 and 6 plus eight conference papers, the reader is referred to the spreadsheed in the Supplementary Materials.

Table 5. Data-driven thermal comfort models in reviewed journal articles (2017–2019).

Reference	Inputs	Outputs	Algorithm
Hilliard et al. (2017) [62]	Zone air dry-bulb temperature, ambient air temperature and solar radiation	Zone mean radiant temperature	Regression + adjustment based on occupants' feedback
Li et al. (2017) [63]	Metabolic data, environmental measurements, clothing, thermal preference feedback from app	Thermal preference	Classification (random forest)
Auffenberg et al. (2017) [28]	Operative temperature and relative humidity	Optimal comfort temperature, vote and user's thermal sensitivity	Bayesian network
Xu et al. (2018) [64]	Current and historical feedback	Personalized thermal comfort profile	Softmax regression
Pazhoohesh and Zhang (2018) [65]	Thermal comfort votes and corresponding indoor temperatures	Thermal perception index	Fuzzy classification and fuzzy map
Gupta et al. (2018) [66]	User's thermal comfort preference for various temperatures	Individual discomfort function (simplification: comfort range limits)	Piecewise approximation (simplifications: values provided direclty)
Kruusimagi et al. (2018) [67]	Feedback of thermal sensation and corresponding measured indoor air temperature	Neutral temperature	Regression
Qiao et al. (2019) [68]	Thermal sensation feedback, indoor temperature	Thermal satisfaction rate function	Linear regression
Chaudhuri et al. (2019) [32]	Skin temperature and conductance, clothing, surface body area conductance, oxygen saturation, pulse rate	Thermal state index	Support vector machine, random forest, convolutional neural network
Jung and Jazizadeh (2019) [69]	Actual and synthesized thermal votes from the literature	Thermal comfort profile	Stochastic modeling
Lu et al. (2019) [70]	Subset of ASHRAE RP-884 dataset	Thermal sensation	K-nearest neighbors, support vector machine, random forest
Aguilera et al. (2019) [71]	Thermal preference vote feedback and corresponding indoor temperature	Thermal preference profile	Fuzzy logic
Lee et al. (2019) [72]	Subset of ASHRAE RP-884 dataset + assumptions on metabolic rate, clothing insulation and air velocity	Thermal preference	Bayesian clustering; online classification

Table 6. Data-driven thermal comfort models in reviewed journal articles (2020–2021).

Reference	Inputs	Outputs	Algorithm
Gao et al. (2020) [73]	Indoor temperature and humidity	Thermal comfort value	Feedforward neural network
Mohamadi and Ahmed (2020) [74]	Personal factors and indoor environmental parameters	Comfort coefficient	Neural network
Alsaleem et al. (2020) [75]	Biometric data, environmental data, comfort feedback	Thermal comfort level	Decision tree, adaptive boosting, gradient boosting classifier, random forest, support vector machine
Kumar Yadav et al. (2020) [76]	Preferred temperature via app	Individual temperature preference	Value provided directly
Deng and Chen (2020) [77]	Thermal sensation feedback and environmental measurements and physiological parameters	Thermal sensation	Artificial neural network
Li et al. (2021) [78]	Thermal sensation and thermal satisfaction feedback, heart rate, and wrist skin temperature and its variation	Thermal sensation	Linear regression
Aryal et al. (2021) [79]	Thermal comfort feedback, environmental indoor and outdoor mreasurements, clothing level, HVAC equipment states	Thermal sensation and thermal satisfaction	Random forests, k-nearest neighbors
Li and Chen (2021) [44]	Classified garment image database; thermal sensation vote feedback, air and face temperature	Clothing level classification, comfortable air temperature	Convolutional neural network

Adaptive thermal models are the second non-PMV category for number of papers. The adaptive approach is founded on the evidence that the static method tends to overestimate discomfort range in naturally ventilated buildings, especially when the occupants can act on the surrounding environment and adapt it to their preference [80]. The theory thus relates comfort operative temperature to outdoor environmental conditions, generally in the form of a linear correlation. The single dependent variable was initially taken as the monthly average of outdoor air temperature (Humphreys, 1978 [81]), and subsequently replaced with an exponentially weighted running mean (EWRM) to include the memory of weather history. Adaptive model is included in the reference standards [4,6] and its use is recommended only in the case of naturally ventilated buildings and within a limited outdoor temperature interval. However, the recent literature is exploring adaptive model potentiality also in case of mixed-mode or mechanically ventilated buildings, as can be observed in Table 7. The mathematical formulation is quite simple to implement and requires only one type of measurement (outdoor temperature). Moreover, experimental measurements and thermal comfort surveys can be carried out to calibrate the coefficients of the adaptive formulation to a specific location, building, or group of people.

A third category of non-PMV-based models is worth mentioning: the automatic inference of thermal comfort preferences from users' interactions with control devices, made possible by available current technologies. Table 8 reports the papers characterized by this approach. Some predominant features can be identified: the use of machine learning techniques, the personalized connotation of this approach, and the preliminary stage of the works (five out of eight conference proceedings, mainly theoretical or simulation-based). The solutions developed with this class of methods are difficult to generalize, in that there is no underlying model and, differently from data-based approaches, the preferences are inferred and not asked directly. For example, Laftchiev et al. [82] exploited occupants' actions on the thermostat, and decided to use only two of the three pieces of information that can be extracted from them (discomfort condition and direction of corrective action), because the temperature set by the user cannot be assumed as the ultimate preferred value.

Table 7. Adaptive thermal comfort models in reviewed contributions.

Reference	Formulation Reference	Outdoor Temperature Source	Ventilation
Arballo et al. (2017) [83]	Adaptive model by Kuchen (2008) [84]	Measurements on site in San Juan, AR	Mixed-mode
Kramer et al. (2017) [85]	Adaptive formulation calibrated with one-year survey	Museum BMS measurements, Amsterdam, NL	Mechanical
Menconi et al. (2017) [30]	EN 15251 standard [86]	Energy Plus Weather file for Perugia, IT	Mechanical
Stazi et al. (2017) [87]	EN 15251 standard [86] or CIBSE Guide A [88]	Measurements by weather station in Ancona, IT	Mixed-mode
Aparicio-Ruiz et al. (2018) [89]	Adaptive formulation calibrated experimentally [90]	Measurements in mixed-mode buildings in Seville, ES	Mixed-mode
Frătean and Dobra (2018) [31]	Humphreys (1978) [81]	TMY weather data for Bucharest, RO	Mechanical
Sghiouri et al. (2018) [91]	EN 15251 standard [86]	Weather data from TMY of three Moroccan cities	Natural
Gabsi et al. (2020) [92]	McCartney and Nicol (2001) [93]	Measurements in Nancy, FR	Mechanical
Sánchez-García et al. (2020) [94]	EN 15251 standard [86]	Energy Plus Weather file for Seville, ES	Mechanical
Tan and Deng (2020) [95]	Tong et al. (2017) [96]	Measurements by local weather station in Wollongong, AU	Mixed-mode
Aguilera et al. (2021) [97]	EN 16798-1 [6] and EN 15251 [86] standards	IWEC weather data for Copenhagen, Edinburgh, Palermo, Tokyo and Zurich	Mixed-mode
Lin et al. (2021) [98]	EN 15251 standard [86] with EWRM temperature	Measurements at experimental site in Hsinchu, TW	Mechanical
Vázquez-Torres et al. (2021) [99]	Szokolay (2003) [100], Auliciems and Szokolay (2007) [101]	Average air temperature from IWEC historical data for MX	Natural
Xu et al. (2021) [102]	Adaptive model by Yang et al. (2014) [103] for cold regions of China	Outdoor climate data from National Weather Service, location not specified	Mechanical

Table 8. Thermal comfort models based on occupants' actions in reviewed papers.

Reference	Preference-Related Actions	Model Development
Yano (2018) [104]	Set-point temperature operating time	Statistical model to define acceptable set-point temperatures based on their operating (unchanged) time
Marche and Nitti (2019) [105]	Interactions with HVAC comprehensive smartphone app	Thermal profile for each user with Gaussian function based on previous actions
Shetty et al. (2019) [106]	Personal fan operation (on/off and speed setting)	Classification and regression algorithms to predict on/off state and preferred air speed in case of "on" state
Cicirelli et al. (2020) [107]	User's interactions with HVAC system (e.g., the user turns on the heating)	Deep reinforcement learning with penalty given each time the user operates on the HVAC switch
Chenaru and Popescu (2020) [108]	Corrective actions (e.g., local temperature adjustment)	Relevant actions incorporated in learning phase to train comfort model
Amasyali and El-Gohary (2021) [109]	Thermostat adjustment, operation of doors and shading devices	Classification algorithm to develop group and individual models from action recordings
Zhu et al. (2021) [110]	Air-conditioning switching on/off and set-point adjusting	Classification rules returning preference patterns for the specific action (on/off or set-point)
Laftchiev et al. (2021) [82]	Temperature set-point adjustment	Endpoints of default comfort temperature range shifted to current temperature based on change direction

In addition to the previous three categories, other non-PMV approaches found in the analyzed papers include thermal comfort predictions based on physiology and sensation models [111], evaluation of discomfort degree-hours according to the preferred approach [112], rule-based indicators [113], direct preference from the user [114], and literature-based or self-developed sensation and comfort indicators [115,116].

3.4. Control Strategies

As outlined in Figure 5, thermal-comfort-based control is performed by means of methods and algorithms which use inputs and thermal comfort information to define settings and actions that can be passed to the physical system. To examine the algorithms adopted in the selected papers, the following macro-categories of methods have been identified that can be used individually or combined with each other:

- Rule-based (RB): settings are determined with knowledge-based rules.
- Model-predictive control (MPC): a model predicts the system state on a desired time horizon and finds optimal actions minimizing an objective function.
- Machine learning (ML): models are based on continuous data collection.
- Optimization (O): optimal settings are obtained by minimizing an objective function.
- Mathematical model (MM): settings are the solution of a mathematical equation or system of equations.

An overview of the techniques is given in Figure 9, where a slight prevalence of rule-based and optimization methods is observed. RB algorithms include strategies in which the proper action is chosen based on a set of knowledge-based simple instructions. However, the category also includes fuzzy rule-based systems, such as in [78,113,117–119]. Optimization allows to calculate output quantities by minimizing a cost function subject to constraints. In these methods, thermal comfort can be in the cost function or in the set of constraints, typically combined with energy-saving objectives. Examples of techniques used in the analyzed papers are particle swarm optimization, genetic algorithms, cuckoo search, proximal policy optimization, gray-wolf optimization, and firefly algorithms. Together with MPC and ML methods, optimization usually requires elaborate mathematical formulation and attention to computational resources. Finally, MM indicates any type of physics-based description that is developed for control purposes; examples range from simple functions, such as adaptive models to directly calculate comfort temperature, to large sets of equations describing building or HVAC systems used in optimization or rule-based processes.

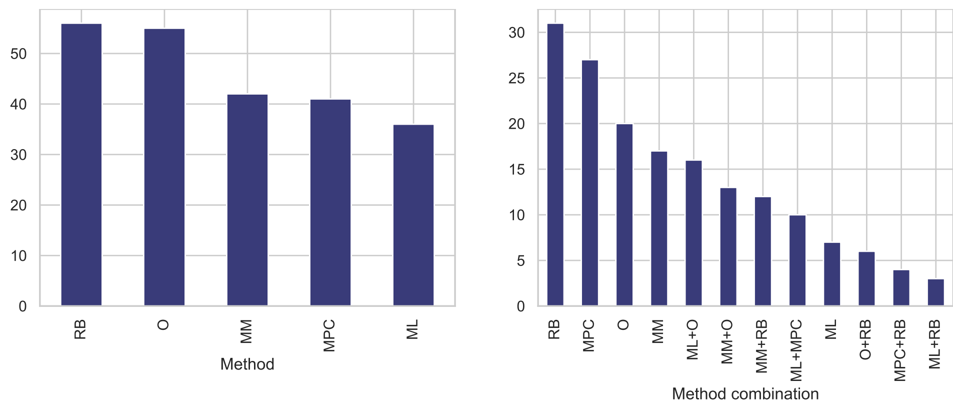

Figure 9. Methods used to determine control settings in the analyzed papers. (**Left**): occurrences of each method; (**right**): method combinations.

In 40% of the occurrences, two techniques have been used together, the most frequent occurrence being the combination of a mathematical or machine learning model with optimization techniques (Figure 10). ML is generally used to build a model instead of a physics-based solution. Therefore, no combination can be found of MM and ML in Figure 10. It is worth noting that the MPC definition includes both a model and an optimization stage. This is the reason why no combination of MPC + MM, nor of MPC + O, is present in Figure 10, either. MPC exploiting a physics-based model is adopted in almost one-fifth of the studies. The use of an ML-based model instead of a physics-based model in an MPC system is indicated by ML + MPC; if compared with its physics-based counterpart, this solution is exploited in one third of the cases.

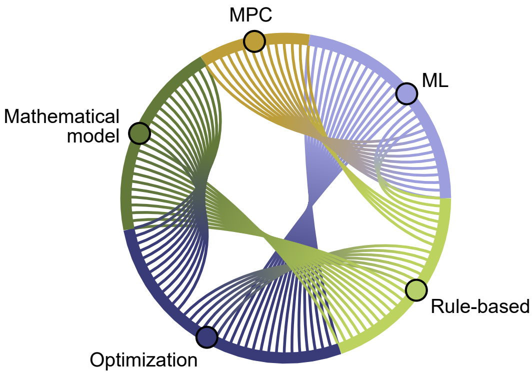

Figure 10. Use of methodology combinations in the analyzed papers.

Such methods have been used to calculate the values of a wide range of control variables, as summarized in Figure 11. Temperature set-points are the most popular choices, mainly as room—air, operative, thermostat, or, generically, indoor—temperature, but also in terms of HVAC working parameters (for example, supply air [120,121] or water [122,123] temperature). In air conditioning systems, some authors proposed to operate on the air flow by determining air flow rate setting or fan speed, the former being mainly used in central systems (e.g., [34,124]) and the latter in personal devices (e.g., [125,126]). Several studies exploited window control for natural ventilation (e.g., [33,87,95,118]) or solar shading (e.g., [127–130]). The category marked as “Actuators” in Figure 11 indicates the thermal-comfort-based determination of settings and working parameters for valves [131,132], dampers [133,134], and other HVAC equipment such as compressors [135] and heat pumps [136]. In some works, humidity was one of the controlled parameters, mostly in combination with PMV-based thermal comfort models [117,137]. Other studies included direct control of comfort parameters, especially at a simulation stage [138,139], energy or power supply [140–142], or the choice of the ventilation mode [33,95]. A distinct category, labeled as “Design” in Figure 11, gathers all the studies in which thermal comfort analysis was not finalized to the real-time control of HVAC equipment, but to comfort-oriented decisions such as material selection, as in [30,112,143], design of building elements and layouts (see, for example, [91,144,145] and [68]), or HVAC installation recommendations, such as in [36,97,146]. In the same category, studies are also included that aimed to provide operating schedules [99,119] or suggestions on most comfortable areas in relation to the occupant’s preferences [65,147]. Lastly, it is worth noting that only rarely is thermal comfort satisfaction the sole objective of the control strategy. As discussed in Section 3.2, energy saving is often the main goal of the study or a constraint, but other indoor quality parameters may be considered, too, such as CO_2 concentration [148–152] and visual comfort [109,129,130,153].

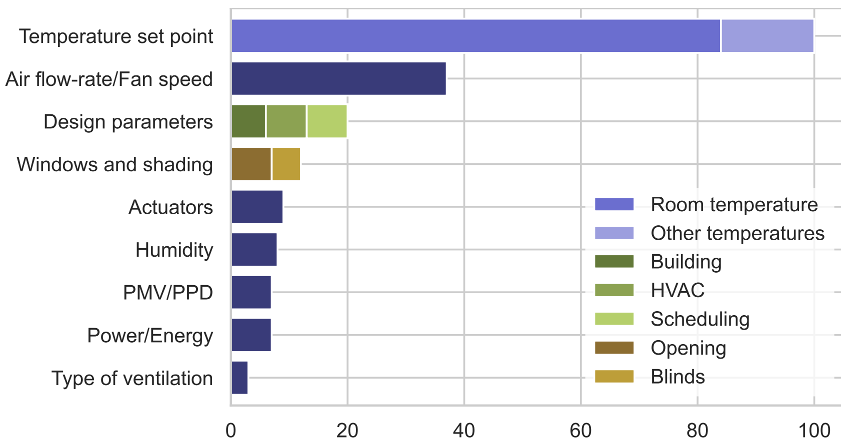

Figure 11. Variables and settings for thermal-comfort-based control in the analyzed papers.

Focusing on HVAC systems, Figure 12 shows that in almost 60% of the cases the control strategy has been applied to air conditioning (AC) systems. The reason is arguably that advanced control methodologies nowadays are employed, especially in office or commercial buildings, usually heated and cooled through mechanical ventilation. Hydronic systems are an interesting subgroup due to their diffusion in the residential sector, especially in Europe. In Table 9, it can be observed that this category covers mostly heating applications (with the obvious exception of chilled beams) with no building type restriction. Control variables in this case include temperature set-points, control valve position, and other water circuit parameters such as pump speed and heating curve.

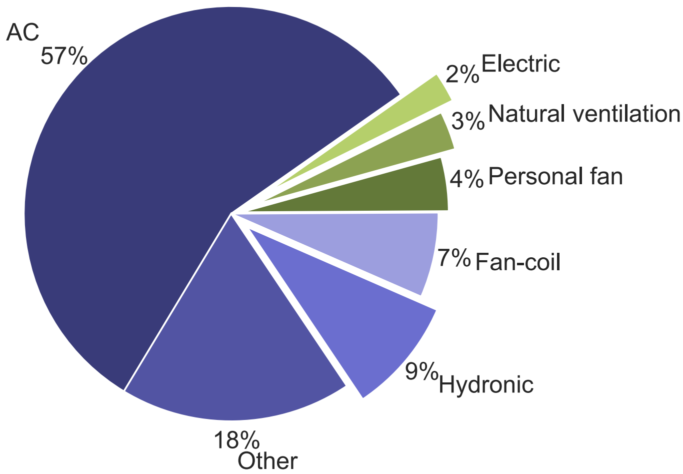

Figure 12. HVAC systems in the analyzed papers.

Table 9. Hydronic heating (H) and/or cooling (C) systems in the analyzed literature.

Reference	HVAC	H/C	Control Variables	Building	Control
Wu et al. (2021) [154]	Chilled beams	C	Chilled water flow rate, room temperature set-point	Any	MM + O
Xu et al. (2020) [155]	Radiant system	H	Room temperature set-point	Any	MPC
Hawila et al. (2018) [59]	Radiators	H	Indoor air set-point temperature	Any	MM
Potočnik et al. (2018) [136]	Radiant system	H	Optimized heating curve for heat pump flow temperature	Residential	MPC
Hong et al. (2018) [60]	Radiant system	Any	PMV	Residential	MM
Uguz and Ipek (2017) [131]	Radiators	H	Radiator valve position	Any	MM
Lin et al. (2021) [98]	Radiant system	H	Heating/cooling device status	Any	MM
Karatzoglou et al. (2018) [156]	Radiators	H	Thermostat set-point	Any	MM + O
Yang et al. (2021) [132]	Chilled beams	C	Pump speed; valve opening	Office	MPC + RB
Ke et al. (2020) [157]	Radiators	Any	Indoor temperature	Any	MPC + ML
Ascione et al. (2019) [158]	Baseboard radiators	H	Hourly room set-point temperatures in typical days	Residential	MPC
Aguilera et al. (2019) [71]	Radiators	H	Room temperature set-point	Office	O
Lee et al. (2019) [72]	Radiant system	C	State of radiant coil valves	Office	MPC
Zhang and Lam (2018) [123]	Radiant system	Any	Supply water set-point	Office	ML + O
Yano (2018) [104]	Radiators	H	Thermostat set-point	Residential	RB

3.5. Putting It All Together: Thermal Comfort Control Systems

All the studies included in this survey feature both a thermal comfort model and a control strategy; thus, it is possible to give a general overview of the analyzed systems and find correlations between the two aspects. Focusing on the two most advanced levels of readiness, which are 90% of the analyzed works, it can be observed that many simulation studies used PMV thermal comfort models and MPC (Figure 13). The choice of a standard thermal comfort model and a complex control system indicates that the focus was on the latter aspect in these studies. Switching to papers presenting prototypes, purely rule-based systems prevail in conjunction with non-PMV comfort models, which can be explained with the trend to use real data to define the thermal comfort preferences of the occupants. Contrary to simulations, here, a generally simple control strategy was chosen, with a considerable effort invested in thermal comfort evaluation.

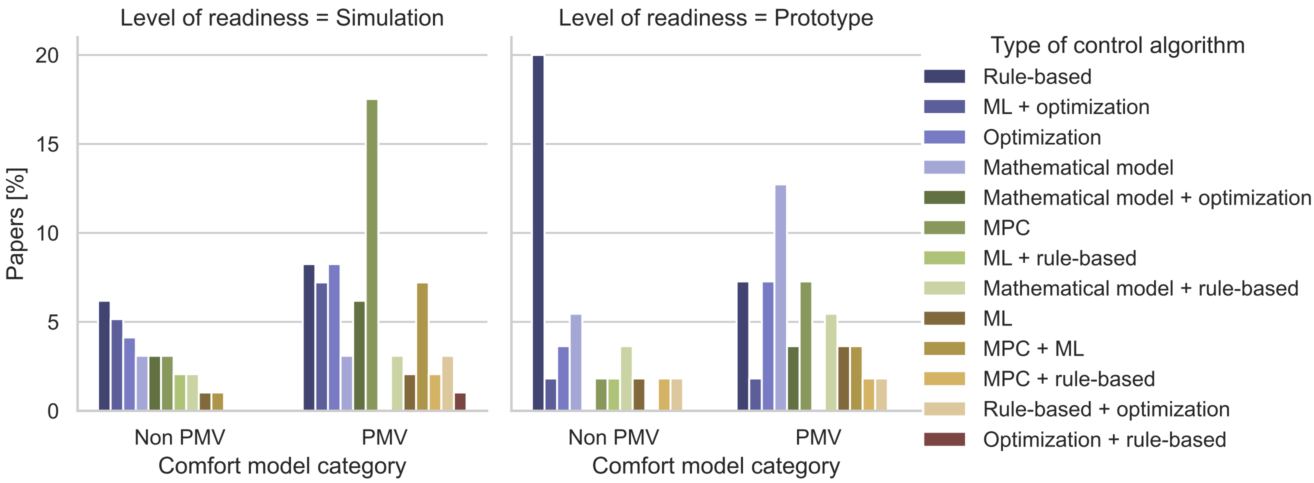

Figure 13. Thermal comfort model category at varying control algorithms and levels of readiness. Percentages are relative to the total number of papers considered in either chart (i.e., with the specific level of readiness).

Figure 14 qualitatively illustrates the composition of model complexities. Here, PMV and adaptive methods are defined as "simple" thermal comfort approaches. "Simple" control-related methods include RB, MM, and the combination of the two. Many works can be observed with simple thermal comfort model and complex control systems (quadrant "S–C"), and they are mainly at a simulation level. On the other hand, most of the works with complex thermal comfort approaches and simple control methods (quadrant "C–S") are prototypical. It is worth noting that "simple" in this context does not mean "simplistic", but it, rather, indicates a basic approach (for example, standardized, or not requiring high-level algorithmical skills).

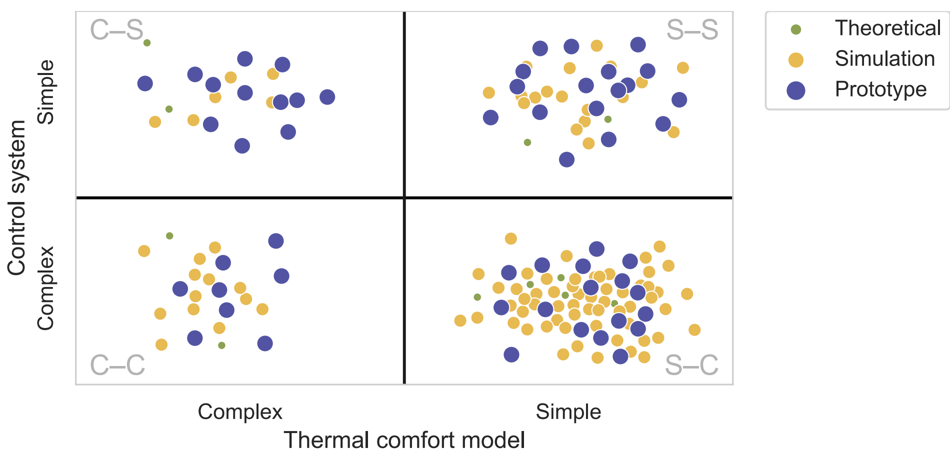

Figure 14. Qualitative illustration of thermal comfort model and control system complexities in the analyzed papers. The distribution of points within quadrants is random.

Among "simple" thermal comfort models, the adaptive comfort model was used in all the analyzed studies with simulations or prototypes characterized by natural ventilation

(Figure 15). However, it was also adopted in a significant number of cases with air conditioning or hydronic systems. In case of relatively unsophisticated appliances, such as personal or electric heaters, PMV and data-based approaches were preferred.

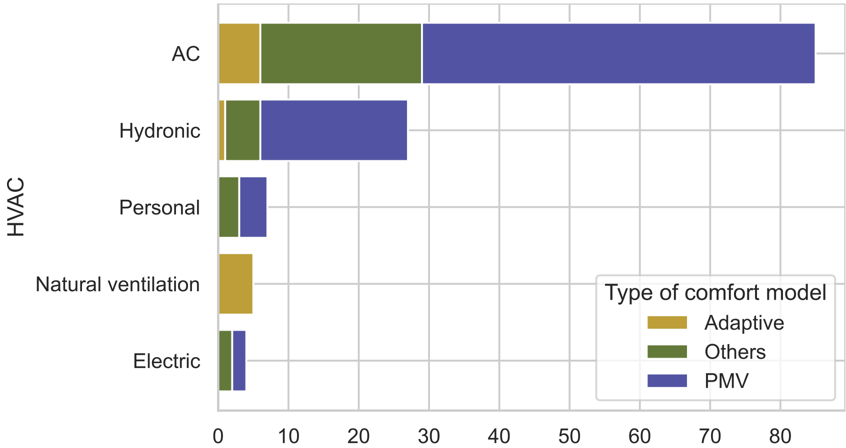

Figure 15. Type of comfort model by HVAC type (level of readiness simulation or prototype).

Figure 16 shows the breakdown of works making use of ML in the definition of thermal comfort models and indoor environment controls over the years. The exploitation of this family of techniques grew steadily until 2020, whereas the trend reversed in 2021. Though the sample is too small for accurate conclusions, COVID 19 pandemic effects may have had a role in this anomaly from two points of view. On the one hand, the requirement for machine learning is the availability of data, which might have been more difficult to collect in 2020 than in previous years (hence the brake on ML-driven works in 2021). On the other hand, the pandemic caused a change of habits in various fields [159], and it may take longer to process and understand data collected in this period; this may have been the cause of a publication delay.

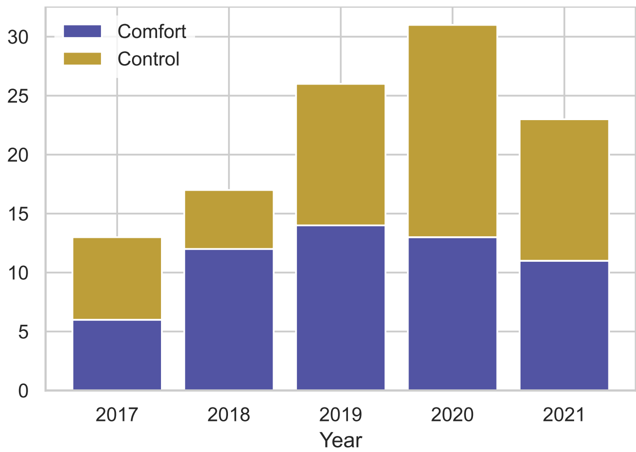

Figure 16. Use of ML in comfort models and control algorithms through the years.

There is no clear correlation between the use of ML techniques, the thermal comfort model category, and the level of readiness (Figure 17). It can be noted that in simulation works, ML was mainly used in control system development, while in prototypes it was often adopted in thermal comfort assessment. This confirms the trends illustrated in Figures 13 and 14.

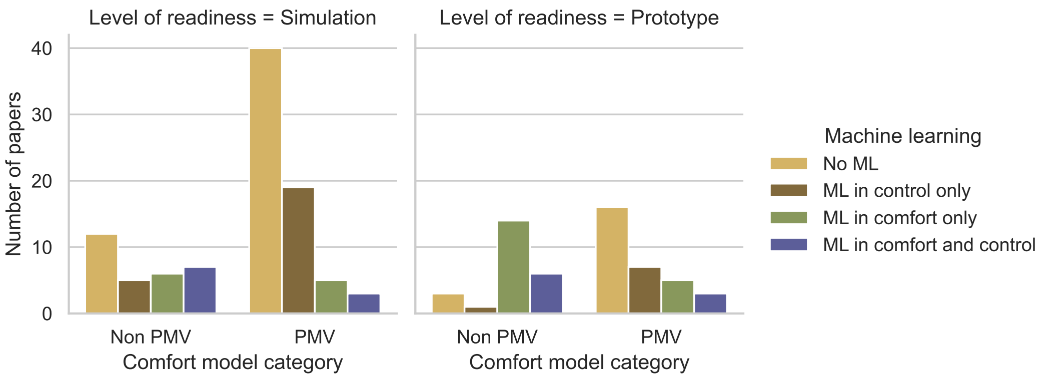

Figure 17. Use of ML by comfort model category and level of readiness.

In terms of field of application, a large portion of the papers focused on commercial and office buildings (Figure 18), for two main reasons: a usually higher level of readiness of the control and management infrastructure, and the driving force of attractive energy savings. In this respect, there is a correlation with the predominant number of AC systems and of cooling applications, which are typical of tertiary facilities. Residential and educational buildings are also investigated frequently, while few studies focus on thermal-comfort-based control of indoor recreational, social, guest accommodation, and healthcare environments. The last are delicate facilities, in that their occupants include vulnerable people with special needs that must be taken into consideration (see Section 4).

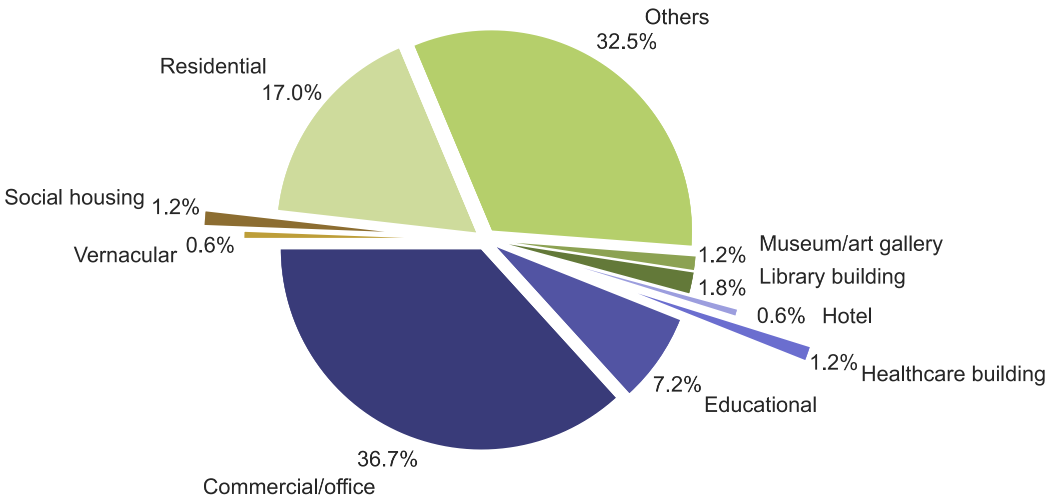

Figure 18. Type of buildings considered in the studies.

With reference to shared spaces, the problem of evaluating thermal comfort for multiple occupants can be of relevance, and has been tackled in several studies. Three ways of satisfying individual preferences can be identified:

1. With personal devices, such as desk fans;
2. By providing thermal comfort models with "average" inputs representing the occupants, for example through machine learning techniques;
3. By collecting individual thermal preferences and applying decision algorithms.

The first category is the actual expression of personalized thermal comfort paradigm, but it is not always applicable or energetically convenient. The second approach uses "average" information to describe a group of people; thus, its modeling capabilities depend on the quality of input data and on the homogeneity of the occupants. The third is an intermediate option, in which individual preferences are computed and synthesized into group settings. A summary of studies using this approach is given in Table 10.

Concerning software, the adoption of the MATLAB® platform has been reported in 40% of the analyzed studies. The most popular alternative was Python, chosen in 20% of the cases. Open-source software EnergyPlus was generally preferred to its commercial competitor TRNSYS for building energy simulations (29 vs. 11 cases). Hardware always included environmental parameter sensors, while data collection, communication, storage, and processing equipment and infrastructure have rarely been described in detail. Raspberry Pi, Arduino, and compatible low-cost sensors have been frequently encountered to build affordable data collection systems, especially at the experimental stage. More detailed information can be found on the spreadsheet available in Supplementary Materials.

Table 10. Decision approach to synthesize individual preference into group settings (multi-occupancy).

Reference	Decision Approach	Building	Comfort
Li et al. (2017) [63]	Collective decision algorithm aiming to satisfy at least half of the occupants	Any	Data-driven
Auffenberg et al. (2017) [28]	Comfort compromiser algorithm taking the maximum of the lower bounds and the minimum of the upper bounds of occupants' ranges	Any	Data-driven
Xu et al. (2018) [64]	Aggregated profiles of multiple occupants	Office	Data-driven
Liu et al. (2018) [125]	Cooperative approach: worst-case deviation from set-point minimized	Educational	PMV
Gupta et al (2018) [66]	Minimization of total discomfort from zone occupants' profiles	Any	Data-driven
Laing and Kühl (2018) [147]	Compatibility between personal preference and zone characteristics	Commercial	Data-driven
Yang et al. (2019) [160]	Minimization of total PPD or largest PPD among communities	Not discussed	PMV
Aguilera et al. (2019) [71]	Minimization of group thermal discomfort	Office	Data-driven
Lou et al. (2020) [57]	Worst-case PMV of occupants in different positions	Residential	PMV
Anasyali and El-Gohary (2021) [109]	Group and individual comfort models	Office	Occupants' actions
Zhang et al. (2021) [130]	Occupancy-weighted average of multiple occupants' thermal comfort	Commercial	PMV

To conclude, it is worth observing that the number of papers validated through simulations almost doubles the studies presenting field deployments (Figure 19). In one-fourth of the cases with prototypes, a rough estimation of costs has been possible, which is reported in Figure 20 limitedly to the two most numerous building types encountered (office/commercial, and residential). In particular, the analysis is based on a group of twenty-two works [33,44,47,49,51,52,60,67,72,78,79,83,105,106,113,126,161–166]. Prices of equipment described in the papers have been estimated based on Internet searches, whereas the cost for software licenses has not been considered. The cost for equipment not required by ordinary operation (for example, a black globe thermometer only required at model development stage) has not been included, either. The graph shows costs as a function of floor area of conditioned space. Different symbols indicate building category and featured devices. This rough estimation shows a slight dependency of costs from the application scale. More evidently, some systems were designed to be low-cost by incorporating hardware such as Raspberry Pi or Arduino ecosystem devices; measurement equipment featuring—visible or thermal—cameras has intermediate cost, while the most expensive setup arrangements tend to be the ones including biometric devices, locally installed weather stations, and building management systems (BMS).

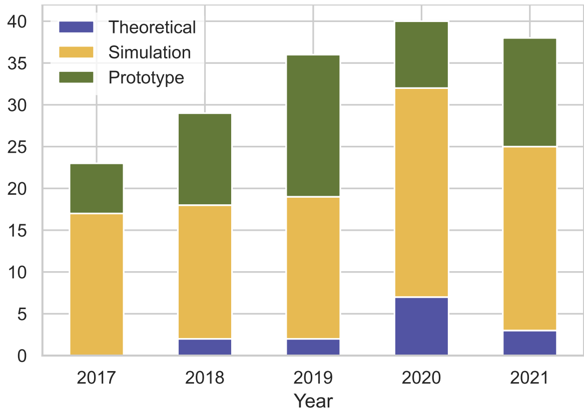

Figure 19. Readiness level of the analyzed papers.

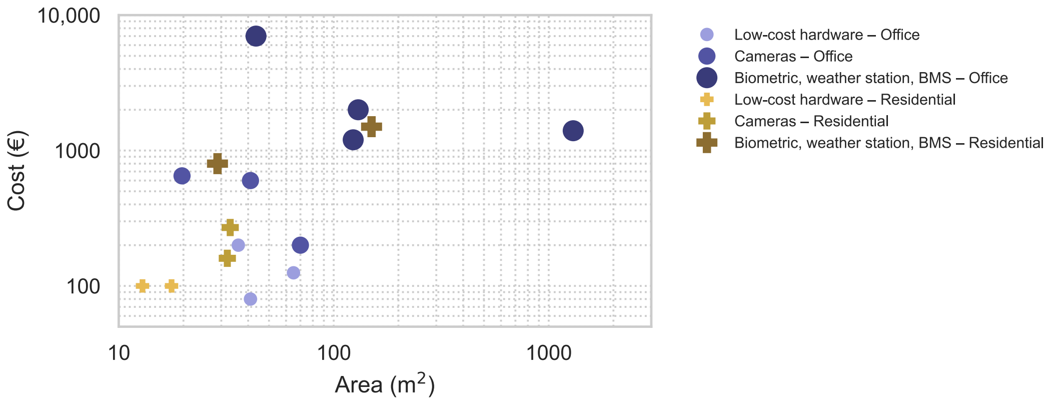

Figure 20. Costs estimated for office/commercial and residential building applications as a function of conditioned area (bi-logarithmic scale).

3.6. Limitations of the Study

This brief paragraph summarizes the research method limitations. Although the search was designed to be as comprehensive as possible, some relevant works may have been overlooked due to the following reasons. First, keywords in the query string may not be exhaustive, because authors may have chosen other terms to identify similar concepts. Second, occasionally abstracts may be misleading, causing the paper exclusion already at stage 2 of the selection process. Third, in some cases, the final inclusion in the reference database was debatable, and was ultimately decided based on a subjective evaluation of relevance and pertinence of the paper.

Concerning the detailed analysis of the selected works, the field of building control has been especially problematic to describe, because the method categories often overlap, and control variables are not homogeneous in terms of practical usability (for example, PMV, operative temperature, and thermostat set-point are three control variables with different distances from field application). Even at this stage, information extraction has been made with automatized processing (Python scripts) following human actions (feature classification). The authors are aware that this approach may have led to over-simplifications; thus, the present work (including the paper and the spreadsheet in the Supplementary Materials) should be intended as a guiding tool; the referenced papers remain the primary source for in-depth analyses.

4. Open Issues: Vulnerable People and Special Environments

Describing adaptive approach in ASHRAE Standard 55, Mora and Bean [167] state that "adaptive principles assume the persons are able-bodied without physiological and physical challenges [. . .] or mental health and/or cognitive disabilities preventing the ability to adapt", and that "Standard 55-2017 does not directly cover vulnerable populations".

Indeed, studies on the thermal comfort perception of some categories of vulnerable people exist in the literature, but practical implementations are almost entirely missing. Therefore, they cannot be found among the publications that the analysis in Section 3 is built upon. This subsection has the purpose to touch on this subject by providing references to recent studies that focus on the peculiarities of vulnerable groups in terms of thermal comfort needs. The aim is to outline some situations in which a tailored thermal comfort-based system may be useful, but few or no application-oriented work has been carried out yet.

Differences in thermal comfort perception due to age have been widely explored by researchers, with elderly people being a particularly interesting group due to their frailty and to the aging of the world's population. Wang et al. [15] noted that the presence of secondary factors is indeed the reason behind such differences, rather than age, per se. Hughes and co-authors investigated summer [168] and winter [169] thermal conditions of elderly people in the UK by means of extensive surveys, revealing that modeling frameworks according to reference standards often fail to provide reliable predictions. The specific effect of dementia on the applicability of different thermal comfort approaches was analyzed in the recent survey by Yi et al. [170].

Conversely, few studies can be found on thermal-comfort-related needs of people with physical disabilities. These people may have different thermal requirements due not only to the disability itself, but also to postural and mobility impairment, and possibly to pharmacological treatments (Parsons, 2002 [171]). Recently, the work by Brik et al. [172] proposed an IoT-based modeling approach to make comfort evaluation possible even in case of difficulties in expressing a feedback; the study confirmed that differences exist between people with and without disabilities, and between people with different disabilities as well. Similar attention to the survey planning stage can be found in Bouzidi et al. [173], whose study reaffirmed that PMV tends to predict excessive comfort temperatures, and proposed a tailored adaptive model.

Cognitive impairment has not been frequently associated with indoor comfort requirements, although authors have demonstrated that these vulnerable people can benefit from a comfortable environment because it reduces triggers of negative behavior [174]. Bettarello et al. [175] stressed the importance of adapting the environment to the needs of people with neurodevelopmental disorders to give them the opportunity of "independent living projects". Caniato et al. [176,177] reported that experimental observations from questionnaires (filled in by "proxy respondents", such as parents or caregivers, in case of people with severe disorders) do not indicate thermo-hygrometric conditions as a cause of stress in people with autistic spectrum disorder. However, they noted how very few investigations can be found in the literature on the individuals' sensitivity to the different comfort domains, and they anticipated the need for more studies to develop quality thresholds and design guidelines for indoor environments.

Healthcare facilities are especially challenging spaces to deal with. Both patients and healthcare workers should feel thermally comfortable in places where they have to spend long time periods. Shajahan et al. [178] summarized the impact on patients of HVAC-related parameters such as indoor air temperature, pointing out that medications and drugs affect the patient's thermoregulatory system. As discussed by Pereira et al. in their recent review on hospital environments [179], only a small number of papers investigated the relationship between patients with specific conditions and the thermal environment, but thermal comfort dependency on patient category still has to be explored. The need to reconcile thermal comfort requirements of different types of occupants, including operators, makes the identification and control of thermal comfort conditions particularly problematic in practice. A typical example is the operating room [180], where the patient would need a warm environment due to being under anesthesia and wearing only a gown, whereas the medical staff prefer a cool, well-ventilated room due to the mentally and physically demanding procedures they have to sustain for a long time.

It is worth noting that the full comfort spectrum should be evaluated in sensitive indoor environments. This suggests considering a wide range of possibly intertwined indicators, and to apply diverse control strategies, even at the design stage. Orosa et al. [181] modeled the effect of internal building covering materials in a region with very high relative humidity throughout the year; the authors used the “percentage of dissatisfied due to decreased respiratory cooling” [182] and the “percentage of persons dissatisfied with the air quality” [183] as local comfort indicators, and related the results to expected energy consumption. Although the paper focused on office buildings, this is an example of an integrated strategy that could be well suited also to healthcare facilities.

The cases presented above represent some of the situations in which a wise assessment of thermal comfort and the implementation of adequate indoor environmental control systems can make a difference for the occupants. In these and many other cases, however, designers have limited support from the literature and the reference standards; thus, they must perform specific investigations and resort to their experience.

5. Conclusions

This study reviewed literature works presenting practical ways to control indoor environment based on thermal comfort analysis. Journal articles and conference papers were searched in the Scopus database limited to the five-year period between 2017 and 2021. The analyzed papers showed clear trends both in thermal comfort analysis and in control strategies. PMV is the dominant framework for the prediction of thermal comfort, although often with simplified formulation or input assumptions, especially concerning personal factors and mean radiant temperature. Data-based thermal comfort evaluation is the most frequently used non-PMV approach. This choice corresponds to a growing attention towards personal preferences, and already finds implementation in prototypical studies. The applicability of another popular approach, adaptive thermal comfort, was found to be explored also outside of the contexts recommended by the reference standards—for example, some studies utilized it even in the presence of mechanical systems. A vast majority of the studies focused on thermal-comfort-based control of air conditioning, followed by hydronic systems. Not surprisingly, the preferred control variable is indoor temperature to be used as a thermostat set-point, although it was not always clear whether it referred to air temperature or operative temperature. Concerning control aspects, the methods to calculate control settings range from expert rules to complex modeling techniques such as machine learning and model-predictive control. Overall, two-thirds of the analyzed papers include one or more optimization steps carried out with one of the several methods available in the literature. In general, it was found that many studies on innovative control systems are still at a simulation level. Office or commercial buildings with air-conditioning systems were the most investigated environments; the reasons are probably linked to higher available budget, more advanced monitoring and control infrastructure, desire to increase productivity, and perspective of energy savings. The number of journal papers and of works presenting prototypes has increased through the years, proving that this research area is vital and that it is moving closer and closer to field deployment. However, some categories of vulnerable people have special needs that are only beginning to be investigated and will require more research effort. The wide variety of analyzed studies shows that there is no one-fits-all solution to the problem, but many options are available and more will follow. The key is putting it all together: the synergy between building and HVAC designers, energy saving experts, and thermal comfort specialists, who still tend to work separately, could be the real breakthrough in the definition of pleasant sustainable indoor environments.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app12115473/s1, Spreadsheet S1: Full-featured database of reviewed papers.

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References

1. Frontczak, M.; Wargocki, P. Literature survey on how different factors influence human comfort in indoor environments. *Build. Environ.* **2011**, *46*, 922–937. [CrossRef]
2. Fanger, P.O. *Thermal Comfort: Analysis and Applications in Environmental Engineering*; McGraw-Hill: New York, NY, USA, 1970.
3. de Dear, R.J.; Schiller Brager, G. Developing an adaptive model of thermal comfort and preference. In *Proceedings of the 1998 ASHRAE Winter Meeting. Part 1 (of 2)*; American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE): Peachtree Corners, GA, USA, 1998; Volume 104, pp. 145–167.
4. ASHRAE. *Standard 55: Thermal Environmental Conditions for Human Occupancy*; American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE): Peachtree Corners, GA, USA, 2020.
5. ISO/TC 159/SC 5. *ISO 7730:2005*; 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. International Organization for Standardization: Geneva, Switzerland, 2005.
6. CEN/TC 156. *EN 16798-1:2019*; Energy performance of buildings—Ventilation for Buildings—Part 1: Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics. European Committee for Standardization, CEN: Brussels, Belgium, 2019.
7. Zhao, Q.; Lian, Z.; Lai, D. Thermal comfort models and their developments: A review. *Energy Built Environ.* **2021**, *2*, 21–33. [CrossRef]
8. Arakawa Martins, L.; Soebarto, V.; Williamson, T. A systematic review of personal thermal comfort models. *Build. Environ.* **2022**, *207*, 108502. [CrossRef]
9. Bean, R. *Thermal Comfort Principles and Practical Applications for Residential Buildings*; Indoor Climate Consultants Inc.: Calgary, AB, Canada, 2020.
10. Park, J.Y.; Nagy, Z. Comprehensive analysis of the relationship between thermal comfort and building control research—A data-driven literature review. *Renew. Sust. Energy Rev.* **2018**, *82*, 2664–2679. [CrossRef]
11. Manfren, M.; Nastasi, B.; Piana, E.; Tronchin, L. On the link between energy performance of building and thermal comfort: An example. In *AIP Conference Proceedings*; American Institute of Physics Inc.: Beirut, Lebanon, 2019; Volume 2123, p. 020066. [CrossRef]
12. Caniato, M.; Bettarello, F.; Ferluga, A.; Marsich, L.; Schmid, C.; Fausti, P. Thermal and acoustic performance expectations on timber buildings. *Build. Acous.* **2017**, *24*, 219–237. [CrossRef]
13. Enescu, D. A review of thermal comfort models and indicators for indoor environments. *Renew. Sust. Energy Rev.* **2017**, *79*, 1353–1379. [CrossRef]
14. Nägele, F.; Kasper, T.; Girod, B. Turning up the heat on obsolete thermostats: A simulation-based comparison of intelligent control approaches for residential heating systems. *Renew. Sustain. Energy Rev.* **2017**, *75*, 1254–1268. [CrossRef]
15. Wang, Z.; de Dear, R.; Luo, M.; Lin, B.; He, Y.; Ghahramani, A.; Zhu, Y. Individual difference in thermal comfort: A literature review. *Build. Environ.* **2018**, *138*, 181–193. [CrossRef]
16. Kim, J.; Schiavon, S.; Brager, G. Personal comfort models—A new paradigm in thermal comfort for occupant-centric environmental control. *Build. Environ.* **2018**, *132*, 114–124. [CrossRef]
17. Xie, J.; Li, H.; Li, C.; Zhang, J.; Luo, M. Review on occupant-centric thermal comfort sensing, predicting, and controlling. *Energy Build.* **2020**, *226*, 110392. [CrossRef]
18. Jung, W.; Jazizadeh, F. Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions. *Appl. Energy* **2019**, *239*, 1471–1508. [CrossRef]
19. Tomat, V.; Ramallo-González, A.P.; Skarmeta Gómez, A.F. A Comprehensive Survey about Thermal Comfort under the IoT Paradigm: Is Crowdsensing the New Horizon? *Sensors* **2020**, *20*, 4647. [CrossRef] [PubMed]
20. Halhoul Merabet, G.; Essaaidi, M.; Ben Haddou, M.; Qolomany, B.; Qadir, J.; Anan, M.; Al-Fuqaha, A.; Abid, M.R.; Benhaddou, D. Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques. *Renew. Sust. Energy Rev.* **2021**, *144*, 110969. [CrossRef]

21. Čulić, A.; Nižetić, S.; Šolić, P.; Perković, T.; Čongradac, V. Smart monitoring technologies for personal thermal comfort: A review. *J. Clean. Prod.* **2021**, *312*, 127685. [CrossRef]
22. Day, J.; McIlvennie, C.; Brackley, C.; Tarantini, M.; Piselli, C.; Hahn, J.; O'Brien, W.; Rajus, V.; De Simone, M.; Kjærgaard, M.; et al. A review of select human-building interfaces and their relationship to human behavior, energy use and occupant comfort. *Build. Environ.* **2020**, *178*, 106920. [CrossRef]
23. Ponce, P.; Peffer, T.; Molina, A. Framework for communicating with consumers using an expectation interface in smart thermostats. *Energy Build.* **2017**, *145*, 44–56. [CrossRef]
24. Idahosa, L.O.; Akotey, J.O. A social constructionist approach to managing HVAC energy consumption using social norms—A randomised field experiment. *Energy Policy* **2021**, *154*, 112293. [CrossRef]
25. Li, Z.; Loveday, D.; Demian, P. Nudging and usage of thermal comfort-related systems. *Energy Build.* **2021**, *252*. [CrossRef]
26. van Eck, N.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]
27. Van Hoof, J. Forty years of Fanger's model of thermal comfort: Comfort for all? *Indoor Air* **2008**, *18*, 182–201. [CrossRef]
28. Auffenberg, F.; Snow, S.; Stein, S.; Rogers, A. A comfort-based approach to smart heating and air conditioning. *ACM Trans. Intell. Syst. Technol.* **2017**, *9*, 1–20. [CrossRef]
29. Li, D.; Menassa, C.; Kamat, V. Framework for improved indoor thermal comfort through personalized HVAC control. In *Routledge Handbook of Sustainable and Resilient Infrastructure*; Routledge: Abingdon, UK; New York, NY, USA, 2018; pp. 706–732. [CrossRef]
30. Menconi, M.; Chiappini, M.; Hensen, J.; Grohmann, D. Thermal comfort optimisation of vernacular rural buildings: Passive solutions to retrofit a typical farmhouse in central Italy. *J. Agric. Eng.* **2017**, *48*, 127–136. [CrossRef]
31. Frătean, A.; Dobra, P. The impact of control strategies upon the energy flexibility of nearly zero-energy buildings: Energy consumption minimization versus indoor thermal comfort maximization. In Proceedings of the 2018 IEEE International Conference on Automation, Quality and Testing, Robotics, AQTR 2018—THETA 21st Edition, Cluj-Napoca, Romania, 24–26 May 2018; pp. 1–6. [CrossRef]
32. Chaudhuri, T.; Soh, Y.; Li, H.; Xie, L. A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings. *Appl. Energy* **2019**, *248*, 44–53. [CrossRef]
33. Fiorentini, M.; Serale, G.; Kokogiannakis, G.; Capozzoli, A.; Cooper, P. Development and evaluation of a comfort-oriented control strategy for thermal management of mixed-mode ventilated buildings. *Energy Build.* **2019**, *202*, 109347. [CrossRef]
34. Zhang, S.; Cheng, Y.; Fang, Z.; Huan, C.; Lin, Z. Optimization of room air temperature in stratum-ventilated rooms for both thermal comfort and energy saving. *Appl. Energy* **2017**, *204*, 420–431. [CrossRef]
35. Hang, L.; Kim, D.H. Enhanced model-based predictive control system based on fuzzy logic for maintaining thermal comfort in IoT smart space. *Appl. Sci.* **2018**, *8*, 1031. [CrossRef]
36. Alizadeh, M.; Sadrameli, S. Numerical modeling and optimization of thermal comfort in building: Central composite design and CFD simulation. *Energy Build.* **2018**, *164*, 187–202. [CrossRef]
37. Chen, Y.; Luo, F.; Dong, Z.; Meng, K.; Ranzi, G.; Wong, K. A day-ahead scheduling framework for thermostatically controlled loads with thermal inertia and thermal comfort model. *J. Mod. Power Syst. Clean* **2019**, *7*, 568–578. [CrossRef]
38. Buratti, C.; Ricciardi, P.; Vergoni, M. HVAC systems testing and check: A simplified model to predict thermal comfort conditions in moderate environments. *Appl. Energy* **2013**, *104*, 117–127. [CrossRef]
39. Vallianos, C.; Athienitis, A.; Rao, J. Hybrid ventilation in an institutional building: Modeling and predictive control. *Build. Environ.* **2019**, *166*, 106405. [CrossRef]
40. Yao, R.; Li, B.; Liu, J. A theoretical adaptive model of thermal comfort—Adaptive Predicted Mean Vote (aPMV). *Build. Environ.* **2009**, *44*, 2089–2096. [CrossRef]
41. Kalaimani, R.; Jain, M.; Keshav, S.; Rosenberg, C. On the interaction between personal comfort systems and centralized HVAC systems in office buildings. *Adv. Build. Energy Res.* **2020**, *14*, 129–157. [CrossRef]
42. Carli, R.; Cavone, G.; Othman, S.; Dotoli, M. IoT based architecture for model predictive control of HVAC systems in smart buildings. *Sensors* **2020**, *20*, 781. [CrossRef] [PubMed]
43. Fang, J.; Ma, R.; Deng, Y. Identification of the optimal control strategies for the energy-efficient ventilation under the model predictive control. *Sustain. Cities Soc.* **2020**, *53*, 101908. [CrossRef]
44. Li, X.; Chen, Q. Development of a novel method to detect clothing level and facial skin temperature for controlling HVAC systems. *Energy Build.* **2021**, *239*, 110859. [CrossRef]
45. Deng, Y.; Feng, Z.; Fang, J.; Cao, S.J. Impact of ventilation rates on indoor thermal comfort and energy efficiency of ground-source heat pump system. *Sustain. Cities Soc.* **2018**, *37*, 154–163. [CrossRef]
46. Yang, S.; Wan, M.; Chen, W.; Ng, B.; Dubey, S. Experiment study of machine-learning-based approximate model predictive control for energy-efficient building control. *Appl. Energy* **2021**, *288*, 116648. [CrossRef]
47. Yang, S.; Wan, M.; Ng, B.; Zhang, T.; Babu, S.; Zhang, Z.; Chen, W.; Dubey, S. A state-space thermal model incorporating humidity and thermal comfort for model predictive control in buildings. *Energy Build.* **2018**, *170*, 25–39. [CrossRef]
48. Ainsworth, B.; Haskell, W.; Herrmann, S.; Meckes, N.; Bassett Jr., D.; Tudor-Locke, C.; Greer, J.; Vezina, J.; Whitt-Glover, M.; Leon, A. 2011 compendium of physical activities: A second update of codes and MET values. *Med. Sci. Sport. Exerc.* **2011**, *43*, 1575–1581. [CrossRef]

49. Calvaresi, A.; Arnesano, M.; Pietroni, F.; Revel, G. Measuring metabolic rate to improve comfort management in buildings. *Environ. Eng. Manag. J.* **2018**, *17*, 2287–2296. [CrossRef]
50. Park, H.; Rhee, S.B. IoT-Based Smart Building Environment Service for Occupants' Thermal Comfort. *J. Sens.* **2018**, *2018*, 1757409. [CrossRef]
51. Tanaka, K.; Wada, K.; Kikuchi, T.; Kawakami, H.; Tanaka, K.; Takai, H. Study on air-conditioning control system considering individual thermal sensation. In *IOP Conference Series: Earth and Environmental Science*; Institute of Physics Publishing: Tokyo, Japan, 2019; Volume 294. [CrossRef]
52. Choi, H.; Na, H.; Kim, T.; Kim, T. Vision-based estimation of clothing insulation for building control: A case study of residential buildings. *Build. Environ.* **2021**, *202*, 108036. [CrossRef]
53. Zang, M.; Xing, Z.; Tan, Y. IoT-based personal thermal comfort control for livable environment. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1550147719865506. [CrossRef]
54. Park, J.; Kim, T.; Lee, C.S. Development of thermal comfort-based controller and potential reduction of the cooling energy consumption of a residential building in Kuwait. *Energies* **2019**, *12*, 3348. [CrossRef]
55. Nagarathinam, S.; Doddi, H.; Vasan, A.; Sarangan, V.; Venkata Ramakrishna, P.; Sivasubramaniam, A. Energy efficient thermal comfort in open-plan office buildings. *Energy Build.* **2017**, *139*, 476–486. [CrossRef]
56. Haniff, M.; Selamat, H.; Khamis, N.; Alimin, A. Optimized scheduling for an air-conditioning system based on indoor thermal comfort using the multi-objective improved global particle swarm optimization. *Energy Effic.* **2019**, *12*, 1183–1201. [CrossRef]
57. Lou, R.; Hallinan, K.; Huang, K.; Reissman, T. Smart wifi thermostat-enabled thermal comfort control in residences. *Sustainability* **2020**, *12*, 1919. [CrossRef]
58. Park, J.; Choi, H.; Kim, D.; Kim, T. Development of novel PMV-based HVAC control strategies using a mean radiant temperature prediction model by machine learning in Kuwaiti climate. *Build. Environ.* **2021**, *206*, 108357. [CrossRef]
59. Hawila, A.W.; Merabtine, A.; Chemkhi, M.; Bennacer, R.; Troussier, N. An analysis of the impact of PMV-based thermal comfort control during heating period: A case study of highly glazed room. *J. Build. Eng.* **2018**, *20*, 353–366. [CrossRef]
60. Hong, S.; Lee, J.; Moon, J.; Lee, K. Thermal comfort, energy and cost impacts of PMV control considering individual metabolic rate variations in residential building. *Energies* **2018**, *11*, 1767. [CrossRef]
61. Farag, W. ClimaCon: An Autonomous Energy Efficient Climate Control Solution for Smart Buildings. *Asian J. Control* **2017**, *19*, 1375–1391. [CrossRef]
62. Hilliard, T.; Swan, L.; Qin, Z. Experimental implementation of whole building MPC with zone based thermal comfort adjustments. *Build. Environ.* **2017**, *125*, 326–338. [CrossRef]
63. Li, D.; Menassa, C.; Kamat, V. Personalized human comfort in indoor building environments under diverse conditioning modes. *Build. Environ.* **2017**, *126*, 304–317. [CrossRef]
64. Xu, Y.; Chen, S.; Javed, M.; Li, N.; Gan, Z. A multi-occupants' comfort-driven and energy-efficient control strategy of VAV system based on learned thermal comfort profiles. *Sci. Technol. Built. Environ.* **2018**, *24*, 1141–1149. [CrossRef]
65. Pazhoohesh, M.; Zhang, C. A satisfaction-range approach for achieving thermal comfort level in a shared office. *Build. Environ.* **2018**, *142*, 312–326. [CrossRef]
66. Gupta, S.; Kar, K.; Mishra, S.; Wen, J. Incentive-Based Mechanism for Truthful Occupant Comfort Feedback in Human-in-the-Loop Building Thermal Management. *IEEE Syst. J.* **2018**, *12*, 3725–3736. [CrossRef]
67. Kruusimägi, M.; Sharples, S.; Robinson, D. A novel spatiotemporal home heating controller design: System emulation and field testing. *Build. Environ.* **2018**, *135*, 10–30. [CrossRef]
68. Qiao, Y.; Zhang, S.; Wu, N.; Wang, X.; Li, Z.; Zhou, M.; Qu, T. Data-driven approach to optimal control of ACC systems and layout design in large rooms with thermal comfort consideration by using PSO. *J. Clean. Prod.* **2019**, *236*, 117578. [CrossRef]
69. Jung, W.; Jazizadeh, F. Comparative assessment of HVAC control strategies using personal thermal comfort and sensitivity models. *Build. Environ.* **2019**, *158*, 104–119. [CrossRef]
70. Lu, S.; Wang, W.; Lin, C.; Hameen, E. Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884. *Build. Environ.* **2019**, *156*, 137–146. [CrossRef]
71. Aguilera, J.; Kazanci, O.; Toftum, J. Thermal adaptation in occupant-driven HVAC control. *J. Build. Eng.* **2019**, *25*, 100846. [CrossRef]
72. Lee, S.; Joe, J.; Karava, P.; Bilionis, I.; Tzempelikos, A. Implementation of a self-tuned HVAC controller to satisfy occupant thermal preferences and optimize energy use. *Energy Build.* **2019**, *194*, 301–316. [CrossRef]
73. Gao, G.; Li, J.; Wen, Y. DeepComfort: Energy-Efficient Thermal Comfort Control in Buildings Via Reinforcement Learning. *IEEE Internet Things* **2020**, *7*, 8472–8484. [CrossRef]
74. Mohamadi, S.; Ahmed, A. Thermal comfort control via air conditioning system using fuzzy neural network feedback controller. *Indones. J. Electr. Eng. Comput. Sci.* **2020**, *19*, 586–592. [CrossRef]
75. Alsaleem, F.; Tesfay, M.; Rafaie, M.; Sinkar, K.; Besarla, D.; Arunasalam, P. An IoT Framework for Modeling and Controlling Thermal Comfort in Buildings. *Front. Built Environ.* **2020**, *6*, 87. [CrossRef]
76. Kumar Yadav, M.; Verma, A.; Ketan Panigrahi, B.; Mishra, S. User comfort driven time-table linked AHU scheduling for ancillary service maximization of an educational building. *Energy Build.* **2020**, *225*, 110317. [CrossRef]
77. Deng, Z.; Chen, Q. Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband. *Energy Build.* **2020**, *214*, 109872. [CrossRef]

78. Li, W.; Zhang, J.; Zhao, T.; Ren, J. Experimental study of an indoor temperature fuzzy control method for thermal comfort and energy saving using wristband device. *Build. Environ.* **2021**, *187*, 107432. [CrossRef]
79. Aryal, A.; Becerik-Gerber, B.; Lucas, G.; Roll, S. Intelligent Agents to Improve Thermal Satisfaction by Controlling Personal Comfort Systems under Different Levels of Automation. *IEEE Internet Things* **2021**, *8*, 7069–7100. [CrossRef]
80. Carlucci, S.; Bai, L.; de Dear, R.; Yang, L. Review of adaptive thermal comfort models in built environmental regulatory documents. *Build. Environ.* **2018**, *137*, 73–89. [CrossRef]
81. Humphreys, M. Outdoor temperatures and comfort indoors. *Batim. Int. Build. Res. Pract.* **1978**, *6*, 92. [CrossRef]
82. Laftchiev, E.; Romeres, D.; Nikovski, D. Dynamic Thermal Comfort Optimization for Groups. In Proceedings of the American Control Conference, Virtual, 25–28 May 2021; Institute of Electrical and Electronics Engineers Inc.: New Orleans, LA, USA, 2021; Volume 2021, pp. 1456–1463. [CrossRef]
83. Arballo, B.; Kuchen, E.; Chuk, D. An energy efficiency optimization method applying adaptive thermal comfort in a public office building in San Juan-Argentina. In Proceedings of the 33rd PLEA International Conference: Design to Thrive, PLEA 2017, NCEUB 2017—Network for Comfort and Energy Use in Buildings, Edinburgh, Scotland, 2–5 July 2017; Volume 2, pp. 2022–2029.
84. Kuchen, E. *Spot-Monitoring zum Thermischen Komfort in Bürogebäuden*; Der Andere Verlag: Osnabrück, Germany, 2008.
85. Kramer, R.; van Schijndel, J.; Schellen, H. Dynamic setpoint control for museum indoor climate conditioning integrating collection and comfort requirements: Development and energy impact for Europe. *Build. Environ.* **2017**, *118*, 14–31. [CrossRef]
86. CEN/TC 156. *EN 15251:2007*; Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics. European Committee for Standardization, CEN: Brussels, Belgium, 2007.
87. Stazi, F.; Naspi, F.; Ulpiani, G.; Di Perna, C. Indoor air quality and thermal comfort optimization in classrooms developing an automatic system for windows opening and closing. *Energy Build.* **2017**, *139*, 732–746. [CrossRef]
88. CIBSE. *Guide A Environmental Design*, 8th ed.; Chartered Institution of Building Services Engineers: London, UK, 2007.
89. Aparicio-Ruiz, P.; Barbadilla-Martín, E.; Salmerón-Lissén, J.; Guadix-Martín, J. Building automation system with adaptive comfort in mixed mode buildings. *Sustain. Cities Soc.* **2018**, *43*, 77–85. [CrossRef]
90. Barbadilla-Martín, E.; Salmerón Lissén, J.; Guadix Martín, J.; Aparicio-Ruiz, P.; Brotas, L. Field study on adaptive thermal comfort in mixed mode office buildings in southwestern area of Spain. *Build. Environ.* **2017**, *123*, 163–175. [CrossRef]
91. Sghiouri, H.; Mezrhab, A.; Karkri, M.; Naji, H. Shading devices optimization to enhance thermal comfort and energy performance of a residential building in Morocco. *J. Build. Eng.* **2018**, *18*, 292–302. [CrossRef]
92. Gabsi, F.; Hamelin, F.; Sauer, N.; Yame, J. ℓ_ε-Regularized Economic Model Predictive Control for Thermal Comfort in Multizone Buildings. In *SMARTGREENS 2020—Proceedings of the 9th International Conference on Smart Cities and Green ICT Systems, Virtual, 2–4 May 2020*; SciTePress: Setubal, Portugal, 2020; pp. 137–148.
93. McCartney, K.; Nicol, J. Developing an adaptive control algorithm for Europe. *Energy Build.* **2002**, *34*, 623–635. [CrossRef]
94. Sánchez-García, D.; Rubio-Bellido, C.; Tristancho, M.; Marrero, M. A comparative study on energy demand through the adaptive thermal comfort approach considering climate change in office buildings of Spain. *Build. Simul.* **2020**, *13*, 51–63. [CrossRef]
95. Tan, Z.; Deng, X. An optimised window control strategy for naturally ventilated residential buildings in warm climates. *Sustain. Cities Soc.* **2020**, *57*, 102118. [CrossRef]
96. Tong, Z.; Chen, Y.; Malkawi, A. Estimating natural ventilation potential for high-rise buildings considering boundary layer meteorology. *Appl. Energy* **2017**, *193*, 276–286. [CrossRef]
97. Aguilera, J.; Bogatu, D.I.; Kazanci, O.; Angelopoulos, C.; Coakley, D.; Olesen, B. Comfort-based control for mixed-mode buildings. *Energy Build.* **2021**, *252*, 111465. [CrossRef]
98. Lin, Y.B.; Tseng, S.K.; Hsu, T.H.; Tseng, C. HouseTalk: A House That Comforts You. *IEEE Access* **2021**, *9*, 27790–27801. [CrossRef]
99. Vázquez-Torres, C.; Gómez-Amador, A.; Bojórquez-Morales, G.; Beizaee, A.; Eliás-López, P. Natural Ventilation Strategy in a Social Housing with Sub-humid Warm Climate Based on Thermal Comfort. *Environ. Clim. Technol.* **2021**, *25*, 508–524. [CrossRef]
100. Szokolay, S. *Introduction to Architectural Science: The Basis of Sustainable Design*, 1st ed.; Architectural Press: Oxford, UK, 2003.
101. Auliciems, A.; Szokolay, S. *PLEA Note 3: Thermal Comfort*; PLEA Notes; Design Tools and Techniques; PLEA: Passive and Low Energy Architecture International in association with Department of Architecture, The University of Queensland: Brisbane, Australia, 2007.
102. Xu, X.; Fu, B.; Wu, Z.; Sun, G. Predictive control for indoor environment based on thermal adaptation. *Sci. Prog.* **2021**, *104*, 00368504211006971. [CrossRef] [PubMed]
103. Yang, L.; Yan, H.; Lam, J. Thermal comfort and building energy consumption implications—A review. *Appl. Energy* **2014**, *115*, 164–173. [CrossRef]
104. Yano, T. Space heating control using acceptable set-point temperature estimation by a statistical approach in the lyon smart community project. In Proceedings of the IEEE International Conference on Industrial Technology, Lyon, France, 20–22 February 2018; Volume 2018, pp. 1645–1650. [CrossRef]
105. Marche, C.; Nitti, M. IoT for the users: Thermal comfort and cost saving. In Proceedings of the International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc), Catania, Italy, 2–5 July 2019; Association for Computing Machinery: Catania, Italy, 2019; pp. 55–60. [CrossRef]
106. Shetty, S.; Hoang, D.; Gupta, M.; Panda, S. Learning desk fan usage preferences for personalised thermal comfort in shared offices using tree-based methods. *Build. Environ.* **2019**, *149*, 546–560. [CrossRef]

107. Cicirelli, F.; Guerrieri, A.; Mastroianni, C.; Spezzano, G.; Vinci, A. Thermal comfort management leveraging deep reinforcement learning and human-in-The-loop. In Proceedings of the 2020 IEEE International Conference on Human-Machine Systems, ICHMS 2020, Virtual, 7–9 September 2020. [CrossRef]
108. Chenaru, O.; Popescu, D. IoT gateway for personalized user comfort management in smart home applications. In Proceedings of the 2020 28th Mediterranean Conference on Control and Automation, MED 2020, Saint-Raphaël, France, 16–18 September 2020; Institute of Electrical and Electronics Engineers Inc.: Saint-Raphaël, France, 2020; pp. 921–926. [CrossRef]
109. Amasyali, K.; El-Gohary, N. Real data-driven occupant-behavior optimization for reduced energy consumption and improved comfort. *Appl. Energy* **2021**, *302*, 117276. [CrossRef]
110. Zhu, M.; Pan, Y.; Wu, Z.; Xie, J.; Huang, Z.; Kosonen, R. An occupant-centric air-conditioning system for occupant thermal preference recognition control in personal micro-environment. *Build. Environ.* **2021**, *196*, 107749. [CrossRef]
111. Bouclier, K.; Hoffmann, S. Modeling decentralized systems for energy savings based on detailed local thermal comfort calculations. In Proceedings of the Building Simulation Conference, Rome, Italy, 2–4 September 2019; International Building Performance Simulation Association: Rome, Italy, 2019; Volume 4, pp. 2278–2285.
112. Chegari, B.; Tabaa, M.; Simeu, E.; Moutaouakkil, F.; Medromi, H. Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms. *Energy Build.* **2021**, *239*, 110839. [CrossRef]
113. Turhan, C.; Simani, S.; Gokcen Akkurt, G. Development of a personalized thermal comfort driven controller for HVAC systems. *Energy* **2021**, *237*, 121568. [CrossRef]
114. Dutta, S.; Zhang, Z.; Sahin, C.; Omagari, Y.; Kotani, S.; Watahiki, K.; Ng, Y.; Wong, Y. An optimized air-conditioning set-point temperature selection approach in a shared office based on thermal comfort and energy efficiency. In *ECOS 2020—Proceedings of the 33rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Osaka, Japan, 29 June–3 July 2020*; ECOS 2020 Local Organizing Committee: Osaka, Japan, 2020; pp. 2005–2015.
115. Lopez, G.; Aoki, T.; Nkurikiyeyezu, K.; Yokokubo, A. Model for thermal comfort and energy saving based on individual sensation estimation. *Sensor. Mater.* **2020**, *32*, 693–702. [CrossRef]
116. Ghaddar, D.; Itani, M.; Ghaddar, N.; Ghali, K.; Zeaiter, J. Model-based adaptive controller for personalized ventilation and thermal comfort in naturally ventilated spaces. *Build. Simul.* **2021**, *14*, 1757–1771. [CrossRef]
117. Sung, W.T.; Hsiao, S.J.; Shih, J.A. Construction of Indoor Thermal Comfort Environmental Monitoring System Based on the IoT Architecture. *J. Sensors* **2019**, *2019*, 2639787. [CrossRef]
118. Bretones, M.; Alvarez, J.; Del Mar Castilla, M.; Berenguel, M. A Fuzzy Controller for Thermal Comfort and Indoor Air Quality in a Bioclimatic Building. In Proceedings of the European Control Conference 2020, ECC 2020, Saint-Petersburg, Russia, 12–15 May 2020; Institute of Electrical and Electronics Engineers Inc.: Saint Petersburg, Russia, 2020; pp. 1029–1036.
119. Duman, A.; Erden, H.; Gönül, Ö.; Güler, Ö. A home energy management system with an integrated smart thermostat for demand response in smart grids. *Sustain. Cities Soc.* **2021**, *65*, 102639. [CrossRef]
120. Kannan, T.; Lork, C.; Tushar, W.; Yuen, C.; Wong, N.; Tai, S. Energy Management Strategy for Zone Cooling Load Demand Reduction with Occupancy Thermal Comfort Margin. In Proceedings of the 2019 IEEE PES GTD Grand International Conference and Exposition Asia, GTD Asia 2019, Bangkok, Thailand, 19–23 March 2019; Institute of Electrical and Electronics Engineers Inc.: Bangkok, Thailand, 2019; pp. 247–252. [CrossRef]
121. Zhang, S.; Lu, Y.; Lin, Z. Coupled thermal comfort control of thermal condition profile of air distribution and thermal preferences. *Build. Environ.* **2020**, *177*, 106867. [CrossRef]
122. Pałaszyńska, K.; Bandurski, K.; Porowski, M. Energy demand and thermal comfort of HVAC systems with thermally activated building systems as a function of user profile. In *E3S Web of Conferences*; EDP Sciences: Wroclaw, Poland, 2017; Volume 22. [CrossRef]
123. Zhang, Z.; Lam, K. Practical implementation and evaluation of deep reinforcement learning control for a radiant heating system. In Proceedings of the 5th Conference on Systems for Built Environments—BuildSys 2018, Shenzen, China, 7–8 November 2018; Association for Computing Machinery, Inc.: Shenzen, China, 2018; pp. 148–157. [CrossRef]
124. Yang, Y.; Hu, G.; Spanos, C. Stochastic Optimal Control of HVAC System for Energy-Efficient Buildings. *IEEE Trans. Control Syst. Technol.* **2022**, *30*, 376–383. [CrossRef]
125. Liu, S.; Yin, L.; Schiavon, S.; Ho, W.; Ling, K. Coordinate control of air movement for optimal thermal comfort. *Sci. Technol. Built. Environ.* **2018**, *24*, 886–896. [CrossRef]
126. Chinh, H.; Shetty, S.; Gupta, M.; Panda, S. A wireless sensor and actuator network (WSAN) framework for personalized thermal comfort in office buildings. In Proceedings of the IEEE International Conference on Sustainable Energy Technologies, ICSET, Hanoi, Vietnam, 14–16 November 2016; IEEE Computer Society: Hanoi, Vietnam, 2017; pp. 42–47. [CrossRef]
127. Utkarsh, U.; Natarajan, M.; Framewala, A. Ambient Energy Saving with Predictive Thermal Comfort in Green Building using Smart Blinds. In Proceedings of the 2021 International Conference on Future Internet of Things and Cloud, FiCloud 2021, Virtual, 23–25 August 2021; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021; pp. 123–127. [CrossRef]
128. Navarro, A.; Cadena, J.; Favoino, F.; Donato, M.; Poli, T.; Perino, M.; Overend, M. Occupant-centred control strategies for adaptive facades: A preliminary study of the impact of shortwave solar radiation on thermal comfort. In Proceedings of the Building Simulation Conference, Rome, Italy, 2–4 September 2019; International Building Performance Simulation Association: Rome, Italy, 2019; Volume 7, pp. 4910–4917.

129. Eini, R.; Abdelwahed, S. A Neural Network-based Model Predictive Control Approach for Buildings Comfort Management. In Proceedings of the 2020 IEEE International Smart Cities Conference, ISC2 2020, Virtual, 28 September–1 October 2020; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2020. [CrossRef]
130. Zhang, T.; Baasch, G.; Ardakanian, O.; Evins, R. On the Joint Control of Multiple Building Systems with Reinforcement Learning. In *e-Energy 2021—Proceedings of the 2021 12th ACM International Conference on Future Energy Systems, Virtual, 28 June–2 July 2021*; Association for Computing Machinery, Inc.: New York, NY, USA, 2021; pp. 60–72. [CrossRef]
131. Uguz, S.; Ipek, O. The Management of Indoor Thermal Comfort with Wireless Sensor Networks. *Meas. Control* **2017**, *50*, 206–213. [CrossRef]
132. Yang, S.; Wan, M.; Ng, B.; Dubey, S.; Henze, G.; Chen, W.; Baskaran, K. Model predictive control for integrated control of air-conditioning and mechanical ventilation, lighting and shading systems. *Appl. Energy* **2021**, *297*, 117112. [CrossRef]
133. Ahn, J.; Cho, S. Development of an intelligent building controller to mitigate indoor thermal dissatisfaction and peak energy demands in a district heating system. *Build. Environ.* **2017**, *124*, 57–68. [CrossRef]
134. Yoon, S.; Ahn, J. Comparative analysis of energy use and human comfort by an intelligent control model at the change of season. *Energies* **2020**, *13*, 6023. [CrossRef]
135. Zhai, D.; Soh, Y. Balancing indoor thermal comfort and energy consumption of ACMV systems via sparse swarm algorithms in optimizations. *Energy Build.* **2017**, *149*, 1–15. [CrossRef]
136. Potočnik, P.; Vidrih, B.; Kitanovski, A.; Govekar, E. Analysis and optimization of thermal comfort in residential buildings by means of a weather-controlled air-to-water heat pump. *Build. Environ.* **2018**, *140*, 68–79. [CrossRef]
137. Schito, E.; Conti, P.; Urbanucci, L.; Testi, D. Multi-objective optimization of HVAC control in museum environment for artwork preservation, visitors' thermal comfort and energy efficiency. *Build. Environ.* **2020**, *180*, 107018. [CrossRef]
138. Peng, B.; Hsieh, S.J. Simulation model of automated HVAC system control strategy with thermal comfort and occupancy considerations. In *ASME 2017 12th International Manufacturing Science and Engineering Conference, MSEC 2017 Collocated with the JSME/ASME 2017 6th International Conference on Materials and Processing*; American Society of Mechanical Engineers: Los Angeles, CA, USA, 2017; Volume 3. [CrossRef]
139. Li, H.; Shan, M.; Yu, Y.; Duan, P. Dynamic simulation of a VAV system based on dynamic PMV control. In *IOP Conference Series: Earth and Environmental Science*; Institute of Physics Publishing: Hong Kong, China, 2018; Volume 238. [CrossRef]
140. Xu, R.; Jin, W.; Kim, D. Environment optimization scheme based on edge computing using pso for efficient thermal comfort control in resident space. *Actuators* **2021**, *10*, 241. [CrossRef]
141. Zhu, J.; Lauri, F.; Koukam, A.; Hilaire, V.; Lin, Y.; Liu, Y. A hybrid intelligent control based cyber-physical system for thermal comfort in smart homes. *Int. J. Ad Hoc Ubiq. Co.* **2019**, *30*, 199–214. [CrossRef]
142. Jin, W.; Ullah, I.; Ahmad, S.; Kim, D. Occupant comfort management based on energy optimization using an environment prediction model in smart homes. *Sustainability* **2019**, *11*, 997. [CrossRef]
143. Ghaderian, M.; Veysi, F. Multi-objective optimization of energy efficiency and thermal comfort in an existing office building using NSGA-II with fitness approximation: A case study. *J. Build. Eng.* **2021**, *41*, 102440. [CrossRef]
144. Ebrahimi-Moghadam, A.; Ildarabadi, P.; Aliakbari, K.; Fadaee, F. Sensitivity analysis and multi-objective optimization of energy consumption and thermal comfort by using interior light shelves in residential buildings. *Renew. Energy* **2020**, *159*, 736–755. [CrossRef]
145. Yılmaz, Y.; Yılmaz, B. A weighted multi-objective optimisation approach to improve based facade aperture sizes in terms of energy, thermal comfort and daylight usage. *J. Build. Phys.* **2021**, *44*, 435–460. [CrossRef]
146. Wang, X.; Liu, T.; Lee, W. Using revised ADPIs to identify an optimum positioning for installation of reversible room air-conditioners in bedroom for maximum thermal comfort. *Build. Environ.* **2021**, *188*, 107333. [CrossRef]
147. Laing, S.; Kühl, N. Comfort-as-a-service: Designing a user-oriented thermal comfort artifact for office buildings. In Proceedings of the International Conference on Information Systems 2018, ICIS 2018, San Francisco, CA, USA, 13–16 December 2018; Association for Information Systems: San Francisco, CA, USA, 2018.
148. Mei, J.; Xia, X. Energy-efficient predictive control of indoor thermal comfort and air quality in a direct expansion air conditioning system. *Appl. Energy* **2017**, *195*, 439–452. [CrossRef]
149. Mei, J.; Xia, X.; Song, M. An autonomous hierarchical control for improving indoor comfort and energy efficiency of a direct expansion air conditioning system. *Appl. Energy* **2018**, *221*, 450–463. [CrossRef]
150. Valladares, W.; Galindo, M.; Gutiérrez, J.; Wu, W.C.; Liao, K.K.; Liao, J.C.; Lu, K.C.; Wang, C.C. Energy optimization associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm. *Build. Environ.* **2019**, *155*, 105–117. [CrossRef]
151. Sung, W.T.; Hsiao, S.J. The application of thermal comfort control based on Smart House System of IoT. *Meas.: J. Int. Meas. Confed.* **2020**, *149*, 106997. [CrossRef]
152. Yang, X.; Chen, Z.; Huang, X.; Li, R.; Xu, S.; Yang, C. Robust capacity optimization methods for integrated energy systems considering demand response and thermal comfort. *Energy* **2021**, *221*, 119727. [CrossRef]
153. Martell, M.; Rodríguez, F.; Castilla, M.; Berenguel, M. Multiobjective control architecture to estimate optimal set points for user comfort and energy saving in buildings. *ISA Trans.* **2020**, *99*, 454–464. [CrossRef]
154. Wu, B.; Cai, W.; Chen, H. A model-based multi-objective optimization of energy consumption and thermal comfort for active chilled beam systems. *Appl. Energy* **2021**, *287*, 116531. [CrossRef]

155. Xu, J.; Wang, S.; Zhang, X.; Xu, K.; Li, J.; Du, L. A Optimal Control Strategy of Building Energy System Considering Thermal Comfort. In Proceedings of the 2020 8th International Conference on Smart Grid and Clean Energy Technologies, ICSGCE 2020, Kuching, Malaysia, 4–7 October 2020; pp. 35–39. [CrossRef]
156. Karatzoglou, A.; Janßen, J.; Srikanthan, V.; Urbaczek, C.; Beigl, M. A predictive comfort- and energy-aware mpc-driven approach based on a dynamic pmv subjectification towards personalization in an indoor climate control scenario. In Proceedings of the SMARTGREENS 2018—7th International Conference on Smart Cities and Green ICT Systems, Madeira, Portugal, 16–18 March 2018; Volume 2018, pp. 89–100. [CrossRef]
157. Ke, J.; Qin, Y.; Wang, B.; Yang, S.; Wu, H.; Yang, H.; Zhao, X. Data-driven predictive control of building energy consumption under the IoT architecture. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 8849541. [CrossRef]
158. Ascione, F.; Bianco, N.; Mauro, G.; Napolitano, D.; Vanoli, G. Weather-data-based control of space heating operation via multi-objective optimization: Application to Italian residential buildings. *Appl. Therm. Eng.* **2019**, *163*, 114384. [CrossRef]
159. Caniato, M.; Bettarello, F.; Gasparella, A. Indoor and outdoor noise changes due to the COVID-19 lockdown and their effects on individuals' expectations and preferences. *Sci. Rep.* **2021**, *11*, 16533. [CrossRef] [PubMed]
160. Yang, J.; Liu, T.; Wang, H.; Tian, Z.; Liu, S. Optimizing the regulation of aggregated thermostatically controlled loads by jointly considering consumer comfort and tracking error. *Energies* **2019**, *12*, 1757. [CrossRef]
161. Ali, A.; Shukor, S.; Rahim, N.; Razlan, Z.; Jamal, Z.; Kohlhof, K. IoT-Based Smart Air Conditioning Control for Thermal Comfort. In Proceedings of the 2019 IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2019, Selangor, Malaysia, 29 June 2019; Institute of Electrical and Electronics Engineers Inc.: Selangor, Malaysia, 2019; pp. 289–294. [CrossRef]
162. Lu, S.; Wang, S.; Hameen, E.; Shi, J.; Zou, Y. Comfort-based integrative HVAC system with non-intrusive sensing in office buildings. In *Intelligent and Informed, Proceedings of the 24th International Conference on Computer-Aided Architectural Design Research in Asia, CAADRIA, Wellington, New Zealand, 15–18 April 2019*; The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA): Wellington, New Zealand, 2019; Volume 1; pp. 785–794.
163. Pandey, B.; Bohara, B.; Pungaliya, R.; Patwardhan, S.; Banerjee, R. A thermal comfort-driven model predictive controller for residential split air conditioner. *J. Build. Eng.* **2021**, *42*, 102513. [CrossRef]
164. Zahid, H.; Elmansoury, O.; Yaagoubi, R. Dynamic Predicted Mean Vote: An IoT-BIM integrated approach for indoor thermal comfort optimization. *Automat. Constr.* **2021**, *129*, 103805. [CrossRef]
165. Wang, X.; Liu, S.; Xiong, L.; Wu, D.; Zhang, Y. Research on intelligent regulation of air conditioning energy saving based on human thermal comfort. *J. Ambient Intell. Human Comput.* **2021**, 1–14. [CrossRef]
166. Zhao, D.; Watari, D.; Ozawa, Y.; Taniguchi, I.; Suzuki, T.; Shiochi, S.; Shimoda, Y.; Onoye, T. Online management framework for building HVAC systems considering peak shaving and thermal comfort: An experimental study. In Proceedings of the 9th Workshop on Modeling and Simulation of Cyber-Physical Energy Systems, MSCPES 2021, Held as part of the Cyber-Physical Systems and Internet-of-Things Week, Virtual, 18 May 2021; Association for Computing Machinery, Inc.: New York, NY, USA, 2021. [CrossRef]
167. Mora, R.; Bean, R. Thermal comfort: Designing for people. *ASHRAE J.* **2018**, *60*, 40–46.
168. Hughes, C.; Natarajan, S. Summer thermal comfort and overheating in the elderly. *Build. Serv. Eng. Res. Technol.* **2019**, *40*, 426–445. [CrossRef]
169. Hughes, C.; Natarajan, S.; Liu, C.; Chung, W.J.; Herrera, M. Winter thermal comfort and health in the elderly. *Energy Policy* **2019**, *134*, 110954. [CrossRef]
170. Yi, C.; Childs, C.; Peng, C.; Robinson, D. Thermal comfort modelling of older people living in care homes: An evaluation of heat balance, adaptive comfort, and thermographic methods. *Build. Environ.* **2022**, *207*, 108550. [CrossRef]
171. Parsons, K. The effects of gender, acclimation state, the opportunity to adjust clothing and physical disability on requirements for thermal comfort. *Energy Build.* **2002**, *34*, 593–599. [CrossRef]
172. Brik, B.; Esseghir, M.; Merghem-Boulahia, L.; Snoussi, H. An IoT-based deep learning approach to analyse indoor thermal comfort of disabled people. *Build. Environ.* **2021**, *203*, 108056. [CrossRef]
173. Bouzidi, Y.; El Akili, Z.; Gademer, A.; Tazi, N.; Chahboun, A. How Can We Adapt Thermal Comfort for Disabled Patients? A Case Study of French Healthcare Buildings in Summer. *Energies* **2021**, *14*, 4530. [CrossRef]
174. Karol, E.; Smith, D. Impact of Design on Emotional, Psychological, or Social Well-Being for People with Cognitive Impairment. *Health Environ. Res. Des. J.* **2019**, *12*, 220–232. [CrossRef] [PubMed]
175. Bettarello, F.; Caniato, M.; Scavuzzo, G.; Gasparella, A. Indoor Acoustic Requirements for Autism-Friendly Spaces. *Appl. Sci.* **2021**, *11*, 3942. [CrossRef]
176. Caniato, M.; Zaniboni, L.; Marzi, A.; Gasparella, A. Evaluation of the main sensitivity drivers in relation to indoor comfort for individuals with autism spectrum disorder. Part 1: Investigation methodology and general results. *Energy Rep.* **2022**, *8*, 1907–1920. [CrossRef]
177. Caniato, M.; Zaniboni, L.; Marzi, A.; Gasparella, A. Evaluation of the main sensitivity drivers in relation to indoor comfort for individuals with autism spectrum disorder. Part 2: Influence of age, co-morbidities, gender and type of respondent on the stress caused by specific environmental stimuli. *Energy Rep.* **2022**, *8*, 2989–3001. [CrossRef]
178. Shajahan, A.; Culp, C.H.; Williamson, B. Effects of indoor environmental parameters related to building heating, ventilation, and air conditioning systems on patients' medical outcomes: A review of scientific research on hospital buildings. *Indoor Air* **2019**, *29*, 161–176. [CrossRef]

179. Pereira, P.F.d.C.; Broday, E.E.; Xavier, A.A.d.P. Thermal Comfort Applied in Hospital Environments: A Literature Review. *Appl. Sci.* **2020**, *10*, 7030. [CrossRef]
180. Deiana, G.; Arghittu, A.; Dettori, M.; Deriu, M.; Palmieri, A.; Azara, A.; Castiglia, P.; Masia, M. Ten-Year Evaluation of Thermal Comfort in Operating Rooms. *Healthcare* **2022**, *10*, 307. [CrossRef]
181. Orosa, J.A.; Vergara, D.; Costa, n.M.; Bouzón, R. A Novel Method Based on Neural Networks for Designing Internal Coverings in Buildings: Energy Saving and Thermal Comfort. *Appl. Sci.* **2019**, *9*, 2140. [CrossRef]
182. Toftum, J.; Jørgensen, A.S.; Fanger, P.O. Upper limits of air humidity for preventing warm respiratory discomfort. *Energy Build.* **1998**, *28*, 15–23. [CrossRef]
183. Fang, L.; Clausen, G.; Fanger, P.O. Impact of Temperature and Humidity on Perception of Indoor Air Quality During Immediate and Longer Whole-Body Exposures. *Indoor Air* **1998**, *8*, 276–284. [CrossRef]