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Review

A Systematic Literature Review of Non-Invasive Indoor Thermal Discomfort Detection

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Abstract: Since 1997, scientists have been trying to utilize new non-invasive approaches for thermal discomfort detection, which promise to be more effective for comparing frameworks that need direct responses from users. Due to rapid technological development in the bio-metrical field, a systematic literature review to investigate the possibility of thermal discomfort detection at the work place by non-invasive means using bio-sensing technology was performed. Firstly, the problem intervention comparison outcome context (PICOC) framework was introduced in the study to identify the main points for meta-analysis and, in turn, to provide relevant keywords for the literature search. In total, 2776 studies were found and processed using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology. After filtering by defined criterion, 35 articles were obtained for detailed investigation with respect to facility types used in the experiment, amount of people for data collection and algorithms used for prediction of the thermal discomfort event. The given study concludes that there is potential for the creation of non-invasive thermal discomfort detection models via utilization of bio-sensing technologies, which will provide a better user interaction with the built environment, potentially decrease energy use and enable better productivity. There is definitely room for improvement within the field of non-invasive thermal discomfort detection, especially with respect to data collection, algorithm implementation and sample size, in order to have opportunities for the deployment of developed solutions in real life. Based on the literature review, the potential of novel technology is seen to utilize a more intelligent approach for performing non-invasive thermal discomfort prediction. The architecture of deep neural networks should be studied more due to the specifics of its hidden layers and its ability of hierarchical data extraction. This machine learning algorithm can provide a better model for thermal discomfort detection based on a data set with different types of bio-metrical variables.

Keywords: thermal comfort; non-invasive discomfort detection; machine learning; indoor environment; bio-sensing

1. Introduction

Over the last 50 years, people have become increasingly bound to the indoor workplace. The regular worker spends around 35 hours per week in front of the computer, at brainstorming sessions and meetings. Due to this fact, there is a need to provide good indoor environment quality, not only because it will result in fewer sick leave periods but also because it will result in improved productivity. A number of studies have been conducted to determine ways in which indoor comfort can bring an increase in quality and productivity among the employees [1–7], and even more studies have been conducted to find a way to reduce energy consumption while still providing comfortable indoor conditions [8–13]. In general, comfort can be divided into three groups: physical, functional and psychological. The given review is focused only on indoor thermal comfort which is a part of physical comfort within indoor environment quality (IEQ) [14]. It is an important topic due to current climate change conditions, abnormality in temperature peaks concerning different seasons and general overheating and over-cooling challenges.

Indoor thermal comfort is assured by the combination of different aspects such as clothing insulation, levels of activity, radiation exchange, air temperature, air movement and humidity [15]. A variety of these factors can be predefined by age, sex, diet or even clothing requirements at the workplace [16,17]. Therefore, a number of the studies have been performed in order to find a correlation between measurable parameters and actual comfort.

Thermal comfort is traditionally evaluated by using predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) models (indexes). The PMV model developed by Fanger [18] represents the mean thermal sensation vote on a standard 7-point scale:

+ 3 Hot
+ 2 Warm
+ 1 Slightly warm
0 Neutral
- 1 Slightly cold
- 2 Cool
- 3 Cold

It is also referred to as the seven-point ASHRAE thermal sensation scale. The PPD is a quantitative measure of the thermal comfort for a group of people within a given thermal environment [9]. Both PPD and PMV were adopted by several international standards and guidelines, such as ASHRAE Standard 55 [19] and ISO 7730 [20]. The PMV model was widely used for different building types and within different climate zones around the world, which resulted in a deviation between predicted and actual thermal sensations. Such a deviation may be explained by the fact that the given model was developed in a laboratory setting, which means it contains constraints that are not typical for buildings in real life [21]. Due to given circumstances, the adaptive thermal comfort model was proposed in 1970 [22]. Nicol et al. [23] suggested a feedback approach for thermal comfort field surveys' interpretation, which was based on the fact that unpleasant sensations would lead to physical reactions and cause a change in the comfort control system itself. Humphreys and Nicol [24] suggested a list of physiological, psychological, social and behavioral actions which can restore comfort conditions in response to cold or heat. Since people live in different climate zones, they can experience different perceptions of the indoor thermal environment, and as a result, have their levels of "usual" indoor temperature altered. The same can be applied for seasonal outdoor temperature change. If a person enters a room with indoor temperature 21 °C, he/she would feel warmer if the outside temperature is −1 °C but a totally different response will accrue if it is summer and the outside temperature is 30 °C.

That is why many studies have been conducted for thermal comfort evaluation on a personal level. Such studies are focused more on creating numerical thermal comfort models that take into account cultural identities, human body heat exchange, metabolic activities and other parameters which define each person individually [25]. Additionally, a number of studies have been done for HVAC control automation based on the usage of artificial neural networks (ANN) and other machine learning (ML) algorithms for personal thermal comfort evaluation [26].

In recent years, the field of non-invasive bio-sensing technology has made huge progress, creating good conditions for research aimed at studying ways for such technology introduction within the field of indoor thermal comfort. This combination has a potential to reduce bias in the HVAC system that has originated from the continuous request of personal feedback on thermal conditions or the need for manual user adjustment of the thermostat or opening of the windows. Such a personal bio-sensing system may provide a better user experience, while reducing energy consumption and prevention of the overheating/over-cooling period within the individual's thermal environment.

The main research question for this study is: What are the options for determining thermal discomfort by non-invasive means using bio-sensing technology? Within the given paper, the approaches and (or) models which were developed in order to track comfort or to predict/prevent thermal discomfort events within office work space are evaluated. If proven that thermal discomfort can be tracked and prevented in advance, the deployment of such a system can revolutionize indoor environment quality and personal experience within office space.

2. Methodology

This research is based on the systematic literature review (SLR) methodology which allows for the combination of empirical and theoretical literature in order to provide conclusions or present results among different sources on a selected topic [27]. The given methodology was initially used in health studies and the social sciences, but, due to its clear sequential steps, SLR can be implemented in other fields, too. The results of such research can be easily reproduced or updated in time if the following general steps are fulfilled during SLR:

- Definition of the review question;
- Systematic search and selection of the literature;
    - Definition of the framework;
    - Specification of the keywords;
    - Selection of the literature search engines;
- Quality evaluation;
- Selection and organization of the important information;
- Analysis of the collected data;
- Presentation and discussion of the results;

In the given study, the research question is focused on indoor thermal discomfort detection by non-invasive means in the workplace. The problem intervention comparison outcome context (PICOC) framework is used to define the main points of the meta-analysis. As presented in Figure 1, the "problem" section describes the key question for investigation, or in other words, "What is the problem that we are trying to solve?" For the purpose of given SLR, "problem" can be described as the "detection of thermal discomfort". "Intervention" explains ways for solving the above-mentioned problem, and, for given study, this is the "non-invasive means for discomfort detection". The "comparison" section should provide ways through which it is possible to quantify and evaluate how the system was functioning before and after the intervention. As was discussed in the previous section, it is common practice to evaluate thermal comfort prediction accuracy by implementing surveys among people. Such an approach is going to also be considered for the "comparison" section of the PICOC. The "outcome" describes the desired result from the intervention, which is a comfortable temperature for the given case. The last section is the "context" that defines the boundaries of the problem. The boundary for SLR was defined as a workplace.

A variety of keywords were selected to fit the specific case of research. Relevant keywords for each PICOC section are described in Table 1.

In total, three search engines for peer reviewed literature were used for screening the studies. The following electronic databases were selected due to their high relevance for the given research field: Scopus, Web of Science and Engineering Village. The PICOC set of keywords returned few results, which may be because the search query contains too many constraints so it is not able to generalize and find results within the database. Additionally, it is very uncommon to use comparison methods as a keyword for the article if a method for comparison of performance is a survey. Based on given circumstances, it was decided to split searches into two rounds: one with PIOC and another with PIO. A detailed description of the selected search tags and the syntax of queries for both cases are presented in Table 2.

Table 1. Selected key words for PICOC framework.

	Problem	Intervention	Comparison	Outcome(s)	Context
	Who?	*What or How?*	*Compared to what?*	*What is going to be accomplished?*	*In what kind of circumstances?*
Keywords	Discomfort	Non-invasive	Questionnaire	HVAC	Workplace
	Thermal stress	Biometr	Survey	Control signal	Work place
	Thermal strain	Physiological response	Audit	Indoor environment	Work space
	Thermal tolerance	Physiological state	Preliminary studies	Personalized control system	Work unit
	Acceptability	Biosensor		Personal comfort model	Work units
	Thermal sensation	Bio-sensor		Personal thermal comfort	Office
	Thermal preference	Biosignal		Building control	Commercial building
	Thermal comfort	Bio-signal		Building management system	Desktop
	Human response	Wearable		Energy efficiency	Built environment
	Human reaction	Sensing		Heating	Building
	Thermal state	Skin temperature		Cooling	Construction
	Duty activities	Remote sensor		Thermal-conditioning	
		Non-intrusive		Productivity	
		Sensor fusion		Indoor environmental quality	
		Contactless		Indoor clima	
				Building automation	

Table 2. PIOC and PIO sets of keywords used to search relevant literature in selected databases.

	Tag Words Used (Web of Science)	Tag Words Used (Scopus)	Tag Words Used (Engineering Village)
PIOC	TS = (("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR"personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation") AND ("Workplace" OR "Work place" OR "Work unit" OR "Work units" OR "Office" OR "Commercial building" OR "Desktop" OR "built environment" OR "building" OR "construction")) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=All years	TITLE-ABS-KEY (("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR "personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation") AND ("Workplace" OR "Work place" OR "Work unit" OR "Work units" OR "Office" OR "Commercial building" OR "Desktop" OR "built environment" OR "building" OR "construction"))	(("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR"personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation") AND ("Workplace" OR "Work place" OR "Work unit" OR "Work units" OR "Office" OR "Commercial building" OR "Desktop" OR "built environment" OR "building" OR "construction"))
	Tag Words Used (Web of Science)	**Tag Words Used (Scopus)**	**Tag Words Used (Engineering Village)**
PIO	TS = (("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR"personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation")) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=All years	TITLE-ABS-KEY (("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR "personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation"))	(((("Discomfort" OR "thermal stress" OR "thermal strain" OR "thermal tolerance" OR "acceptability" OR "Thermal sensation" OR "Thermal preference" OR "Thermal comfort" OR "human response" OR "Human reaction" OR "thermal state" OR "duty activities") AND ("Non-invasive" OR "Biometr*" OR "Physiological response" OR "Physiological state" OR "Biosensor" OR "Bio-sensor" OR "Biosignal" OR "Bio-signal" OR "wearable" OR "sensing" OR "skin temperature" OR "remote sensor" OR "non-intrusive") AND ("HVAC" OR "Control signal" OR "Indoor environment" OR "personalized control system" OR "personalised control system" OR"personal comfort model" OR "personal thermal comfort" OR "building control" OR "building management system" OR "energy efficiency" OR "heating" OR "cooling" OR "thermal-conditioning" OR "productivity" OR "Indoor environmental quality" OR "indoor clima" OR "Building automation"))) WN All fields)

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology was implemented after the initial literature search without any specific filters for language or publication type. In general, the PRISMA framework consists of six steps [28], and each of them provides specific criteria for filtering the collected database. The first exclusion criterion is based on extraction of the literature by type of publication and language preferences. For the given research, literature types other than article, book chapter and proceedings with the main language of "English" were excluded. The second exclusion criterion is based on filtering with respect to the keywords and titles of the collected literature. The third exclusion criterion is based on filtering with respect to the quality and relevance of the abstracts. Finally, the fourth exclusion criterion is based on the quality and relevance of the article itself. It is worth mentioning that no limitations with respect to the year of publication were introduced for the given study.

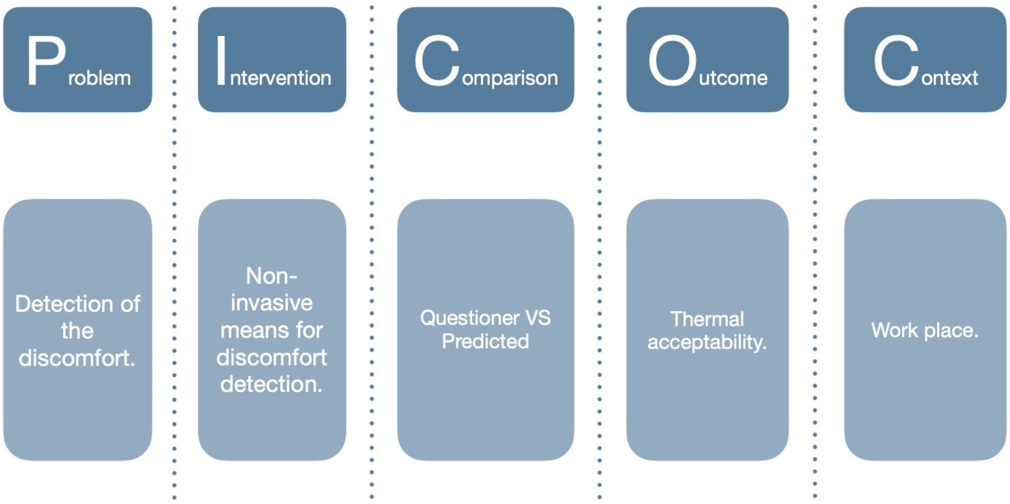

Figure 1. PICOC for given research

3. Results

After the fulfillment of the first step of PRISMA, 306 results for the PIOC search and 2086 results for the PIO search were organized in Excel tables (see Table 3) with the following columns: Authors, Title, Year, Source Title, Document Type, Source. This step provides an overview of the filtering process, specifically, if combined with "sort *Title* by alphabet" function which provides the opportunity to quickly filter out repeated material.

Table 3. PIOC and PIO PRISMA results.

	PIOC			PIO			Step
	Web of Science	Scopus	Engineering Village	Web of Science	Scopus	Engineering Village	
Identification	114	212	250	529	996	675	All literature
	114	191	239	523	936	627	1st exclusion criterion
	544			2086			All together
	306			1175			Duplicates filtered
	PIOC + PIO						
Screening	1481						All
	1154						Duplicates
	207						2nd exclusion criterion
	83						3rd exclusion criterion
Eligibility	35						4th exclusion criterion

Once the third exclusion criterion was performed, 83 articles were allocated in a more detailed table. An ID number was assigned to each unit in order to keep track over publications. The final table had the following columns: ID, Type (Journal article, Conference paper), Year, Keywords, Goal, Measuring Equipment/Used Equipment, Experiment Duration, Facility Type, Fixed Values or Conditions, Number of Males, Number of females, Age, Sensors position, Data collected, Data volume, Target values, Algorithms (used), Algorithms (developed), Results, Notes.

Only 25 articles out of total 35 contained keywords which were repeated at least once among papers. The most popular keyword was "thermal comfort", used in 12 articles (see Figure 2). Some less popular but still repeated keywords were "infrared thermography" (four times), "machine learning" (three times), "skin temperature" (three times) and "thermal sensation" (three times).

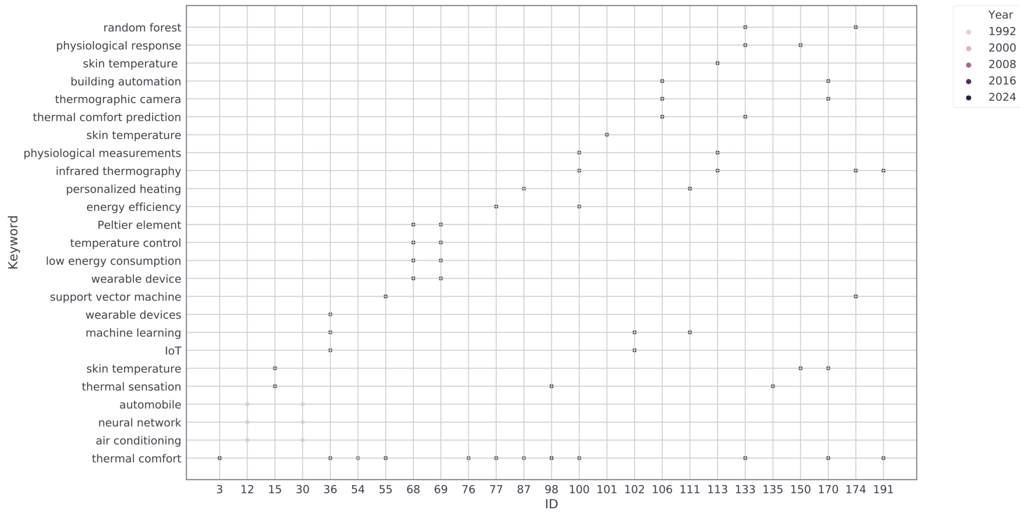

Figure 2. The most common keywords.

According to the analysis, the first article that investigated possibility of determining thermal comfort by non-invasive means was published in 1997 by Yousuke Taniguchi and Hiroshi Aoki. They used a chamber to control the experimental environment and an infrared camera to determine the skin temperature of the person [29]. Further studies showed interest in using an office environment or regular room in addition to a laboratory or thermal chamber (see Figure 3).

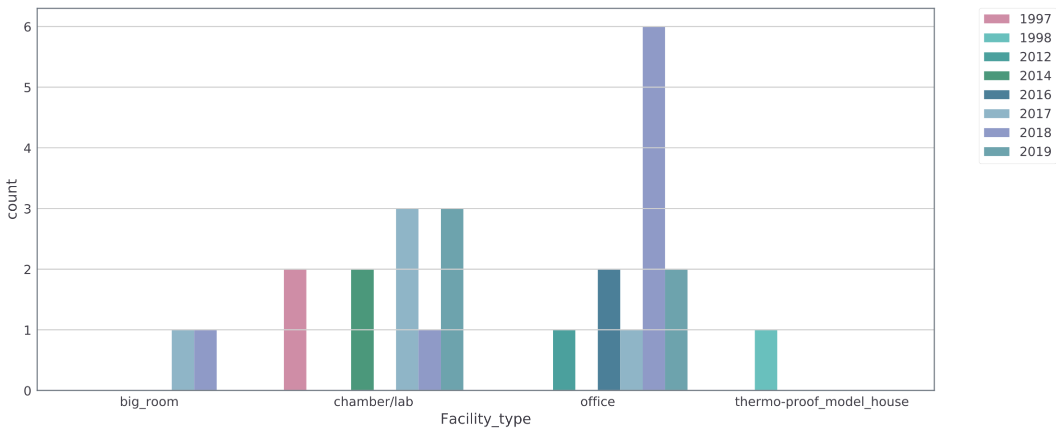

Figure 3. Facility types used for thermal comfort studies.

Each study had its own special set of predictive variables, but all of them may be divided into the following categories: indoor and outdoor parameters (such as temperature, humidity), system parameters (such as HVAC control) and bio-metrical data (such as heart rate, skin temperature).

Bio-metrical data were collected in only 26 studies out of 35 filtered for review (see Table 4). Skin temperature was the most frequent parameter and was detected mainly on the wrist, hand, fingertip or head. Some studies [30–32] combined different body parts for skin temperature extraction. Facial skin temperature was measured in five studies [29,33–36], which performed facial mapping for zonal temperature extraction, and in few of them, the mean value was calculated in order to have only one input for a given type of variable.

While each study that involved temperature collection described the positioning of the sensors for a skin temperature extraction [37–39] and how collected data were pre-processed, the majority of them did not provide biological/medical reasoning for the selected skin regions. Only Ghahramani et al. [34] and Li et al. [35] give proper background information with respect to the skin properties within different regions of the body and why a certain region was chosen. It is important to remember that we should differentiate temperature extraction based on facial skin mapping and temperature extraction from other skin regions (hands for example) because facial skin tissue has different properties compared to other skin areas. Due to the thinner hypodermis layer (the result of a lower percentage of fat accumulation), facial skin has more visible blood vessels. It is also a reason why skin temperature data were divided into two columns, "Skin Temperature" and "Facial Temperature" in Table 4.

Table 4. Overview of the bio-metrical data within processed studies.

Reference	**Bio-Data Collected among Studies**												
	Skin Temp.	**BMI**	**Pulse**	**Sweat Rate**	**Oxygen Sat.**	**SBP**	**DBP**	**GSR**	**EEG**	**ECG**	**SBF**	**Facial Temp.**	**Facial Zones**
Cheng et al. [40]	YES	YES	-	-	-	-	-	-	-	-	-	-	-
Ueda et al. [29]	-	-	-	-	-	-	-	-	-	-	-	YES	measured at 7 points
Matalucci et al. [41]	YES	-	YES	-	-	-	-	-	YES	YES	-	-	-
Laftchiev and Nikovski [42]	YES	-	YES	-	-	-	-	YES	-	-	-	-	-
Chaudhuri et al. [43]	YES	YES	YES	-	YES	YES	YES	-	-	-	-	-	-
Lee et al. [44]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Lopez et al. [45]	-	-	YES	-	-	-	-	-	-	-	-	-	-
Lopez et al. [46]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Wang and Lee [47]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Gwak et al. [30]	YES	-	-	-	-	-	-	-	YES	YES	-	-	-
Jin and Duanmu [33]	-	-	-	-	-	-	-	-	-	-	-	YES	-
Vesely and Zeiler [48]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Li et al. [49]	YES	-	YES	-	-	-	-	-	-	-	-	-	-
Ghahramani et al. [34]	YES	-	-	-	-	-	-	-	-	-	YES	YES	ear, nose, front face, cheekbone
Lu and Cochran Hameen [50]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Salamone et al. [38]	YES	-	YES	-	-	-	-	-	-	-	-	-	-
Cosma and Simha [31]	YES	YES	-	-	-	-	-	-	-	-	-	-	-
Li et al. [35]	-	-	-	-	-	-	-	-	-	-	-	YES	-
Chaudhuri et al. [39]	YES	-	YES	-	YES	-	-	-	-	-	-	-	-
Yang et al. [32]	YES	-	YES	YES	-	-	-	YES	-	-	-	-	-
Choi and Yeom [37]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Barrios and Kleiminger [51]	-	-	YES	-	-	-	-	-	-	-	-	-	-
Cosma and Simha [52]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Lu et al. [53]	YES	-	-	-	-	-	-	-	-	-	-	-	-
Ghahramani et al. [36]	-	-	-	-	-	-	-	-	-	-	-	YES	nose, ear,front of face, cheekbone
Burzo et al. [54]	YES	-	YES	-	-	-	-	-	-	-	-	-	-

Notes: BMI—body mass index, Oxygen sat.—oxygen saturation, SBP—systolic blood pressure, DBP—diastolic blood pressure, GSR—galvanic skin response, EEG—electroencephalogram, ECG—electrocardiogram, SBF—skin blood flow.

The majority of studies held during 2014–2019 had no more than 20 male and 20 female participants (see Figure 4).

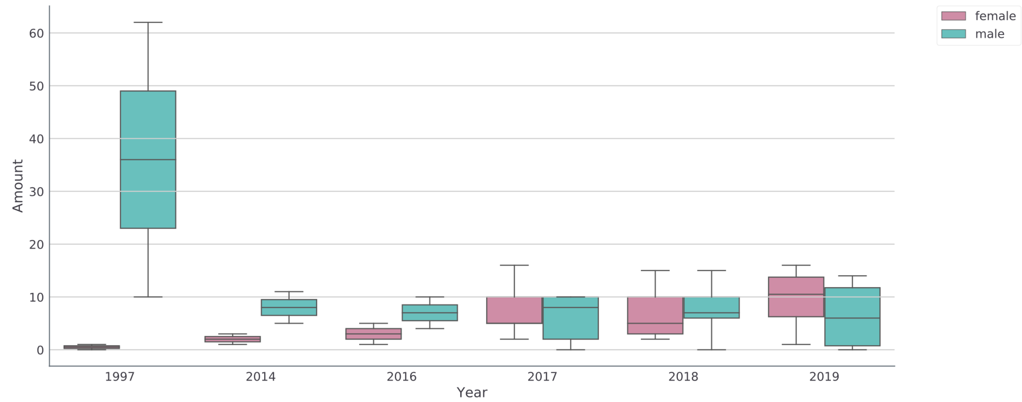

Figure 4. Sex of the participants.

Frequency counts for algorithms used in different studies for non-invasive thermal discomfort detection are presented in Figure 5. The majority of the algorithms do not repeat among studies. In total, 43 different algorithms were implemented, and only eight of them were used in more than one study. The leading approach with respect to the amount of times used is the support vector machines (SVM), which appeared six times among studies [31,38,42,43,53,55]. Random forest and k-nearest neighbor (k-NN) appeared four times [31,35,39,53]. Additionally, ANN was used three times [29,43,56], just like linear regression [49,51,57]. Decision trees, Gaussian process regression and logistic regression were used two times [37,54].

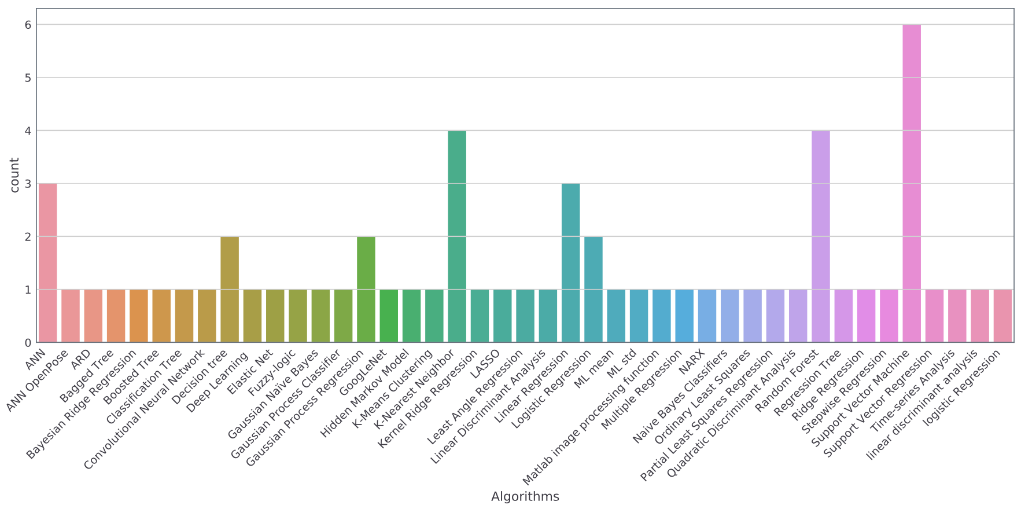

Figure 5. Frequency counts for algorithms used among different studies.

4. Discussion

The discussion of processed studies within the systematic literature review is presented (see Figure 6) in following steps: definition of the data collection space, population sampling, data collection, pre-processing of the data, algorithms' implementations, results and discussion and opportunities for further development.

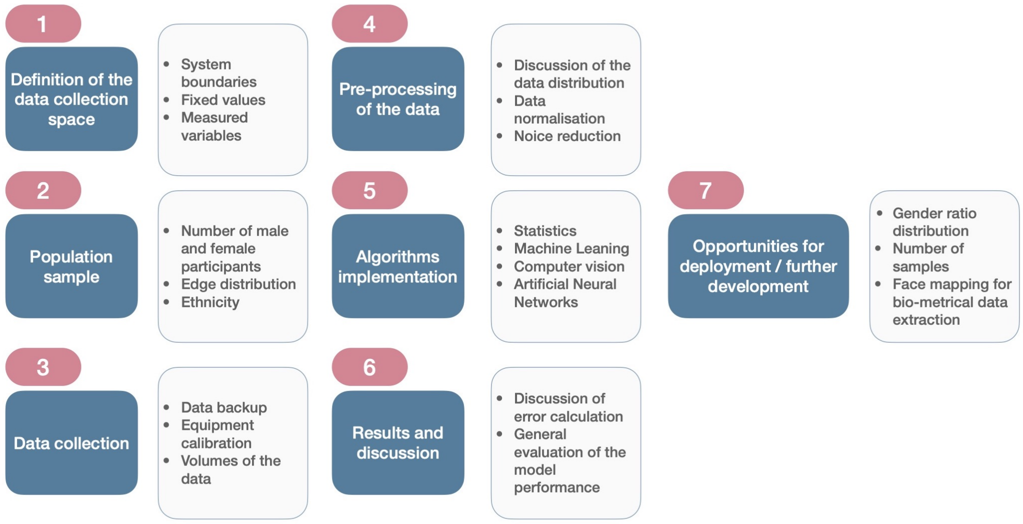

Figure 6. General steps sequence among processed studies.

The usage of diverse experimental space for data collection can be explained by different factors, such as the definition of the study scope and its budget. Environmental chambers and other types of laboratories which provide total control of the environment are quite expensive and should usually be booked in advance. Unfortunately, there is no explanation behind the selection of the variables among processed studies. The frequency of the variables used alters from study to study, which can be explained by the specific criteria behind their use in each study. Some studies were more focused on cheaper and less complicated solutions [29,57,58] which (if proven function properly) may be build quickly and have a good market value. Other studies [42,43,59] were focused on the collection of different types of data by different equipment, which in turn would allow the use of a variety of algorithms in order to detect thermal discomfort and evaluate which algorithms perform better under given conditions.

There is a lack of explanation behind the selection of the population samples in the processed studies. Additionally, some studies [33,37,39–41,48,57] discuss in detail the limitations posed by the number of participants and that the number of people should be increased in order to make their code/models perform better in real life applications. In addition, the sex of participants is not discussed in detail. In general, it is good to see that studies have more or less equal sex distribution during last few years in comparison to earlier studies from 1997–2014, where the number of males was several times larger than that of females [29].

General data utilization flow is shown at Figure 7. It illustrates the broad nature of variables and components used for predicting thermal discomfort via machine learning algorithms, artificial neural network and statistics. The section dedicated to the bio-metrical data covers all data related to participants' biological parameters. This type of data should be handled in a strict way, since the combination of bio-metrical variables can destroy the anonymity of data sampling within a study. Due to given circumstances, the protocol for data collection should be developed with sections that have detailed descriptions of the data protection, encryption and sample ID generation. Such strict rules may be one of the reasons why "Skin Temperature" and "Pulse" were the most commonly used variables among processed studies (see Table 4). For example, "BMI" in combination with "height" can provide private information about a person's lifestyle and general appearance which can compromise the results of the study. Given circumstances create additional milestones within bio-metric data collection, especially in cases where certain facial mapping data collection is involved.

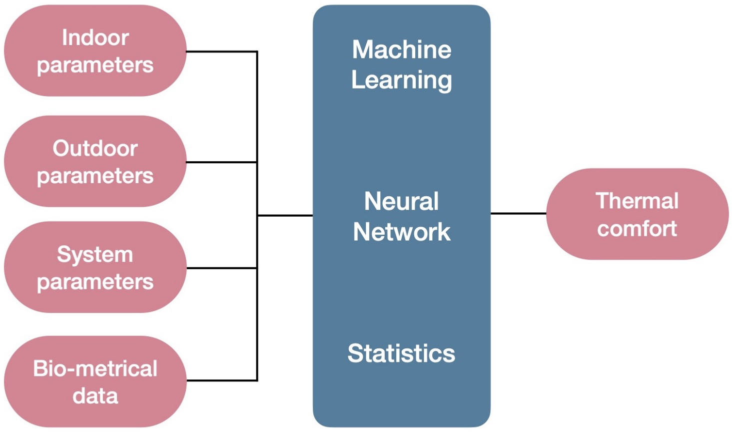

Figure 7. General scheme of data flow among case studies

The algorithm implementation step also differs from study to study. As was previously shown in Figure 5 of the results section, there are only few algorithms which were used repeatedly. One of them was SVM, which is a supervised learning algorithm represented by a discriminative classifier formally defined by a separating hyper plane [60]. Kernel, regularization and gamma are tuning parameters for SVM. Those parameters can easily introduce non-linear data separation into the classes, which, if used correctly, can increase the accuracy of the prediction [61]. A decision tree is also a supervised learning algorithm; since it is based on queries, by building a specific set of questions and answers, the algorithm can gradually reach a specified level of confidence in order to provide the answer to the global question [60]. A decision tree algorithm has no prior knowledge with respect to the outside world, which is why each relationship must be taught/introduced into the system. Each node contains a piece of information gained for predicting the target value. During the implementation of the algorithm, there are two possible options at each step, "true" and "false", in order to evaluate whether a specific criterion is met. By conducting queries, the algorithm will reach some prediction that is the best fit for the relation introduced in the system. The evolution of the decision tree algorithm is a random forest. It combines a number of decision trees into one so called "forest" [62,63]. Since each decision tree naturally has a random subset of features during the process of question formulation, and has access to a random set of training data points, a combination of several decision trees into the forest allows for the introduction of greater diversity, which results in a more robust prediction. For cases where we need to predict continuous variables (skin temperature for example), the random forest takes the average of all individual decision tree predictions. However, if there is a need to solve the classification problem (e.g., "comfortable"; "uncomfortable") instead of regression, the random forest will follow the majority of the vote for a predicted class [64].

Linear regression is another type of algorithm that uses supervised learning. It was developed for statistical purposes but has evolved into other fields. It was originally used to evaluate, understand and study the relationship between input and output numerical variables. On its own, simple form linear regression is shown to perform poorly in some cases due to the complexity of the real world. That is why the given algorithm evolved into ordinary least squares and gradient descent [60]. The following assumptions are made for linear regression: the relationship between input and output data is linear; data are cleaned and all noise is removed; highly correlated data should be treated since overfitting may be a big problem in given case; transforming functions may be implemented in order to make data follow the Gaussian distribution; and standardization or normalization of the parameters should be performed in order to increase the accuracy of the prediction. The k-NN is yet another supervised learning algorithm. Also named the lazy learning algorithm [63], it uses the same data for training and testing. The k-NN does not introduce any assumptions about the provided data set, which makes it non-parametric [65]. It is usually helpful for classification problems such as decision support systems.

ANN can be both a supervised and an unsupervised learning algorithm, depending on the purpose of the neural network and its architecture. ANN is a group of nodes connected with each other in a way that mimics brain behavior and function [60,65]. The deep neural network, which was used in the study by Cheng et al. [40], represents a more complex architecture of neural network layers. Multiple layers were used to extract higher level features from the raw data.

All those algorithms were used to predict whether a person is comfortable or not within provided indoor conditions. In general, it is a good approach for the given task, but, as was mentioned before in the brief description of each algorithm, overfitting is a significant problem that may occur in each algorithm's implementation [60,63]. Only a few articles described how they approached this problem [31,35,40,43,53,55]. For studies which had only few test subjects and a relatively small volume of data, the question of overfitting might not be a problem, but it is common practice to use a number of actions with respect to each algorithm.

The complexity of thermal comfort perception by each human will always raise the question of validity for predictors in a data set. The findings of SLR show different sets of variables in combination with a number of algorithms and potential models. The Achiles heel of this topic is the tenuous link (if any) established between the non-invasive bio marker and that nebulous state of mind. The basic biological theory behind a collection of the skin images, heart rate, blood pressure and other parameters, is that the body is predefined by nature to restore conditions, which are comfortable for the functioning of the organism. Such a biological feature gives the assumption that there is a link between a certain bio-metrical trait and the actual feeling of thermal comfort. Unfortunately, there is a need to perform more targeted research within the field before it will be possible to validate certain bio-metrical parameters as the ones suitable for thermal comfort prediction.

For better validation, it would be beneficial to utilize the link between the thermoregulation system and the subcortical level of the brain (or lower brain). Since the human body must to maintain core temperature within a normal range (e.g., 36.5–37.5 °C), the thermoregulation system needs continuous information flow from temperature-sensitive nerves. The signals travel from temperature-sensitive nerves through the spinal cord to subcortical level of the brain, where they are evaluated and the body's physiological features are adjusted respectively [66]. Based on such human body function, a new approach in non-invasive thermal comfort sensing is envisioned. For artificial intelligence algorithms, it is proposed to synthesize and use only those bio markers, which have direct interaction link to the lower brain that is directly responsible for the thermal comfort evaluation.

5. Conclusions

This study carried out a systematic literature review about the possibilities for determining indoor thermal discomfort by non-invasive means using bio-sensing technology. The review concludes that there is great potential for utilizing digital bio-sensing equipment within the given topic. Bio-metrical data can provide grounds for estimation of the thermal comfort at the workplace [30,39,56]. The facial skin temperature has proven to be a very useful parameter for the training of the machine learning algorithms. The facial skin temperature can be extracted without the placement of the sensors directly on a person's skin, due to the fact that facial skin is always exposed to the indoor conditions without any layers of clothes. It is useful for deployment of the developed models, since the models can directly extract variables on which they were trained.

The majority of the reviewed studies used regular cameras and post-process pictures or thermal cameras which provided images directly [31,34,50]. This approach has a good potential to be used in everyday life, but there are some challenges for the given technology. There should be a large amount of data collected to train algorithms, since skin color is very different for each person; lighting in the office may change during working hours, which may introduce bias into comfort prediction; and people may have different levels of blood circulation within their fingers due to a variety of personal health factors. That is why many studies have been done for thermal comfort evaluation on a personal level. Other studies [38,49,51] tried to use fitness bands and other sensors which might be directly secured on a person's hand or installed in glasses [34]. The given technology can provide good results, but more investigation should be done, since the deployment of such systems has not been fully discussed. It is a complicated task to install all sensors onto glasses that people are using. Additionally, people who are not wearing glasses will be pushed to wear fake ones so that there is a frame to mount sensors [34]. Another issue is a privacy concern with the usage of the fitness band. It is unlikely that people would want to synchronize their private devices with work servers, since such equipment contains personal information such as the hour of waking up and private messages. It is important to provide a user-friendly solution that is not violating personal data privacy while still providing personal comfort. Based on the literature review, it is possible to conclude that there is potential for the creation of non-invasive thermal discomfort detection models via utilization of bio-sensing technologies, which will provide better user interaction with the built environment, potentially decrease energy use and enable better productivity. A deep neural network with multiple hidden layers for learning characteristics of the data in a feature hierarchy way has shown potential for further development and use in future studies. By defining the architecture of the layers in the model, information from different data types can be extracted and processed more efficiently and potentially provide a more accurate prediction of future discomfort events.

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Abbreviations

PICOC	The Problem Intervention Comparison Outcome Context
PIOC	The Problem Intervention Outcome Context
PIO	The Problem Intervention Outcome
PRISMA	The Preferred Reporting Items for Systematic Reviews and Meta-Analyses
IEQ	Indoor Environment Quality
PPD	Predicted Percentage of Dissatisfied
PMV	Predicted Mean Vote
ANN	Artificial Neural Networks
ML	Machine Learning
HVAC	Heating, Ventilation and Air Conditioning
SLR	Systematic Literature Review
BMI	Body Mass Index
Oxygen sat.	Oxygen Saturation
SBP	Systolic Blood Pressure
DBP	Diastolic Blood Pressure
GSR	Galvanic Skin Response
EEG	Electroencephalogram
ECG	Electrocardiogram
SBF	Skin Blood Flow
SVM	Support Vector Machine
k-NN	K-Nearest Neighbors

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