POLITECNICO DI TORINO

Collegio di Ingegneria Energetica e Nucleare

Tesi di Laurea Magistrale

Evaluation of thermal comfort through wearable sensors: new perspectives

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INTRODUCTION

The historical period we are living in sees the need to implement and develop new solutions in the energy field, above all to try to stem the catastrophic future consequences we may face due to climate change.

Reduction of emissions, of the use of fossil fuels and a consequent investment in different, cleaner energy sources are actions that must absolutely be undertaken, without forgetting a fundamental aspect we must absolutely invest on: the energy efficiency of buildings. Its goal is to maintain, if not improve, the comfort of the occupants inside the building while minimizing energy consumption.

Still in this perspective, according to some recent studies [1], we could act on the thermal comfort of people even in the external environment, for instance on the roads. This, above all, in function of these anomalous heat waves that in recent years have followed each other more and more frequently, in order to improve and safeguard the health of the population (especially the weakest and most vulnerable ones) and to improve the efficiency of the buildings.

Pursuing these goals is anything but simple, especially when dealing with the concept of comfort. Beyond the physical parameters that can be measured and controlled by sensors (air temperature, air pressure, air velocity, humidity), there are a whole other set of subjective variables, much more difficult to investigate, which are closely related to the physiological parameters of the occupants and which therefore vary from individual to individual.

It is therefore very important to study the effects that these physiological parameters have on occupants' comfort and how the interaction with the environment and the ability to adapt can condition the well-being and its own perception.

The variables that must be taken into account in this case are many and varied: metabolic activity, heart rate, brain activity (EEG), respiratory rate, skin temperature measured on the wrist and ankle, body temperature, posture, ACT-Activity level.

These variables must be analyzed on the basis of age, health, ability to adapt; it is therefore essential to understand what impact they have on comfort and energy management of the building.

This new approach in the study of thermal comfort tries to investigate much more in depth and objectively the effects that the external environment is able to generate in a person, such as the influence on the actions it performs and how it modifies the perception of comfort, comparing what is the physiological reaction with the subjective one, expressed by the person itself.

Knowing these elements better and deeper, it’s possible to greatly improve thermal comfort and perform a better and a more efficient energy management.

In the first chapter Fanger's theory will be briefly summarized and its main critical points will also be highlighted. Subsequently, the sensors that have been used up until now and the parameters that have been measured and analyzed will be presented. The critical points and the advantages of these sensors will also be discussed, in order to effectively identify which of these devices can be practically used for the assessment of thermal comfort.

1. FUNDAMENTALS

In this chapter the concept of thermal comfort, the theory of comfort theorized by Fanger, the theory concerning the measurement of a physical quantity and the accuracy and sensitivity of the PMV index created by Fanger will be presented and analyzed.

1.1 Thermal comfort and Fanger's model

It is possible to give a subjective and an objective definition of thermal comfort. The former is defined as "the state of mind in humans that expresses satisfaction with the surroundings environment" (ASHRAE standard 55), the latter provides that the following conditions are respected: the heat produced is completely dissipated, behavioral thermal control mechanisms are inactive, peripherical vasomotor mechanisms are inactive.

The international standards used to determine thermal comfort are: ASHRAE 55 and ISO 7730. They use heat balance model for the human body, connecting the perception of comfort to six parameters, four objective and two subjective:

- air temperature;
- mean radiant temperature;
- air velocity;
- relative humidity;
- metabolic rate;
- clothing insulation.

In mechanically ventilated buildings (the case we are interested in), the comfort is evaluated through the ISO 7730 standard, which describes the Fanger's model (the basis behind the standards previously mentioned). For naturally ventilated rooms the adaptive method is used.

Ole Fanger devised a climatic chamber: through it, by varying three environmental parameters (air speed, mean radiant temperature and relative humidity) and two personal parameters (activity level and clothing insulation), he calculated the degree at which most people felt no difference between them and the environment around, the "thermally neutral state".

Thanks to these studies, he developed the *Predicted Mean Vote (PMV)* index and the *Predicted Percentage Dissatisfied (PPD)* index.

The *Predicted Mean Vote (PMV),* see equation (1), it's an index which predicts the conditions at which most occupants will be satisfied at, is a mathematical function of six comfort parameters expressing the average value of thermal sensation of a significant group of people on a seven-point scale from -3 to 3 [2]:

$$PMV = 0.303 * L * \exp\left(-0.036 * M + 0.028\right) \quad (1)$$

Where:

- L is the "load on the human thermal control system" (2). It is defined as the difference between the thermal energy that is generated within the human body and does not transform into mechanical energy (M - W), and the thermal energy that the individual would disperse if he were in a situation of well-being [3]:

$$L = (M - W) - (E_d^* + E_{sw}^* + E_{res}^* + C_{res} + C^* + R^*) \quad (2)$$

  - E_d^* = thermal power dispersed by diffusion of steam through the skin;
  - E_{sw}^*= thermal power dispersed by sweating;
  - E_{res}^*= thermal power lost in breathing as "latent heat";
  - C_{res} = thermal power lost in breathing as "sensitive heat";
  - C^* = thermal power dispersed by convention;
  - R^* = thermal power dispersed by radiation;

  (The asterisks show that these are not real values but those that would occur in fictitious conditions).

- M is the metabolic heat production;

Thermal Sensation Scale

	Scale	Comments
3	hot	intolerably warm
2	warm	too warm
1	slightly warm	tolerably uncomfortable, warm
0	neutral	comfortable
-1	slightly cool	tolerably uncomfortable, cool
-2	cool	too cool
-3	cold	intolerably cool

Figure 1- Thermal sensation scale and comments about scale [4]

The *Predicted Percentage Dissatisfied (PPD)* index predicts what percentages of occupants will be unhappy with a particular set of environmental conditions.

An approximate relationship between PPD and PMV can be seen in the graph below:

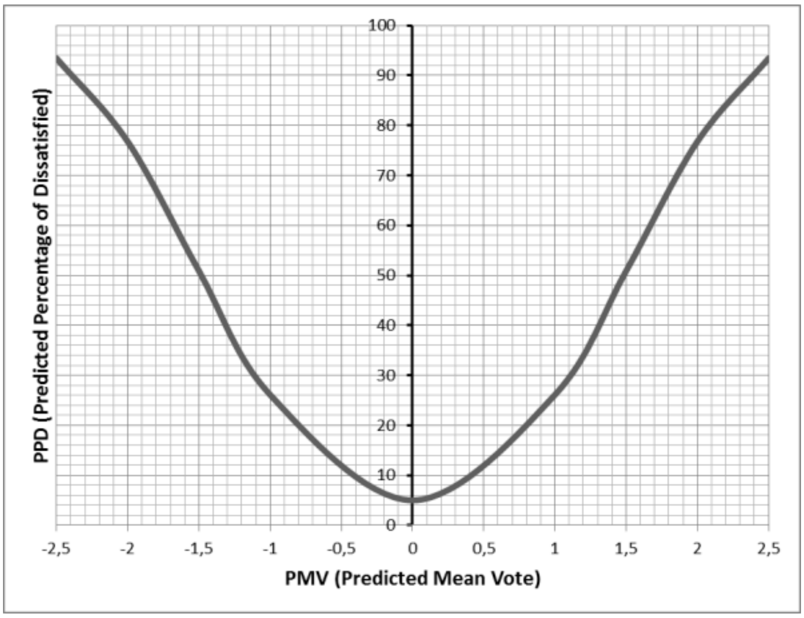


Figure 2 - The relationship between PPD and PMV [4]

5% of the occupants would be dissatisfied even with the most comfortable conditions (PMV=0).

However, this model has some important limitations as shown in the studies of Byron W. Jones [5] and Kate E. Charles [6]:

- It was developed in a closed and air-conditioned environment. The PMV model is based on climate chamber experiments, in which the four physical variables (mean radiant temperature, air temperature, relative humidity and air velocity) can be monitored and controlled;

- It's a static and mono-dimensional model which considers clothing perfectly uniform on the whole body;

- Fanger sees people as passive subjects, they are just the object of the experiment, unable to interact with the surrounding environment;

- People involved in the experiment, did not constitute a representative sample of the population (in terms of climatic, cultural, social factors, i.e.: age, social background, activity performed, etc.), in fact Fanger's original studies (in 1967;1970) were conducted using college-age white subjects: so the model obtained from these studies may not be valid for other occupant populations. In the performed researches (reported in [4]) attention has been paid to gender for example. It has been noticed that when the temperature shifts from the neutral one, the thermal sensation of women changes much more rapidly than that of men; a difference is also found in the type of clothing used, in fact women tend to use lighter clothes than males. Another aspect not to be underestimated is that people from different climatic regions differs in their neutral temperatures;

- The metabolic rate is estimated by calculating the metabolic heat produced and the degree of activity, but not taking due account of age, gender, time of the day in which the calculation is made. In fact, the current tables containing standard values of metabolism provide information for the 'average' person and this obviously does not accurately reflect the differences between people and the context.

Subject activity	*met*	Subject activity	*met*
Lying	0.7	Baker	1.5 - 2.0
Sitting	1.0	Construction worker	4.0 - 6.0
Standing	1.2	Mechanical worker	3.5 - 4.5
Walk slowly	2.0	Electrical worker	2.0 - 2.5
Walk fast	2.6	Store clerk	2.0 - 2.5
Drive a car	1.5	Watchmaker	1.0 - 1.2
Ride a motorbike	2.0	Tennis	3.6 - 4.0
Drive a truck	3.2	Squash	5.0 - 7.0
Drive a plane	2.0	Basketball	5.0 - 7.6
Clean house	2.5	Dance	2.4 - 4.4
Cooking	1.8	Golf	1.5 - 2.5
Shopping	1.6	Fishing	1.2 - 2.0

Table 1 – Metabolism values for different activities [7]

The metabolic rate is influenced by body mass, body type, fitness level and blood flow. The metabolic rate is continuously changing over time, even without performing any remarkable physical activities. The study of Hasan et al. [8] shows for example that simple mental work might lead to some increase in the MET value, which can lead to thermal discomfort.

Therefore, it is necessary to consider much more information in order to have a correct estimate of the metabolic rate, which must be carefully and constantly measured to ensure the reliability of the PMV comfort model. An accurate measurement of metabolism of an occupant can extend the area of application of the PMV model to those who may be involved in physical activities, such as waiters and waitresses in a restaurant, or people working out in the gym;

- The thermal resistance generated by clothing is it is considered uniform on the whole body and calculated in a generic and inaccurate way, the estimate that is made is limited to a standard, tabulated choice of clothes, for example winter clothing, summer clothing, work clothing, short dresses etc.

Clothing	**Icl (clo)**
Skinny trousers, short-sleeved shirt	0.57
Skinny trousers, long-sleeved shirt	0.61
Skinny trousers, long-sleeved shirt, jacket	0.96
Slow pants, long-sleeved shirt, sweater, underwear shirt	1.01
Slow pants, long-sleeved shirt, sweater, jacket, heavy underwear	1.30
Skirt, short-sleeved shirt, tights, sandals	0.54
Skirt, long-sleeved shirt, petticoat, tights	0.67
Long skirt, long-sleeved shirt, jacket, tights	1.10
Long-sleeved suit, shirt	0.72

Table 2 – Clothing table [7]

Many studs, as reported in [4], have shown that the accuracy of PMV predictions is strongly influenced by the value attributed to clothing insulation. The PMV well predicts the values of the neutral temperature for clothing insulation (including the insulation generated by the chair, in a office simulation) in the range from 0.3 to 1.2 clo. For lighter or heavier clothes, the PMV model tends to overestimate the actual neutral temperature.

As proof of the fact that PMV is highly influenced by the metabolic rate and by clothing, Hasan et al. [7] have developed a graph (see figure 3) and a summary table (obtained through a series of experiments) where the sensitivity of the PMV to different parameters is highlighted.

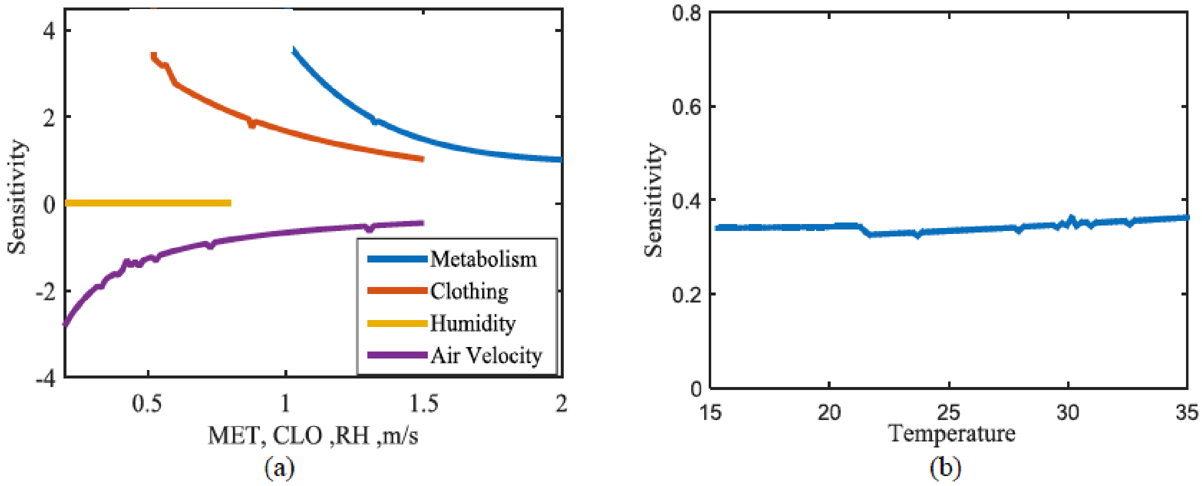


Figure 3 - PMV model sensitivity to (a) metabolism, air velocity, humidity, and air temperature, (b) and to air temperature. [7]

Parameter		Sensitivity (mean)	Sensitivity (range)
Air temperature (t_a)		$S_{AT} \cong 0.34 °C^{-1}$	0.04
Humidity (RH)		$S_{RH} \cong 0.007\ RH^{-1}$	~0
Clothing (CLO>0.5)		$S_{CLO} = 1.3\ CLO^{-1}$	1.22
Clothing (CLO<0.5)		$S_{CLO} = 5.53\ CLO^{-1}$	2.8
Air velocity ($V > 0.5$)		$S_{AV} = -0.72\ m^{-1}s$	0.87
Air velocity ($V < 0.5$)		$S_{AV} = -2.2\ m^{-1}s$	2.9
Metabolism ($MET > 1$)	$t_a = 20\ °C$	$S_{MET} = 2.09\ MET^{-1}$	3.37
	$t_a = 22\ °C$	$S_{MET} = 1.6\ MET^{-1}$	2.0
	$t_a = 28\ °C$	$S_{MET} = 0.79\ MET^{-1}$	1.25

Table 3 – PMV sensitivities to its parameters [7]

The figure 3 show that PMV model is very sensitive to the personal parameters, and its sensitivity to metabolism, clothing, and air velocity, changes with these parameters values and hold constant for air temperature and humidity.

This model is therefore limited and it requires improvements, especially on the estimation of the subjective parameters (metabolism, perception of the occupant and activity performed at the time of measurement).

A first attempt in this direction was made by the creation of questionnaires submitted to the occupants of the room under analysis together with the standard measurements of environmental parameters. These questionnaires were structured in order to make a better comparison between what are the comfort standards calculated theoretically, through the Fanger's theory, and the actual perception that the occupants have of a certain indoor environment.
An example of this type of study was carried out by Castaldo et al [9] in a luxury clothing factory in central Italy (Perugia).
They have adopted the previous mentioned new methodology for the comfort assessment, combining the monitoring of physical environmental variables and a survey campaign.
They monitored indoor air quality, illuminance level, global and local thermal comfort, while the questionnaire deals with:

- personal information (gender, age, clothing);
- working schedule and the possibility to control the environment;
- thermal and lighting perception (sensation perceived, comfort, preferences, acceptability, tolerability);
- general comfort condition adaptability with respect to non-physical influences (work environment perception, environmental quality of the domestic environment compared to the work place, health condition, personal mood).

As can be seen from the construction of the questionnaire, great importance is given to the person and his perception, making a comparison also with the domestic environment. It is also shown how many factors must be considered to have a true representation of the occupants' perception of comfort.
In fact, one of the aims of the study was also to investigate other aspects, not strictly related to physical variables, which can have a positive influence on the perception of thermal comfort and the productivity of workers: for instance an aesthetically pleasant and comfortable work environment, or the view of the greenery of the gardens out of the office windows.

In fact, a discrepancy has been observed between the comfort levels obtained from the monitoring campaign and the ones obtained through the questionnaires: this is precisely due to this whole series of physiological and non-physiological parameters which are not considered or not measured in a truthful way in the Fanger's model.

Therefore, new studies and new researches are focusing on a much more accurate study of the physiological parameters, especially on the more precise estimate of the metabolic rate, which represents one of the most important values to be checked in order to have a truthful representation of the person's activity and consequently of his thermal perceptions.

1.2 Measurements of PMV parameters

The UNI EN ISO 7726 standard "Ergonomics of the thermal environment- Instruments for measuring physical quantities" [10] in paragraph 4 defines the physical quantities to be estimated for the calculation of the PMV index and how these quantities can be measured:

- Air temperature: "it is the temperature of the air around the human body", this parameter can be measured with the following devices: expansion thermometers (liquid or solid), electric thermometers (variable resistance thermometer, thermocouple), thermomanometers (variation liquid pressure as a function of temperature);

- Mean radiant temperature: "it is the uniform temperature of a hypothetical enclosure in which radiant heat transfer from the human body is equal to the radiant heat transfer in the actual non uniform enclosure". Usually the black globe thermometer is used to calculate an approximate value of this quantity starting from the temperature values of the globe and those of the temperature and the air speed around the globe. This parameter can be also calculated from the values of walls temperatures, walls size and their positions with respect to people (calculation of the geometric shape factor);

- Air velocity: "it is a quantity defined by its magnitude and direction. The quantity to be considered in the case of thermal environments is the speed of the air; i.e. the magnitude of the flow velocity vector at the considered measuring point". An anemometer is used to measure this quantity;

- Absolute humidity: "it characterizes any quantity related to the actual amount of water vapor contained in the air", while relative humidity: "it gives the amount of water vapor in the air in relation to the maximum amount that it can contain at a given temperature and pressure". When we talk about evaporative exchange between a person and the environment, we must consider the absolute humidity of the air. This latter can be determined directly (i.e. dew-point instruments) or indirectly, by measuring, for example, relative humidity and air temperature or psychrometric wet temperature and air temperature (in this last case the instrument used is the psychrometer).

As regards the physiological parameters (metabolic rate and insulation generated by clothing), the calculation methods are reported in UNI EN ISO 7730 [11]. The appendices of this standard report the tables containing the standard values of metabolism for different activities and the insulation generated by different combinations of clothing.
As seen before, this method of estimating metabolism and clothing insulation is rather limiting and not very accurate and, therefore, requires improvement.
In the following paragraphs the basic principles of metrology will be deeply explained in order to be able to fully understand the importance of a good measurement and how the errors that can be generated during the measurement process propagate and can influence the reliability of the result itself.

1.3 Measurement theory

In this paragraph, before moving on to the description of wearable devices, a brief mention of the theory concerning the measurement of a physical quantity will be presented [12].

Let's start from the definition of measurement: "measurement is the process by which a number is associated with a physical quantity". Therefore, the measurement of each physical quantity is characterized by a number followed by a symbol that expresses the unit of measurement used.

Measurement operations are always affected by uncertainty, according to UNI ISO 3534-1: 2000: "measurement uncertainty is the estimate of the result of tests that characterize the range of values within which the true value is supposed to fall of the measurand. Uncertainty is the size of a mean square deviation ".

The estimate of the measurement uncertainty is fundamental because it expresses the intrinsic reliability of the measurement result.

To express the uncertainty of the measurement of a quantity x, it is necessary to express the error ϵ_x that is committed during the measurement, i.e. write the number $x=\bar{x} \pm \epsilon_x$, followed by the unit of measurement of the quantity measured, where $\bar{x}$ represents the average value of the measurements made.

The error is calculated by evaluating the mean square deviation, often determined with the standard deviation (3):

$$\epsilon_x = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\bar{x})^2}{N-1}} \quad (3)$$

Systematic errors, contribute to uncertainty; to evaluate them, it is necessary to consider the probability distribution P (x) of the measurand, the mean square difference becomes:

$$\epsilon_x = \sqrt{\int_{\mathbb{P}} P(x)(x_i - \bar{x})\,dx} \quad (4)$$

Where $\mathbb{P}$ is the volume of the probability space considered.

At this point, it is possible to express the uncertainty by indicating the confidence interval built around the result of the measurement. The measured value belongs to the range with a given probability, i.e. the coverage level K

$$\bar{x} - K_{\epsilon_p} < x < \bar{x} + K_{\epsilon_p} \quad (5)$$

If the random effects affecting the measurement have a normal probability distribution, then the probability that the expected value of the measurand is within the confidence interval is:

- 68.3% for k=1;
- 95.4% for k=2;
- 99.7% for k=3.

In summary, when carrying out a measurement operation, errors can be committed and they can be classified as follows:

1. "Systematic errors: caused by factors that always act in the same way and therefore are not immediately detectable";
2. "Gross errors: due to oversights by the operator";
3. "Operator errors: caused by particular aptitudes or dispositions of the experimenter in the use of the instrumentation";

4. “Accidental errors: these are the errors that occur independently of the observer and are due to the accuracy of the measures. For these, there is a statistical treatment that allows you to take them into account”.

Let's see how the error spreads. In the case of linear relationships, the error is treated in this way [7]:

$$x=\bar{x} \pm \epsilon_x\,,\ \ y=\bar{y} \pm \epsilon_y,\ \ z=\bar{z} \pm \epsilon_z$$

	z=x+y	**z=x-y**	**z=xy**	**z=x/y**
$\bar{z}$	$\bar{x}+\bar{y}$	$\bar{x}-\bar{y}$	$\bar{x}\bar{y}$	$\frac{\bar{x}}{\bar{y}}$
ϵ_z	$\epsilon_x + \epsilon_y$	$\epsilon_x + \epsilon_y$	$\frac{\epsilon_x}{\lvert\bar{x}\rvert} + \frac{\epsilon_y}{\lvert y\rvert}$	$\frac{\epsilon_x}{\lvert\bar{x}\rvert} + \frac{\epsilon_y}{\lvert y\rvert}$

Table 4 – Propagation of error [13]

Let’s see also, the measuring instruments in more detail. [14] They are mainly composed of three elements:

1. The sensitive element or sensor that transforms the physical quantity to be measured in another (signal of measure);
2. Processing and transmission element (transformation of the signal into an electrical quantity, linearization, amplification….);
3. Detector or indicator element that allows the reading by the user in an analogical way (index mobile on a graduated scale) or digital (series of numbers on a dial).

There are also introduced some important definition [14]:

Accuracy:” it is the ability of an instrument to indicate or record the exact value of the measured quantity.”

Precision:” it is also called measurement repeatability, i.e. the ability of an instrument to indicate, in the case of repeated measurements with the same method and in same conditions, always the same value as the measured quantity.”

Sensitivity: “it is the smallest variation in size measured that the instrument allows you to observe.”

1.4 Accuracy of the PMV model

Let's now analyze the accuracy of the PMV model and also the role of measurement accuracy on the assessment of the thermal environment using the PMV.

Cheung et al. in 2019 [15] conducted research, funded by the National Foundation of the Republic of Singapore as part of the Singapore-Berkley Building Efficiency and Sustainability in the tropics (SinBerBEST) program, to evaluate the accuracy of the PMV model prediction using the ASHRAE Global Thermal Comfort II database They focused on:

- the accuracy of the PMV to predict the individual observed thermal sensation (OTS) and the observed mean vote (OMV);
- comparing relationships between PMV-PPD and OTS with observed percentage of unacceptability (OPU).

These analyses were performed on different types of buildings (offices, classrooms and houses), strategies of ventilation (air conditioning, natural ventilation and mixed mode) and climatic classifications (tropical, arid, temperate and continental).

PMV has been found to have a low prediction accuracy based on different methods used in other works. The accuracy of the overall forecast was measured at 34% (i.e. the thermal sensation would have been wrongly predicted two out of three times). The PMV model has slightly higher accuracy with sensational marks close to neutral, but has never exceeded 60% in any type of building, ventilation strategy and climatic classification. Its accuracy has decreased towards both ends of the thermal sensation scale and has overestimated OTS in both hot and cold sensations.

Cheung et al. have developed a simple model based on-air temperature and achieved 43% accuracy in predicting thermal sensation. The results demonstrate that in many contexts the inaccuracies are not in the PPD model itself but rather in the PMV model and in its prediction of the thermal sensation.

The authors of the article, on the basis of the results obtained, believe that the accuracy of the PMV is unacceptably low, this suggests that is important to overcome deterministic models of thermal comfort and to develop personal thermal comfort models able to respond to the different needs of the occupants.

Another important aspect to analyze is the sensitivity of the PMV index to measurement errors of its independent variables.

This aspect is well explained in the study of d'Ambrosio Alfano et al. [16], which aim is to perform a sensitivity analysis of numerical models, evaluate the propagation of errors by modifying any quantity that influences PMV.

This method allows an easy interpretation of the results obtained.

Sensitivity analysis was carried out in the same thermal state of the human body for a fixed PMV value. Under these conditions every variable independently involved in PMV equation, with the required precision, was first "disturbed" one at a time and then all together.

For the PMV values examined in this study, the authors worked on a PMV of 0 ± 0.35 and ± 0.60.

The nominal values of the six quantities that affect the PMV are shown in the table below:

Parameter	Symbol (units)	Value
Metabolic rate	M (met)	1.2; 1.4; 1.8; 2.2
Static clothing insulation	I_{cl} (clo)	0.50[1)]; 1.0[2)]
Air humidity	R.H. (%)	30–70
Difference between the mean radiant temperature and the air temperature	$t_r - t_a$ (°C)	0.0
Absolute air velocity	v_a (m/s)	0.10[b]; 0.12[a]

[a] Summer.
[b] winter.

Table 5 – Microclimatic and subjective variables investigated values [16]

For the accuracy of the physical parameters, the author used the values reported in ISO 7726 for comfort applications (see table 6).

The sensitivity analysis has been performed with an accuracy of ± 10% of the nominal metabolic rate.

Parameter	Required accuracy	Desired accuracy
Water partial pressure[a]	± 0.15 kPa	
Air velocity[a]	± (0.05 + 0.05 v_a)	± (0.02 + 0.07 v_a)
Air temperature[a]	± 0.5 °C	± 0.2 °C
Mean radiant temperature[a]	± 2 °C	± 0.2 °C
Static clothing insulation	±10%	
Metabolic rate[b]	±10%	

[a] According to ISO 7726
[b] According to ISO 8996

Table 6 – Accuracy levels used for the whole of parameters affecting the thermal sensation [16]

The sensitivity of the PMV to the accuracy of the measurement of physical quantities is summarized as follows [16]:

- Air temperature: at each value of the metabolic rate studied, the maximum of the PMV did not exceed ± 0.07 with respect to the required level of accuracy in winter conditions and it wasn't influenced by higher metabolic rate values. Furthermore, in summer conditions the uncertainty of the PMV appeared slightly enlarged, probably due to the lighter clothing worn by the occupants which makes the human body more sensitive to changes in air temperature;

- Mean radiant temperature: the accuracy of the measurement of this parameter strongly influenced the evaluation of the PMV. Metabolic rate for a sedentary activity (M = 1.2 met) in winter or summer conditions, it was calculated an average deviation of PMV of approximately ± 0.20 or ± 0.28, respectively.

These results have clearly made the mean radiant temperature measurement a crucial step in the assessment of the thermal environment, since the transfer of radiative heat is related to the fourth power of the mean radiant temperature. Consequently, even small mistakes in its evaluation (i.e. an incorrect calibration procedure) can increase the uncertainty in the evaluation of the thermal environment. A lighter effect was found with higher metabolic rate;

- Air velocity: the effect of errors in this case appeared less significant than the previous one. Indeed, the ΔPMV values calculated in winter condition (at 1.2 and 1.4 met) with the required accuracy, appeared close and were gradually lowered increasing metabolism;

- Air humidity: the effect of errors on partial water pressure was negligible (following Fanger's theory), which refers to a reduced effect of humidity on human thermal sensation.

The sensitivity analysis reported in the study of d'Ambrosio Alfano et al. has shown that the reliability of the PMV calculation is very influenced by the accuracy of the evaluation of each quantity related to the thermal sensation.

In particular, although the mean radiant temperature was measured following the accuracy proposed in ISO 7726, the PMV value calculated can make the classification of the environment quite random. Furthermore, the uncertainty of the PMV with respect to this temperature, decreases if this measurement is carried out with the requested precision (which is very difficult considering the devices available on the market).

Based on these tests, it is necessary to study the modification of the precision requirements presented in the ISO 7726 standard or refer to more reliable measurement procedure.

Only a slight sensitivity of the PMV was detected both at the air temperature and at the air speed with a maximum uncertainty of the PMV of approximately 0.10.

The accuracy of the humidity measurement didn’t affect the PMV estimation.

A significant influence from the metabolism was detected. In moderate environments, the values of the metabolic rate do not change significantly, so the accuracy used in this survey (±10%) must be considered valid.

These results suggest the need of researches focused on measurement protocols leading to a possible reduction in the accuracy levels reported in ISO 7726. Also, due to a significant sensitivity to PMV, the ranges of PMV comfort found in ISO 7730 and EN 15251 standards should be expanded to allow a better classification of thermal environments.

2 WEARABLE SENSORS

Considering all the mentioned limitations concerning Fanger's model and the calculation of the parameters contributing to the estimate of the PMV index, innovative solutions have been investigated for the measurement of the PMV: some of them consider the integration of the measurements of personal parameters included in the calculation of the PMV index (in particular, through the use of wearables sensors) while others are focused on defining personalized thermohygrometric well-being, with the use of measurements that go beyond the assessment of the metabolic rate.

In this chapter then, the sensors used until now for measuring the physiological and physical parameters for the purpose of thermal comfort evaluation are presented. From the analyzed studies, it can be seen that sensor networks have also been generated (e.g. BAN Body Area Network) in order to analyze both physiological and environmental parameters in the most complete and exhaustive way possible.

The key feature that recent studies in the field of thermal comfort have in common is to use small and wearable sensors.

This aspect is fundamental to allow an even more accurate and truthful measurement of a person's physical state in different environments and to carry out measurements that are closer to reality and actually improve the occupant comfort inside a building.

Before proceeding with the description of the individual devices, some mechanism, by which some physiological parameters are measured, will be analyzed:

- **Heart rate**: this is a data that contains a lot of information and allows to understand how human heart is working both at rest and during exercise. Usually these sensors can be found in two different forms: a chest strap or a sensor integrated in a wrist device.

  Usually, sensors that are worn through a chest strap detect the heart pulse through an electrical signal via electrodes and send the data to an external device, be it a smartphone or a fitness tracker. [17] BioHarness for example uses this type of sensor.

On the other hand, there are sensors, usually mounted on smartwatches, that exploit the following principle: when our heart beats, the capillaries expand and contract based on changes in blood volume. To determine the heart rate, the green LEDs of the optical heart rate sensor on your device flash many times per second and the sensor uses light sensitive photodiodes to detect these volume changes in the capillaries above the wrist. So, your device calculates your beats per minute (BPM).

Green LEDs are used to maximize the signal detected by the capillaries near the surface of the skin. The optical heart rate sensor also uses infrared light to determine when the device is on the wrist and improve the accuracy of heart rate data [18]. This type of sensor is used on the devices of the Fitbit family.
Both types of sensors have their pros and cons. Those worn on the chest can be uncomfortable and difficult to wear, but they tend to be more precise as they are pressed firmly against the skin and are pretty close to the heart. On the other hand, wrist sensors are more comfortable to wear, but they need to be positioned carefully to ensure an accurate data reading.

- **Respiration**: these devices works thanks to the use of a pressure sensor pad mounted on to the chest strap of the subject's left-hand side, detecting and analyzing the expansion of the rib cage due to breathing action [19]. A wearable device that uses this type of sensor is BioHarness 3.0;

- **Electrodermal activity**: Galvanic Skin Response (GSR), also known as Electrodermal Activity (EDA) or Skin Conductivity (SC), is a measure of the continuous changes in the electrical characteristics of the skin, such as conductivity, as a result of changes in sweating in the human body. The GSR signal is very easy to record: in general, two electrodes applied to the index and middle fingers of a hand are sufficient. The variation of a low voltage current applied between the two electrodes is used as a measure of electrodermal activity (EDA) [20];

Recently, new commercial devices dedicated to healthcare have been developed, as bracelets, watches, allowing an easier measurement. Empatica E4 is an example of a wearable sensor with an integrated EDA sensor [21];

- **Steps:** wearable devices use 3-axis accelerometer to count steps. This sensor also allows the device to determine frequency, duration, intensity and movement patterns [18];

- **Distance:** for example, Fitbit devices use the following formula to calculate distance. Stride length is determined by height and gender:

  $$\text{Steps x Step length} = \text{Distance traveled}$$

  When the user detects an activity with GPS, the device calculates the distance using GPS data instead of steps. If the user starts moving before a GPS signal is available, the device calculates the distance using the steps until it connects to the GPS [18];

- **Floors:** wearable devices, to count floors, have an altimeter integrated, which is a sensor that detects when you get on. The device registers 1 floor when the person climbs about 3 meters. Barometric pressure changes are used combined with the steps taken to calculate the floors climbed [18];

- **Basal Metabolic Rate:** Basal metabolic rate is the rate at which a person burns calories at rest to maintain vital body functions (i.e. breathing, blood circulation and heart rate), is based on the physical data as height, weight, gender and age and counts for at least half of the calories burned in a day [18];

- **Calories:** wearable devices combine basal metabolic rate (MB), and activity data to estimate calories burned. If the device detects heart rate, this data is also included, particularly to estimate the calories burned during training [18];

- **Activity level**: this parameter is usually measured using a heart rate monitor, a sensor that detects heartbeats per minute (mounted for example on a chest strap) and GPS sensor.

2.1 BioHarness

BioHarness 3.0 (BH3) is a sensor for real-time monitoring of various physiological parameters such as heart rate, respiratory rate, skin temperature, activity (running, walk, etc.), acceleration, position and posture (see figure 4).
It's sattached to a belt made of lightweight Smart Fabric, positioned on the chest directly in contact with the skin. It acts as a sensor, transmitter and data logger.

Figure 4 - BH3 sensor [22]

Its characteristics are reported in the following table.

BIOHARNESS 3.0	
Hardware Characteristics	
Description	Sensor for real-time monitoring of various physiological parameters, attached to a belt made of lightweight Smart Fabric
Dimension	28mm x 7mm
Weight	18g
OPERATING CONDITIONS	
Temperature	-10° to 50° C
Humidity	5% to 90% relative humidity (non-condensing)
Battery	4.2V Li-Ion rechargeable
Battery capacity	24 hrs standby mode, 18 hrs active mode
Charging time	3 hours
Wireless	Up to 2 miles (refer to RAELink3 datasheet for complete details)
Software	Zephyr's OmniSense PC application
DATA MANAGEMENT	
Run time	12 to 28 hours
Data storage	**Hours**
General	*500*
General and ECG	*140*
General and Accelerometer	*280*
Data transfer	Bluetooth or proprietary cradle (USB). BioHarness Log data can also be imported directly into Zephyr's OmniSense Analysis module. (Zephyr Log Downloader Tool)
Data format and analysis	•.csv format (comma separated values) which can be opened using Microsoft Excel, Notepad, or similar, or imported into many data processing applications. •.dat/.hed file pairs. These are data files design for input of large data sets into a 3rd party data processing application such as DaDISP •.kml files, if the BioModule is used in conjunction with a supported Bluetooth GPS device

MEASURED PARAMETERS	
Heart Rate	25 to 240 BPM (±1 BPM)
Respiration	3 to 70 BPM (±1 BPM)
Activity	(±) 16g in each axis (Vertical/Lateral/Sagittal)
Skin Temperature	30° to 40° C ± 2°
Posture	± 180°
GPS Accuracy	(via RAELink3) Within 5 meters
APPLICATIONS	
Better individual activity classification, combining physical and physiological parameters [23]	
Improved measures of metabolic rate [24]	
REFERENCES	

- S. Casaccia, F. Pietroni, A. Calvaresi, G. M. Revel, and L. Scalise, "Smart monitoring of user's health at home: Performance evaluation and signal processing of a wearable sensor for the measurement of Heart Rate and Breathing Rate," *BIOSIGNALS 2016 - 9th Int. Conf. Bio-Inspired Syst. Signal Process. Proceedings; Part 9th Int. Jt. Conf. Biomed. Eng. Syst. Technol. BIOSTEC 2016*, vol. 4, no. Biostec, pp. 175–182, 2016, doi: 10.5220/0005694901750182.
- F. Pietroni, S. Casaccia, G. M. Revel, and L. Scalise, "Methodologies for continuous activity classification of user through wearable devices: Feasibility and preliminary investigation," *SAS 2016 - Sensors Appl. Symp. Proc.*, pp. 326–331, 2016, doi: 10.1109/SAS.2016.7479867.
- A. Calvaresi, M. Arnesano, F. Pietroni, and G. M. Revel, "Measuring metabolic rate to improve comfort management in buildings," *Environ. Eng. Manag. J.*, vol. 17, no. 10, pp. 2287–2296, 2018, doi: 10.30638/eemj.2018.227.
- BioHarness 3.0 User Manual. [25]
- BioHarness BT User Guide.[26]

Table 7 - BH3 characteristics

This device can be used, for example, to classify individual activities carried out by a specific person, characterizing each of them through the measurement of physical and physiological parameters. This type of study can be very useful as it allows to have a more precise estimate of the metabolic rate during different activities and, therefore, it also allows a greater precision in estimating thermal comfort. [23]

The study by Calvaresi et al. [24] uses BioHarness to measure the metabolic rate, which will then be used in the Fanger's comfort model to calculate the PMV.

The methodology introduced in this experiment provides a continuous multi-parametric measurement providing a real time estimate of the metabolic rate. During this test, the subjects involved (5 females and 5 males, age: 21 ±1 year, weight 61 ±13 kg, height 1.71 ± 0.09 m, BMI 20.95 ± 2.72 Kg/m^2) were asked to perform 4 different types of activity:

- sedentary activity;
- walking slowly;
- going down the stairs;
- climbing stairs.

Analyzing the data obtained, it emerged that in order to have an accurate metabolism value, it is necessary to measure physiological parameters such as the heartbeat. This new proposed methodology adapts very well to wearable sensors (chest straps such as BioHarness or smartwatches) allowing a real-time measurement of the metabolic rate with an uncertainty of ± 0.2 met.
This new method of calculating the metabolism has been integrated into a virtual environment consisting of a building simulation model with technical systems allowing the control of the air temperature inside the room through a PMV-based approach.
The virtual PMV sensor has been tested in two different ways: through standard sensors and through the real-time measurement of the metabolism. This way, it was possible to evaluate the impact of PMV uncertainty on building management as a function of the error committed in calculating the metabolic rate.
A typical 8 working hours day was simulated, considering the activities that are normally carried out during these working hours.

From the results, it can then be observed that, in winter conditions and considering a constant value of the metabolism rate, the indoor air temperature is kept almost constant. On the other hand, considering the variation of the metabolic rate we can note that there is a variation of the set point temperature. In particular, temperature decreases with the increase in the metabolic rate.

These results lead to the conclusion that it is very important to monitor the activity of the occupants themselves in order to optimize comfort management. In fact, there is a great discrepancy between the energy consumption simulated with the new methodology and the traditional one (in this specific case there is a 33% difference).

2.2 Fitbit Charge HR

Fitbit Charge HR (figure 5) is a smart watch that is able to continuously monitor heart rate as well as steps, distance, calories, climb plans and sleep.
It is one of the most affordable and easy to wear sensor. It allows continuous and non-invasive monitoring of physiological parameters, which can be integrated into everyday life while maintaining good data acquisition accuracy.
Even the reading of acquired and processed data is easy and extremely user friendly.

Figure 5 - Fitbit Charge HR 4 [18]

Its characteristics are reported in the following table.

FITBIT CHARGE HR	
Hardware Characteristics	
Description	Fitbit Charge HR Bracelet Heart Rate Monitor and Physical Activity
Bracelet Dimension	Small: 14 – 17cm Large: 16-19,3 cm Extra-large: 19,3-23,1 cm
Weight	30g
OPERATING CONDITIONS	
Temperature	-20° to 45° C
Humidity	-
Battery	Rechargeable lithium polymer
Battery capacity	5 days
Charging time	1-2 hours
Wireless	Bluetooth 4.0
Software	Fitbit app (mobile and Pc) or fitbit.com
DATA MANAGEMENT	
Run time	7 days
Data storage	Charge HR stores minute-by-minute detailed data from the past seven days and summaries of daily activities for up to 30 days. The related heart rate data are stored at 1 second intervals in the mode workout and at 5-second intervals at other times. The recorded data include steps, distance traveled, calories burned floors climbed, minutes active, heartbeat and sleep quality.
Data transfer	Charge HR syncs automatically and wirelessly with computer about every 20 minutes only if they come fulfilled the following requirements: • Charge HR is located within 4-6 meters of the computer and logged new data to upload (if you haven't moved, nothing happens automatic synchronization). • The computer is turned on, active and connected to the Internet.
Data transfer	• The wireless sync dongle is inserted into a USB port and has been recognized by the computer. To manually sync Charge HR with the panel, click the Fitbit Connect icon on the computer, then on Sync now.

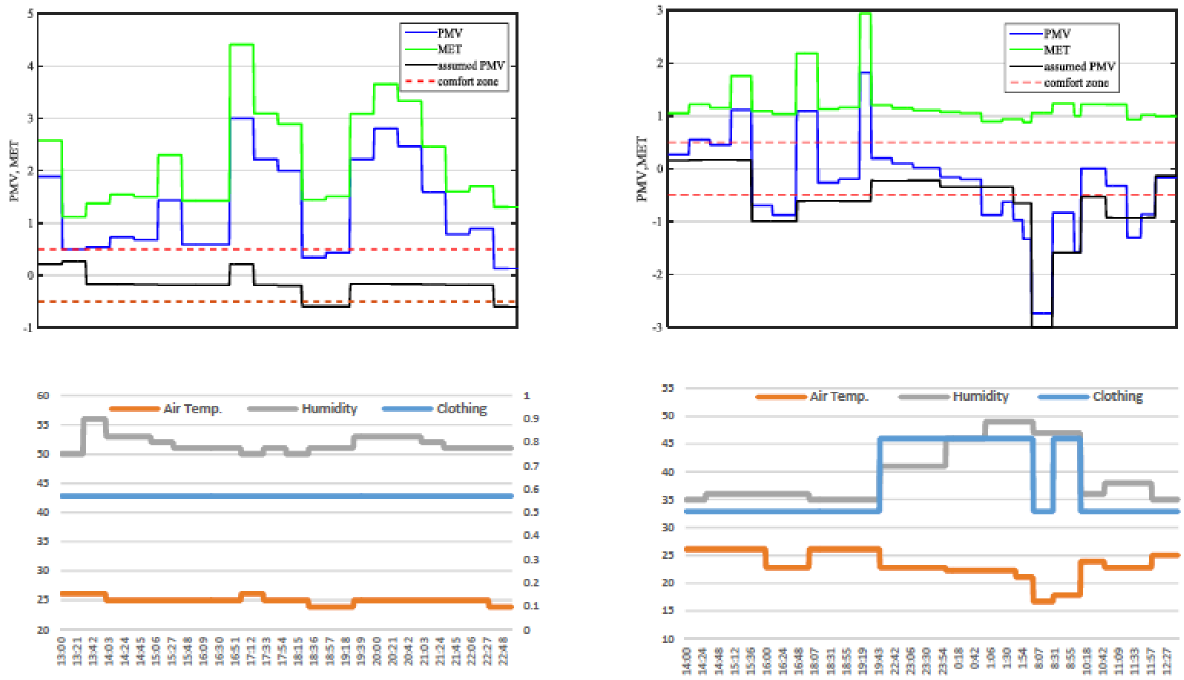
MEASURED PARAMETERS	
Heart Rate	Heart rate is stored at 1 second intervals in the mode workout and at 5-second intervals at other times
Steps taken	Steps
Distance covered	Meters
Calories burned	Calories
Floors climbed	Floors (3 meters)
Active minutes	Minutes
APPLICATIONS	
Evaluation of the metabolism to be included in the PMV calculation [8]	
REFERENCES	
• M. H. Hasan, F. Alsaleem, and M. Rafaie, "Sensitivity study for the PMV thermal comfort model and the use of wearable devices biometric data for metabolic rate estimation," *Build. Environ.*, vol. 110, pp. 173–183, 2016, doi: 10.1016/j.buildenv.2016.10.007. • R. Bdnf and E. Kit, "Product Manual," vol. 40, no. 15, pp. 1–5, 2000, doi: 10.1002/jms.314.[27]	

Table 8 – Fitbit Charge HR

Hasan *et al.* carried out an experimental study [8] to assess the average value of the metabolic rate of the occupants of a building, in order to study the sensitivity of the predicted mean vote model PMV.

The authors conducted a simple experiment on a 22-year-old and 35-year-old male graduate students for more than half a day who were asked to wear the Fitbit Charge HR (to monitor heart rate, activity level, rate of caloric consumption per minute) associated with a HOBO MA 1101 wireless data recorder, which registered the internal environmental conditions (temperature and humidity), and an application on which the occupants of the building had to record the type of clothing they worn during the experimental measurements. They were asked to do normal life activities while working at office or at home.

These data were used to calculate the PMV values for each student for each minute and then the average values for 30 minutes were calculated.



(a) 22-year-old male student (b) 35-year-old male student

Figure 6 - MET and PMV values, clothing, and indoor environmental conditions recorded for two students [8]

Figure 6 (a) and (b) show the graphs for the MET values measured using the Fitbit device together with the corresponding PMV value and the presumed PMV value (i.e., using a rate metabolic constant of 1.0 MET).

These graphs show that the MET value continues to change throughout the day. For example, for the younger student, the metabolic rate was consistently above 1.0 MET throughout the day, the lowest was 1.09.

The figure also shows a very large increase in the MET value, and consequently in the PMV index, during the student's home study hours between (15: 00-17: 00) and (19: 00-21: 00), while it decreases during the student's relaxing hours between (17:00 and 19:00). During most of the study period, the student was thermally dissatisfied, feeling warm, with an average PMV value of 2.5, while it is assumed that he should be comfortable with a PMV value of less than -0.2 (assuming a constant MET value of 1.0).

Even if the student does not perform physical work, the figure show that mental work and just standing and walking seem to increase the MET value to an average higher than 3.0.

The high sensitivity of the PMV model to metabolism, should explain the very large error between the presumed calculation and effective of the PMV.

Therefore, metabolism must be carefully and constantly measured to ensure reliability of the PMV comfort model. The metabolic rate is continuously changing over time, even without performing any remarkable physical activities. For example, this document shows that simple mental work might lead to some increase in the MET value, which can lead to thermal discomfort.

An accurate measure of metabolism of an occupant can extend the area of application of the PMV model to those who may be involved in physical activities, such as waiters and waitresses in a restaurant, or people working out in the gym, underlining also the importance of using wearable devices for this purpose.

2.3 iButtons

The iButton temperature/humidity logger (DS1923) is a rugged, self-sufficient system that measures temperature and/or humidity and records the result in a protected memory section.

Figure 7 - iButton (DS1923) [28]

In the table below are reported its characteristics:

IBUTTONS	
Hardware Characteristics	
Description	The iButton. temperature/humidity logger (DS1923) is a rugged, self-sufficient system that measures temperature and/or humidity and records the result in a protected memory section. [29]
Dimension	17,35mm x 5,89mm
Weight	5 g
OPERATING CONDITIONS	
Temperature	-20° to 85° C
Humidity	0% to 100% relative humidity
Battery	3V to 5,25 V Lithium battery
Battery capacity	Depending on use
Charging time	-
Software	Software for setup and data retrieval through the 1-Wire interface is available for free download from the iButton website. This software also includes drivers for the serial and USB port of a PC and routines to access the general-purpose memory for storing application-specific or equipment-specific data file.
DATA MANAGEMENT	
Run time	Depending on use
Data storage	512 Bytes. A total of 8192 8-bit readings or 4096 16-bit readings taken at equidistant intervals ranging from 1s to 273hrs can be stored. In addition, there are 512 bytes of SRAM for storing application-specific information and 64 bytes for calibration data.
Data transfer	The DS1923 is configured and communicates with a host-computing device through the serial 1-Wire® protocol, which requires only a single data lead and a ground return
Data format and analysis	-

MEASURED PARAMETERS	
Temperature	Temperature Accuracy Better Than ±0.5°C from -10°C to +65°C with Software Correction. Measures Temperature with 8-Bit (0.5°C) or 11-Bit (0.0625°C) resolution.
Humidity	Digital Hygrometer Measures Humidity with 8-Bit (0.6%RH) or 12-Bit (0.04%RH) resolution.

APPLICATIONS
Calculation of skin temperature[30]
REFERENCES
• S. Liu, S. Schiavon, H. P. Das, M. Jin, and C. J. Spanos, “Personal thermal comfort models with wearable sensors,” *Build. Environ.*, vol. 162, no. March, p. 106281, 2019, doi: 10.1016/j.buildenv.2019.106281. • G. Description, “iButton Hygrochron Temperature / Humidity Logger with 8KB Datalog Memory DS1923 iButton Hygrochron Temperature / Humidity Logger with 8KB Datalog Memory Absolute Maximum Ratings,” pp. 1–56. [29]

Table 9 – iButton DS1923

These small sensors were used together with the Polar H7 chest strap in an experiment for the development of personal thermal comfort models using wearable sensors. The accurate description of the study will be presented in the following paragraph.

2.4 Polar H7

Polar H7 is a chest strap equipped with a sensor for heart rate monitoring.

Figure 8 - Polar H7 [31]

Its characteristics are listed in the following table:

POLAR H7	
Hardware Characteristics	
Description	Heart rate sensor (electrodes and transmitter) mounted on a chest strap
Dimension	Sensor 2x1x3 cm
Weight	200 gr
OPERATING CONDITIONS	
Temperature	-10° to 50° C
Humidity	-
Battery	Lithium battery CR 2025
Battery capacity	200 hours

DATA MANAGEMENT	
Run time	200 hours
Data storage	Instant transmission
Data transfer	Bluetooth sync with the Polar Beat app (smartphone or Pc)
Data format and analysis	-
MEASURED PARAMETERS	
Heart Rate	BPM
APPLICATIONS	
Heart rate monitoring for the study of personal thermal comfort through wearable sensors [30]	
REFERENCES	
• S. Liu, S. Schiavon, H. P. Das, M. Jin, and C. J. Spanos, "Personal thermal comfort models with wearable sensors," *Build. Environ.*, vol. 162, no. March, p. 106281, 2019, doi: 10.1016/j.buildenv.2019.106281. • U. Manual, "Polar H7," p. 17953893, 2014, doi: 10.1016/S0262-4079(15)30383-3 [31]	

Table 10 – Polar H7

Liu et al. [30] developed personal thermal comfort models using wearable devices. Data from four subjects (8 males and 6 females) were analyzed. Each subject was monitored with three sensors (shown in the figure 9):

- iButtons (DS1923) for skin temperature, that was detected at the wrist and ankle level with a sampling frequency of one minute;
- the Polar H7 chest strap for heart rate monitoring (with a frequency of one second);
- a small cell phone in a wrist pocket that acts as an accelerometer to record the activity levels (sampling rate of 5 Hz or higher).

The participants were also asked to participate in an online survey every hour during the day (at least 12 times a day) to capture the dynamics of thermal conditions.
To detect the transition between different thermal environments, the temperature of the air near the body was also monitored by pinning an extra iButton to the trousers with a badge (slightly above the ankle to reduce the influence of the body's thermal plume).

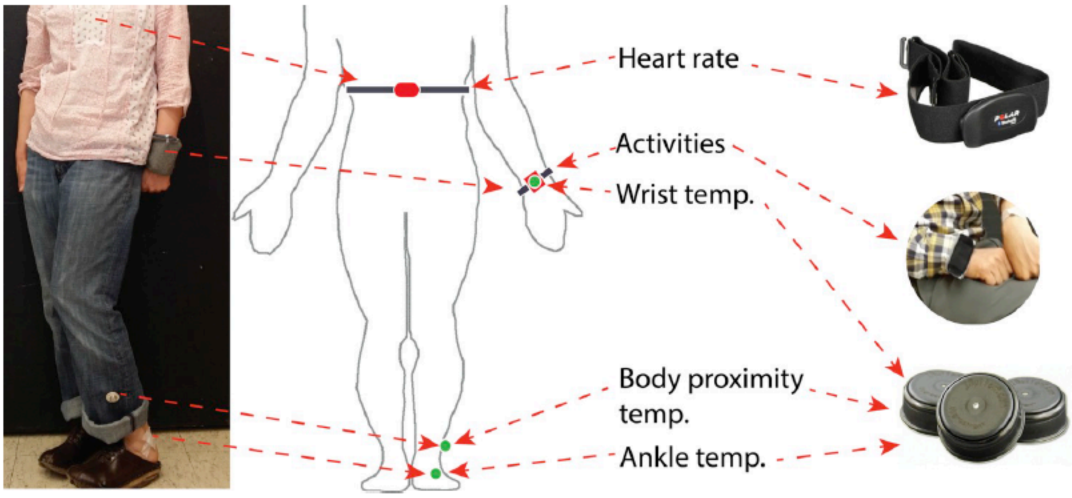


Figure 9 - Physiological sensors and wearing locations [30]

The measurement campaign was conducted for 14 days. Each day, the subjects had to wear the sensors for at least 20 hours to make the survey at least 12 times while the subjects carried out their daily activities.
The analysis also considered the weather conditions, that can influence people's clothing, thermal expectations and also the way buildings are conditioned in (these data were taken from the station https://www.wunderground.com/ close to the position where the participants of the experiment were).

The results obtained are reported below:

- Personal thermal comfort models developed with long term monitoring of physiological and environmental data lead to a median prediction power of 24%/ 78% /79% (Coappa's kappa / accuracy / AUC) which is significantly greater than the conventional PMV and adaptive models.

- The PMV model has the best forecasting accuracy in the thermal and neutral zone and it decays towards the extremes of the thermal sensations scale. The authors have shown that personal thermal comfort models that use wearable sensors do exactly the opposite. They have the highest prediction outside of thermal neutrality. This is very useful in practice because the aim is to prevent people from being too much cool or overheat.

- When the data of all subjects are merged and all features are included, the forecast power is 35% / 76% / 0.80 (baseline). The current smart bracelets with time, heart rate, acceleration data can generate predictive power maximum of 18% / 71% / 0.67. However, the performance of forecast can be increased to 43% / 77% / 0.78 when detection of the skin temperature and meteorological data streaming are present into the bracelets.

- The predictive performance of personal comfort models with wearable sensors could reach 21% / 71% / 0.7 (Cohen's kappa / accuracy / AUC) afterwards about 200 votes.

2.5 Empatica E4 wristband

Empatica E4 bracelets are used for heart rate detection. They consist of a photoplethysmography (PPG) sensor used to monitor the blood volume of the wrist (BVP). BVP can be used to derive cardiovascular characteristics including heart rate (HR) and heart rate variability (HRV). Both HR and HRV have shown promising results for cognitive load and mental stress detection.
E4 provided reliable data even when the subjects are in motion. [32]

Figure 10 – Empatica E4 wristband [21]

Its characteristics are listed in the following table:

EMPATICA E4	
Hardware Characteristics	
Description	Multiple sensors mounted on a wristband to monitor physiological signals
Dimension	44x40x16 mm
Weight	25g
OPERATING CONDITIONS	
Temperature	-
Humidity	0-100% H.R.
Battery	260mAh with 3.7V output
Battery capacity	Streaming mode 20+ h Memory mode 36+ h
Charging time	< 2hours
Wireless	Bluetooth smart
Software	Empatica Manager (Pc), Empatica E4 real-time app
DATA MANAGEMENT	
Memory	Session data is approximately 1MB per recording hour. Device storage capacity exceeds 60 recording hours.
Data storage	60+ h
Data transfer	The E4 wristband connects to a smartphone or desktop computer via Bluetooth, both modes upload the data recorded in Empatica's secure cloud platform – Empatica Connect - which allows users to easily access their data.
Data format and analysis	Download raw data in CSV Format from Empatica cloud platform. It's possible to view graphs of Electrodermal Activity (EDA) also known as Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), Acceleration, Heart Rate (HR), and Temperature
MEASURED PARAMETERS	
Electrodermal activity (EDA)	• Sampling frequency: 4 Hz (Non customizable). • Resolution: 1 digit ~900 pSiemens. • Range: 0.01 µSiemens – 100 µSiemens. • Alternating current (8Hz frequency) with a max peak to peak value of 100 µAmps (at 100 µSiemens). • Electrodes: Placement on the ventral (inner) wrist. Snap-on silver (Ag) plated with metallic core. Electrode longevity: 4–6 months

Blood volume pulse (BVP)	PPG sensor: sampling frequency 64 Hz (Non customizable). Sensor output resolution 0.9 nW / Digit. The heart rate is derived from this measurement.
Temperature	Infrared thermopile: • Sampling frequency: 4 Hz (Non customizable). • Range: -40...85°C for ambient temperature (if available) *, -40...115°C for skin temperature. • Resolution: 0.02°C. • Accuracy ±0.2°C within 36-39°C.
Acceleration	Sampling frequency: 32 Hz (Non customizable). • High sensitivity motion detection across 3 axes: X, Y, and Z. • Default range ±2g. • Ranges of ±4g or ±8g are selectable with custom firmware. • Resolution: 8 bits of the selected range. These measures permit to capture motion-based activity.
APPLICATIONS	
Improved evaluation of thermal comfort of office workers [32]	

REFERENCES
• F. Zhang et al., "The effects of higher temperature setpoints during summer on office workers' cognitive load and thermal comfort," Build. Environ., vol. 123, pp. 176–188, 2017, doi: 10.1016/j.buildenv.2017.06.048. • Empatica, "Empatica E4 User Manual," User Man., pp. 1–32, 2015. [33] • "Get started with your new E4 wristband Follow this simple 10 step guide to quickly get up and." [34]

Table 11 – Empatica E4

This smart bracelet was used together with the Emotiv Insight in an experiment to investigate if office environments with a higher temperature set point can be still comfortable and cognitively efficient. The accurate description of the study will be presented in the following paragraph.

2.6 Emotiv Insight Mobile EEG headsets

This device consists of five sensors positioned on the scalp of the person AF3, AF4, T7, T8, Pz according to the international Jasper 10-20 method and two reference sensors located on the left mastoid process.

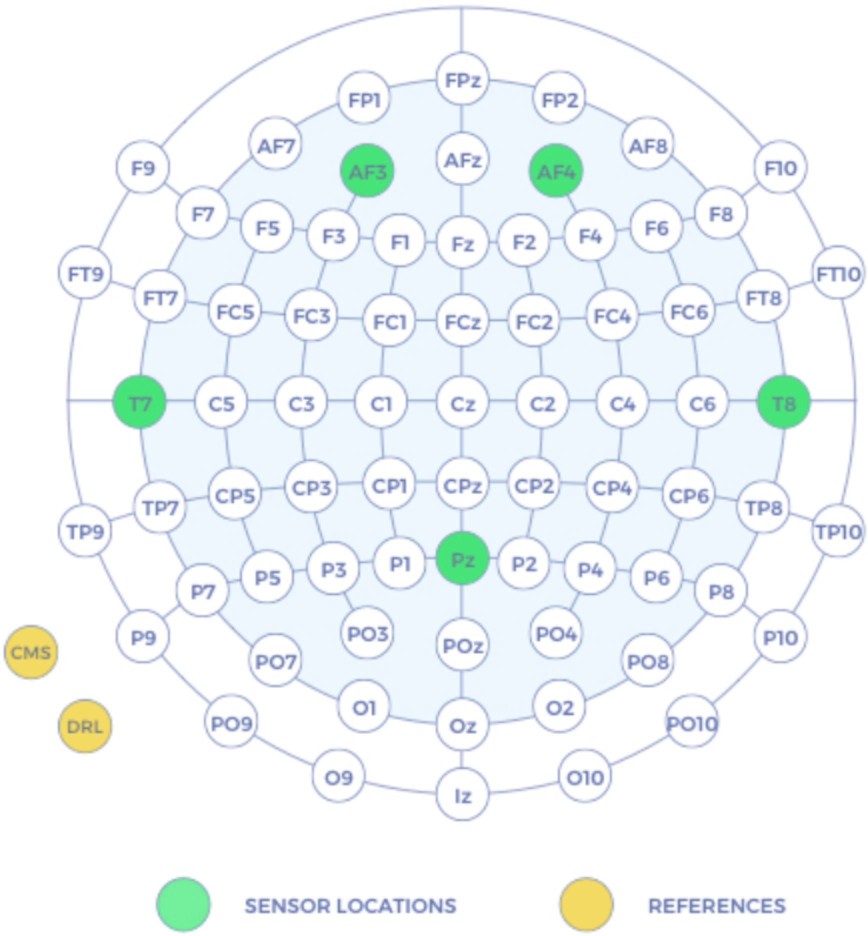


Figure 11- Emotiv insight sensors position [35]

Five-channel brain waves were measured with a minimum voltage resolution of 0.51 mV from the least significant bit and the frequency response from 0-43 Hz.

The sampling frequency of the data was set at 128 samples per second for each channel. [32]

Figure 12 - Emotiv insight [35]

Its characteristics are reported in the table below:

EMOTIV INSIGHT	
Hardware Characteristics	
Description	5-channel mobile EEG system using semi-dry polymer sensors.
Dimension	Adjustable
Weight	About 600 g
OPERATING CONDITIONS	
Temperature	-
Humidity	-
Battery	LiPo battery 480mAh, rechargeable
Battery capacity	Up to 8 hours using USB receiver, up to 4 hours using Bluetooth Low Energy
Charging time	2 hours
Wireless	**Wireless:** Bluetooth Low Energy **Includes proprietary USB receiver:** 2.4GHz band
Software	Myemotiv (Google play and App store), BrainViz, EmotivPro, EmotivBCI
DATA MANAGEMENT	
Data storage	**-**
Data transfer	**Wireless:** Bluetooth Low Energy **Includes proprietary USB receiver:** 2.4GHz band
MEASURED PARAMETERS	
EEG Signals	**Sampling rate:** 128 samples per second per channel **Resolution:** 14 bits with 1 LSB = 0.51µV **Frequency response:** 0.5-43Hz, digital notch filters at 50Hz and 60Hz
Motion sensors	**Accelerometer:** 3-axis +/-8g **Gyroscope:** 3-axis +/-2000 dps **Magnetometer:** 3-axis +/- 12 gauss **Sampling rate:** 64 Hz **Resolution:** 14 bits

APPLICATIONS
Control of brain activity during the variation of the temperature setpoints in a office during summer [32]
REFERENCES
• F. Zhang et al., "The effects of higher temperature setpoints during summer on office workers' cognitive load and thermal comfort," Build. Environ., vol. 123, pp. 176–188, 2017, doi: 10.1016/j.buildenv.2017.06.048.   • "INSIGHT Manual." [36]   • Emotiv Insight official web page [35]

Table 12 – Emotiv Insight

Empatica E4 and Emotiv insight headsets were used in the study of Zhang et al. [32] to investigate whether office environments with high temperature setpoints can be comfortable and allow occupants a cognitively efficient work environment. Three different methods for assessing cognitive load were used: cognitive performance test scores, NASA-TLX measurement, EEG and HR.

The experiment was conducted in an IEQ Lab climate chamber of the University of Sydney. 26 participants (12 males and 14 females) were employed, all of them (in groups of three or four) participated in a 3-hour experiment consisting of two acclimatization periods, two sessions and a break. Session one lasted one hour. During the acclimatization period (30 minutes) and session 1 (control condition), the room temperature setpoint was 22 °C. In the second session, however, the acclimation period was 20 minutes followed by the experiment period (one hour) and the temperature setpoint was set at 25 °C.

The participants' brain activities were monitored both through the control condition and the temperature reduction condition.

The following cognitive performance tests were performed: memory test, concentration test, reasoning test, planning test, the Paced Auditory Serial Addition test (PASAT). Then NASA-TLX was performed, it is a workload assessment technique (based on six subscales: mental demand, physical demand, temporal demand, performance, effort and whipping level).

Brain activity levels and heart rate were then monitored.

Brain activity was controlled with EEG Emotiv Insight Mobile headsets that measure brain waves in five channels with a minimum resolution of 0.5 μV from the least significant bit and the frequency response of 0-43 Hz. The data sampling rate was set at 128 samples per second from each channel.

Heart rate (HR) and heart rate variability are derived from the heart beat detected by Empatica E4.

The HR and EEG data were recorded on 19 subjects, however for the actual analysis only the data of 12 subjects were analyzed (those that had the minimum value of incorrect values and therefore a more reliable dataset).

To analyze the physiological response of the participants Zhang et al. used machine learning based analysis using MATLAB.

Air temperature and humidity were measured every 5 minutes; the air temperature was measured at 0.6 m high in the occupied area using thermistors, the wall humidity sensors at 1.7 m high monitored the atmospheric humidity in the chamber.

As regards to thermal comfort, two different approaches were used to determine the level of acceptability of the thermal environment the subjects were exposed to at the time of the survey.

The first approach was the questionnaire on thermal acceptability, in which the participants were asked to report how they found the thermal environment. The replies indicated that during the control condition, approximately 88% of the subjects considered the environment acceptable. Similarly, the condition of temperature reduction (25°C) was considered acceptable and unacceptable respectively by 81% and 19% of the subjects.

The second approach was based on percentage of people voting for the three central categories of the scale of thermal sensations (i.e. slightly cool, neutral or slightly warm). Therefore, the subjects who voted cold (−3), cool (−2), warm (+2) and hot (+3) were considered unsatisfied from the point of view of thermal comfort.

During the control condition, 88.5% of subjects voted for the three central categories, so the environment was considered satisfying. Another 11.5% of the subjects voted for (−3, −2) and no subjects voted for (+2, +3). They were deemed unsatisfied with the thermal conditions at the temperature of 22 °C.

The results of the CBS performance tests were consistent with the NASA-TLX result: participants' cognitive performance test scores did not differ significantly between the control condition and the varied temperature condition. The measurement of EEG and HR helped confirm that cognitive performances were not influenced by temperature. These physiological responses were analyzed with a machine learning-based method using MATLAB. This process involves four steps: preprocessing, feature extraction, feature generation, clustering.

2.7 Sensors network

Up to now, the characteristics of the individual sensors and their applications have been analyzed. Wireless network technology has allowed the development of systems consisting of sensor networks capable of measuring both physiological, physical and environmental parameters. Regarding the physiological parameters, a technology now widely developed and studied, especially in the medical field, is the Body Area Network (BAN). As for the study of environmental parameters, an example is the Comfort Eye, which finds numerous applications.

The following paragraphs will analyze both the BAN, with its characteristics and applications, and the Comfort Eye.

2.7.1 Body Area Network (BAN)

The BAN was born in the medical field with the aim of carrying out a continuous observation of the patient's state of health to detect a critical condition, thus generating an alarm [37]. To obtain this result, sensors are placed on, in and/or around the human body. The table below, taken from [37], shows the biosensors that are used and their functions.

Biosensors	Functions	Data rate	Power consumption
Temperature	Capture the temperature/provide for temperature measurement	Very low	Low
Blood glucose	Continuously monitor blood sugar levels within the body	High	Very low
ECG: electrocardiogram	Measures electrical potentials produced by the heart	High	Low
EMG: electromyography	Monitoring muscle activity	High	Low
Blood pressure	Measure a minimum pressure of diastolic and maximum pressure of systolic	Low	High
Accelerometer	Measures a proper acceleration on all spatial axis in 3D space	High	High
Visual	Processing and fusing images of scene from a variety of viewpoint into some from more useful than the individual images	Very high	High
CO_2 gas	To monitor the changes in CO_2 levels occurring in respiration of organisms	Very low	Low
Gyroscope	Measures the orientation, based on angular momentum principles	High	High
EEG: electroencephalography	Monitoring brain electrical activity	High	Low
SpO2	Measures the pulsed oxygen saturation	High	Low

Table 13 – Biosensor with their functions

These sensors can be positioned on the human body in different ways, the following figure exemplifies one of the possible ways:

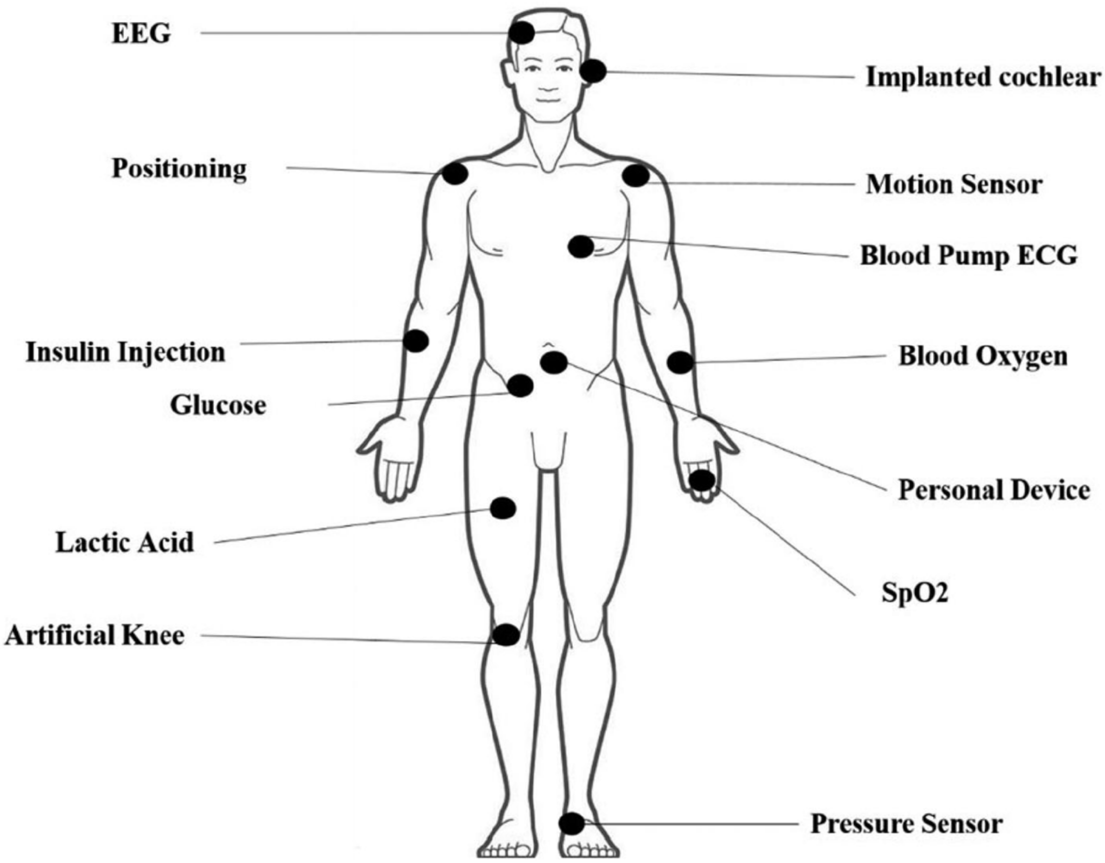


Figure 13 - Example of patient monitoring in wireless body area network [37]

The data collected by the sensors are sent wirelessly. There are three levels of communication: an intra-body, an inter-body and an extra-body which is responsible for the data bundle between personal devices and the internet, i.e. sending the data to the doctor so that he can make a diagnosis.
Monitoring systems have been developed to integrate body sensors with an environmental sensor, in order to evaluate environmental, physiological and behavioral data of the occupants of a given environment. There are also other applications of the BAN [38], for example in the military field to evaluate the

physical performance of soldiers, or in the sports field to evaluate training programs.
An application proposed by Chika S. [39] provides the use of an intelligent system based on wearable wireless sensors, that detect the state of well-being and send these data to a control system of environmental parameters (temperature and humidity).

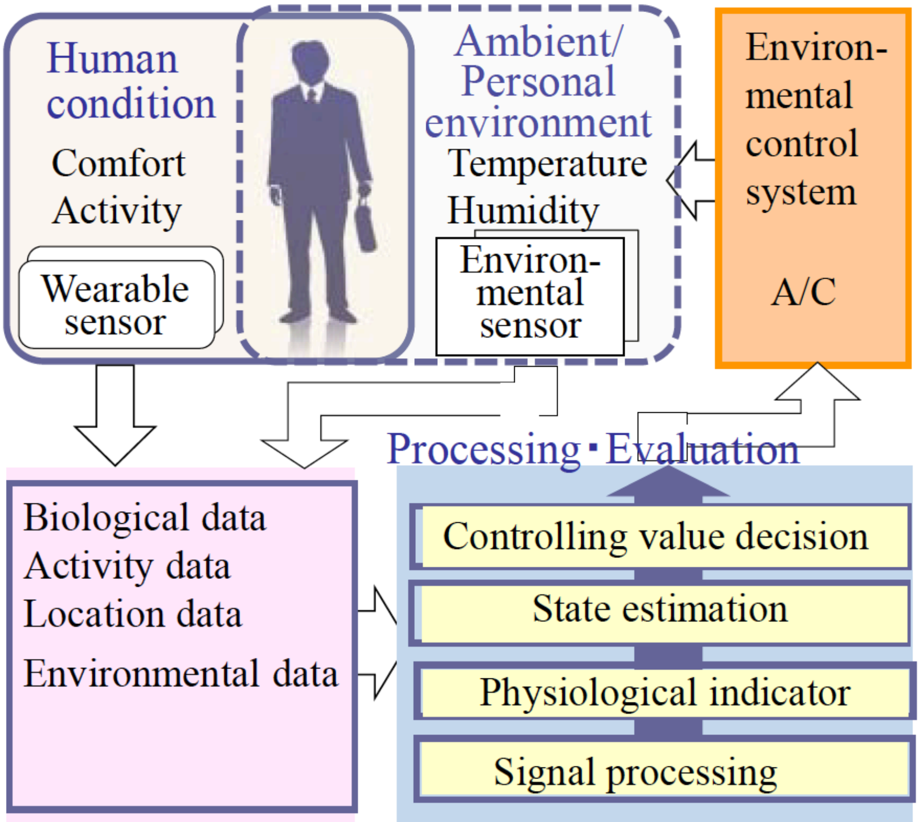


Figure 14 - Conceptual diagram of a smart system [39]

The system consists of a temperature sensor positioned on the ear, skin temperature sensors, an ECG sensor with triaxial accelerometer and thermo-hygrometers as shown in the figure below:

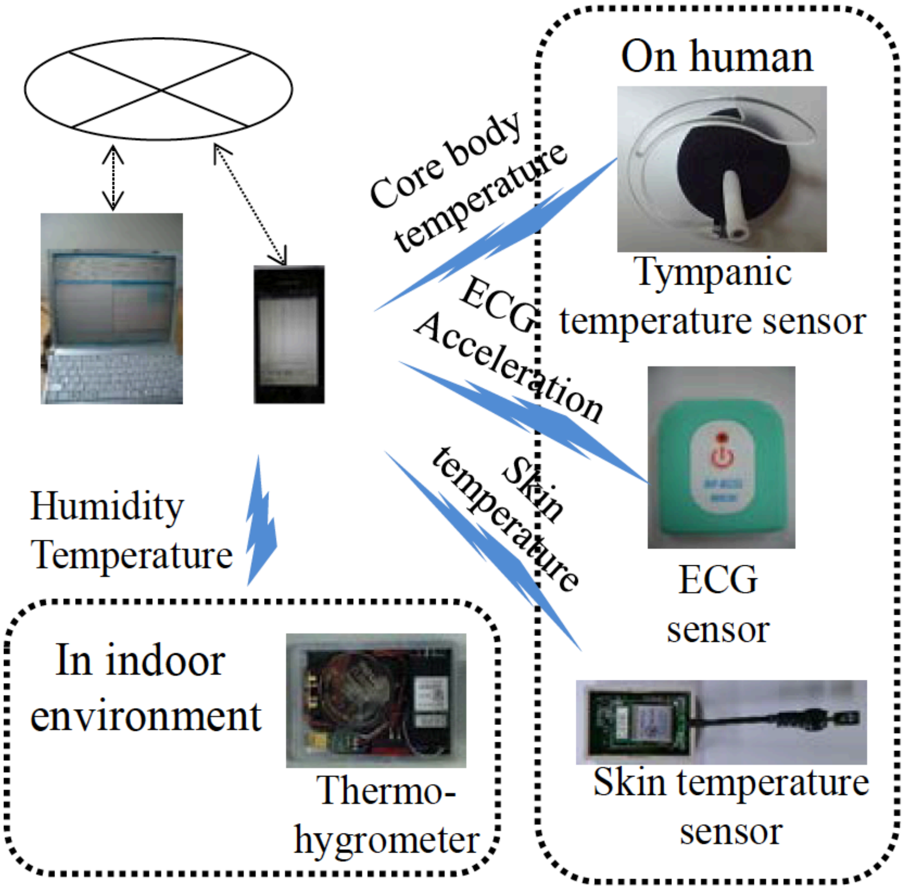


Figure 15 - BAN configuration [39]

The data is transmitted to the coordinator (smartphone or laptop). The sensor micro-controller integrates a 32-bit and 2.4 GHz microprocessor, IEEE 802.15.4 compliant, a transceiver that has A/D conversion, data processing and transmission functions. The sampling frequency of the ECG sensor is 204Hz and that of the other sensors is 1Hz.

The comfort level is assessed by fluctuating peripheral body temperature and sweating. The accelerometer is used to recognize the subject's level of physical activity and correctly estimate the thermal sensation. The estimation of the state of well-being is based on Markov's hidden hierarchical model and allows to intervene on the environmental air conditioning according to the individual's comfort level, creating a smart environment.

2.7.2 Comfort eye

Comfort Eye is a low-cost system for real-time monitoring of comfort conditions in indoor environments. The system is based on an IR (infrared) sensor installed on the ceiling of the room that analyzes the temperature of all the surfaces of the room and calculates the average radiant temperature for each point in the room. It also measures temperature, relative humidity and air speed. The combination of this data allows the calculation of the PMV index for multiple positions in the room. [40]

The information provided by the system can be sent directly to the control system just like the temperature sensor does with a thermostat or with an HVAC control system. The system outputs real-time PMV maps which are suitable for providing modular control feedback that cannot be obtained with standard thermostats. [41]

Figure 16 - Comfort eye [41]

Its characteristics are reported below:

COMFORT EYE	
Hardware Characteristics	
Description	It's a low-cost system for real time monitoring of comfort conditions, it is able to provide continuous monitoring of PMV and average radiant temperature for multiple positions in the environment.
Dimension	-
Weight	-
OPERATING CONDITIONS	
Temperature	-
Humidity	-
Battery	-
Wireless	Wireless Wi-Fi
Software	-
DATA MANAGEMENT	
Run time	-
Data transfer	Real-time data transmission via Wi-Fi.
Data format and analysis	The system sends the results to a local gateway based on raspberry board. Data are sent to a server and processed for being consumed by web clients
MEASURED PARAMETERS	
Mean Radiant Temperature	±0.5°C
Wall Temperature	±0.9°C
Air Temperature	±0.2°C
Relative Humidity	±5 %
Air velocity	± 0.1 m/s (range 0-1 m/s)
PMV	±0.1
APPLICATIONS	
Improved PMV assessment for the evaluation of thermal comfort	

REFERENCES
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Table 14 – Comfort eye

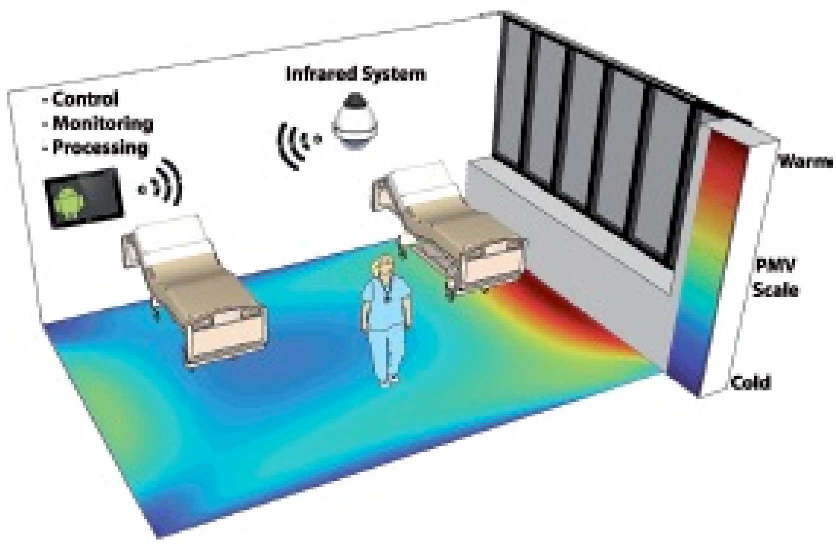


Figure 17 - Concept of the solution for the monitoring of the PMV in multiple positions in the space [41]

An application of comfort has been described by Arnesano et al. [40] in the creation of a system consisting of:

- a real-time, multi-point meter of thermal comfort (Comfort Eye);
- an advanced controller;
- a customized or sub-zone heating/cooling system.

The union of these three components in an integrated system brings closer the possibility of maintaining the comfort of a building with minimum energy consumption. In the experiment described, conducted in an office of the Polytechnic University of Marche, it was shown that this control system is able to achieve an energy saving of 17.1% compared to a traditional control system.

Another study conducted by G.M. Revel, M. Arnesano, F. Pietroni [41] paired the measurements made with comfort eye with the metabolic estimation of occupants, in order to better assess internal comfort. "The metabolic rate M is defined as the amount of daily energy that a person consumes while at rest in an environment that is temperate and neutral, and while in a post-absorptive state." M is one of the most important parameters for estimating thermal comfort, and can be recorded by measuring heart rate during different states of activity in a climatically neutral environment. The instrument used to measure heart rate was a low-cost sensor that consists of a small printed circuit board of 16 mm in diameter, an ambient light sensor as a receiver and a super bright green LED with reverse mounting as an emitter.

The use of these sensors for heart rate measurement integrated with the Comfort Eye has allowed effective concomitant monitoring of the metabolism allowing a better assessment of the PMV index and consequently of the thermal comfort.

Another application of the comfort eye can be found in the ENERGIS project [42] which aims at optimizing the use of energy resources by reducing general costs and emissions, while simultaneously maintaining comfortable living conditions in individual buildings and districts.

Monitoring is used to locally detect energy demand, while optimization is performed on two levels. The first optimization tries to consider different aspects related to the thermal management of the environments supported by the Comfort Eye sensor, capable of controlling the thermal actuators to set a comfort setpoint. The second level of optimization starts from the data of each building to set up a district model capable of mapping and predicting energy needs, allowing energy management based on the concept of sharing.

In particular, the monitoring system provided in the first optimization level is able to measure the following variables:

- electric metering on monophase and triphase (V, I, P, Pact, Preact) connected on RS485 bus;
- water metering;
- thermal metering;
- natural gas metering;
- comfort (thermal);
- indoor air quality.

The use of the Comfort Eye allows the monitoring of the internal thermal conditions allowing to identify the optimal set point that combines thermal comfort with minimum energy consumption.

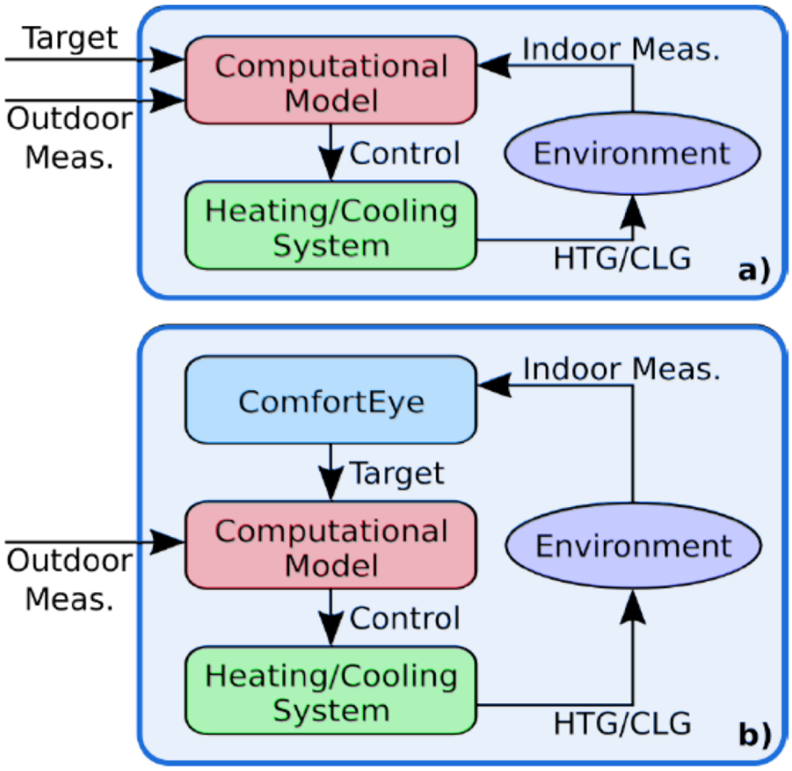


Figure 18 - EnergyPlus simulations diagram: a) standard scenario, b) scenario with Comfort Eye decision. [42]

Comfort Eye data can also be viewed using a panoramic viewer that allows viewing of the RGB panorama developed with a classic camera co-registered with thermal data (see figure 19). This mode can provide very useful information on the performance of the building envelope and on the presence of heat loads in the room.

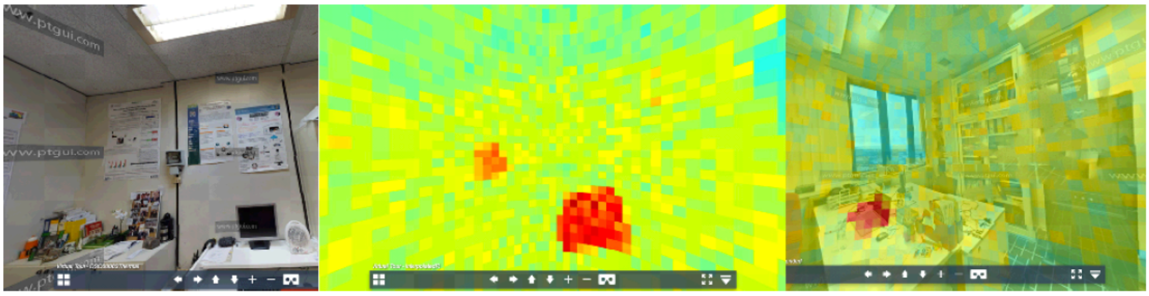


Figure 19 - Visualization of RGB and thermal data by using a panorama viewer. a) Left: RGB panorama. b) Center: Thermal panorama. c) Blended RGB and thermal panorama. [42]

2.8 Considerations

The following table summarizes all the sensors analyzed and compares the parameters they measure:

MEASURED PARAMETERS	SENSORS							
	BIOHARNESS 3.0	FITBIT CHARGE HR	I-BUTTONS	BAN NETWORK	POLAR H7	EMPATICA E4	EMOTIV INSIGTH	COMFORT EYE
Heart rate	√	√		√	√			
Blood volume pulse						√		
Respiration	√							
EEG							√	
EDA (Electrodermal activity)						√		
Skin Temp.	√			√				
Calories		√						
Activity level	√	√						
Acceleration				√		√	√	
Posture	√							
PMV								√
GPS	√							
Steps		√						
Distance		√						
Floors		√						
Humidity			√	√				√
Mean Radiant Temp.								√
Wall Temp.								√
Air Temp.			√	√		√		√
Air velocity								√

Table 15 – Summary table

By analyzing the articles cited above it’s possible to understand how important to is the monitor of the physiological parameters as well, their integration with the measurements of the environmental parameters. One of the most important quantity to take into account is the metabolism. Making measurements in real time of the heart rate, it’s possible to have a reliable and more truthful estimate of the metabolic rate with respect to the Fanger’s model.

The sensors that are heavily targeted for their practicality are smart watches and chest straps that have the ability to be worn easily, are easy to handle, allow the acquisition of different physiological parameters and have the advantage of being able to be worn in a real context and not simply in the laboratory where the experimentation is carried out.

On the other hand, these sensors have a good accuracy but certainly not comparable to a more precise and better calibrated laboratory sensors.

There is the need to find a compromise between the accuracy of the sensor and its handling. The development of "smart shoes" equipped with wearable sensors is also assumed. They would allow continuous and real-world study and data collection, for periods much longer than, for example, studies conducted only in a laboratory.

In fact, another critical aspect concerns the sampling time of these physiological parameters, much of which require different time to stabilize and therefore to be considered reliable and significant. In fact, most of the studies carried out experiments of a few hours and only in the laboratory.

Just one of the articles read [21] reports a different kind of approach, in fact the study was carried out in 4 weeks with data acquisition for about 20 hours per day in a "real" environment, monitoring the actual activities made by the participants. A personal comfort model was then created for each participant in order to have the most truthful representation possible. Although this approach is extremely accurate; it requires considerable data acquisition and processing times and is therefore difficult to apply on a large scale.

3 ANALYSIS OF THE RESULTS

Having studied the sensors and their application in the assessment of thermal comfort, it is necessary to make a detailed analysis of the results obtained from these researches in order to understand whether the introduction of these sensors has actually brought a benefit and an improvement.

Two trends were noted in the studies analyzed: the first sees the use of the PMV model and tries to improve the evaluation of the parameters which influence it and consequently tries to achieve a more accurate prediction of thermal comfort. The second trend, instead, sees the introduction of a new model of thermal comfort for a more truthful assessment of the state of comfort.

Instead, the study conducted by Zhang et al. [32] highlighted a different aspect of the comfort condition, analyzing the impact that comfort can have on human activities. The authors assessed whether the offices with high internal temperatures (from 22 °C to 25 °C) represented a cognitively efficient and productive environment. The results obtained showed that the cognitive load of the subjects involved was not influenced by this moderate temperature variation from 22 °C to 25 °C. The questionnaires on thermal comfort and air quality administered to the participants showed that this temperature variation probably did not significantly compromise thermal comfort, although a warmer sensation was reported at the higher temperature. The acceptability of the thermal environment had therefore not changed significantly.

Surely the analysis of the impacts that, for example, the temperature can have on people and their activities, is very important and needs to be studied in depth and combined with the study of comfort to improve the well-being and productivity inside offices, schools, universities.

The two trends that have been mentioned above are now analyzed.

3.1 Optimization of Fanger's model

Most of the studies analyzed are found in this first case, specifically the research that used: BioHarness 3.0 [24], Fitbit Charge Hr [8] and Comfort Eye [41].

- BioHarness: this study by Calvaresi et al. [24], as already highlighted above, proposes a real time evaluation of the metabolic rate, which, has seen before, is one of the physiological parameters that most influences the calculation of the PMV index. This new measurement was integrated into the simulation of a virtual environment consisting of a building with an internal air temperature control system based on the PMV model. This temperature control sensor has been set with two different working modes.
  The first that used the calculation of the PMV according to the standard model, with the use of constant values of the metabolism taken from tables (according to Fanger's theory); the second that instead used this innovative method for real time estimation of the metabolic rate. This simulation allowed the evaluation of the impact of the PMV uncertainty on the management of the building as a function of the error committed on the estimate of the metabolic rate using standard values instead of a continuous measurement.

  The temperature control simulated in the two tests, which depends on the PMV index, was carried out considering a typical working day of 8 hours, simulating the standard activities that are carried out in such situation.

  From the simulations carried out, it was observed that in winter, using a constant metabolism value, the temperature inside the building was kept almost constant; on the contrary, if you observe the result obtained with the dynamic value of the metabolic rate, a variation in the set point temperature is noticed as shown in the figure below:

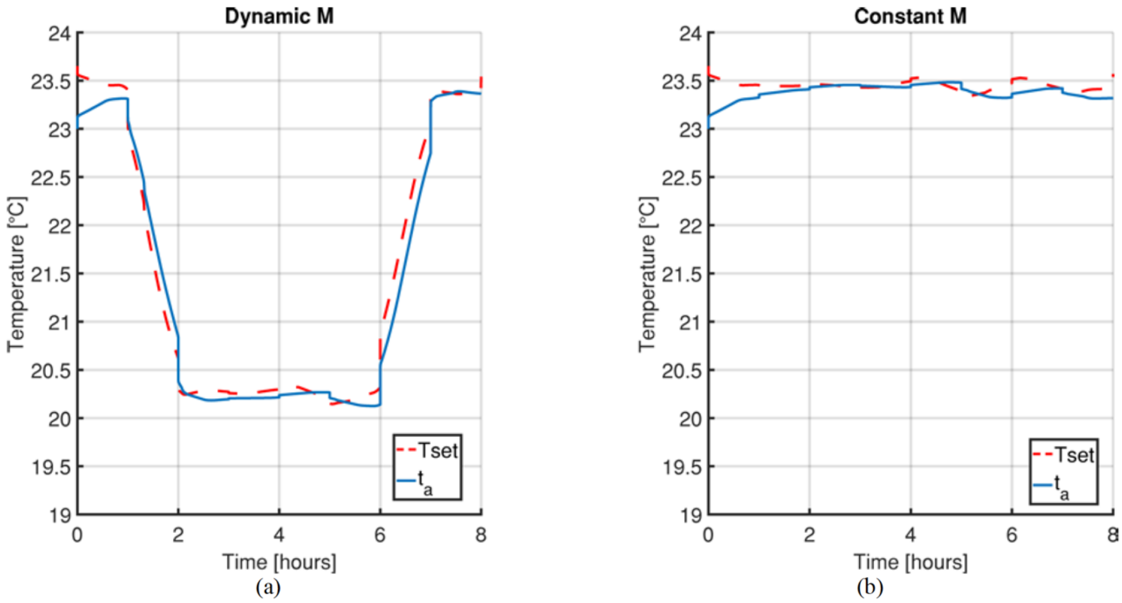


Figure 20 – Trends of the set-point temperatures and air temperature obtained with: (a) dynamic profile of metabolic rate (b) constant value of the metabolic rate

An increase in the metabolic rate corresponds to a lower value of the set point temperature, therefore the set point temperature decreases as the metabolic rate increases. The use of a constant metabolic rate value leads to an error in the calculation of the PMV which induces an error of 3.2 °C in the estimate of the T set. Analyzing the PMV index calculated in the two tests, it can be seen that in the case of dynamic metabolism control, there is an average PMV close to zero, while, in the other case, an environment near the slightly warm sensation is obtained (as shown in figure 21). This happens because the controller is unable to identify the need to reduce the heat (due to the increase in occupant activity), thus leading to a worsening of the comfort conditions.

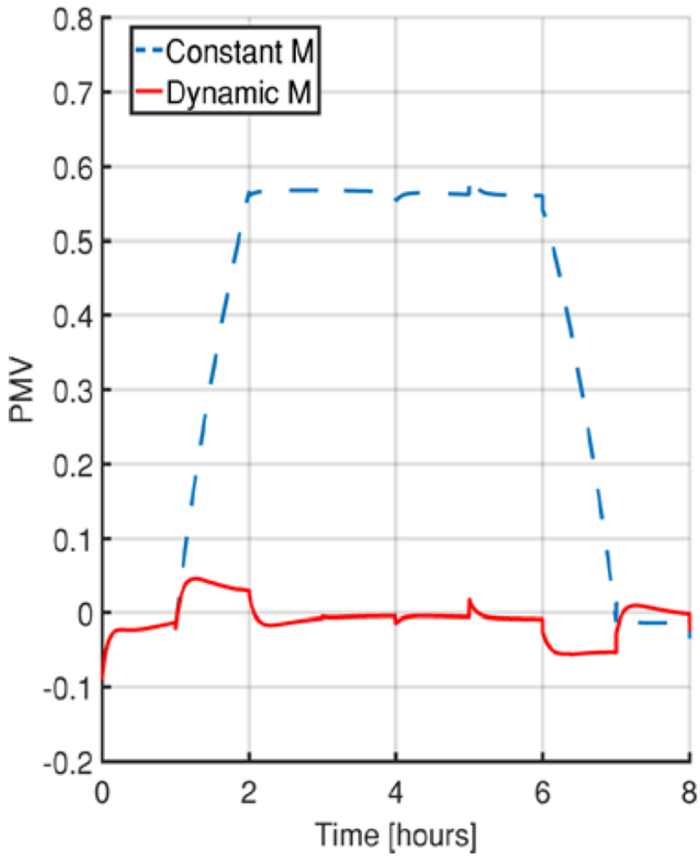
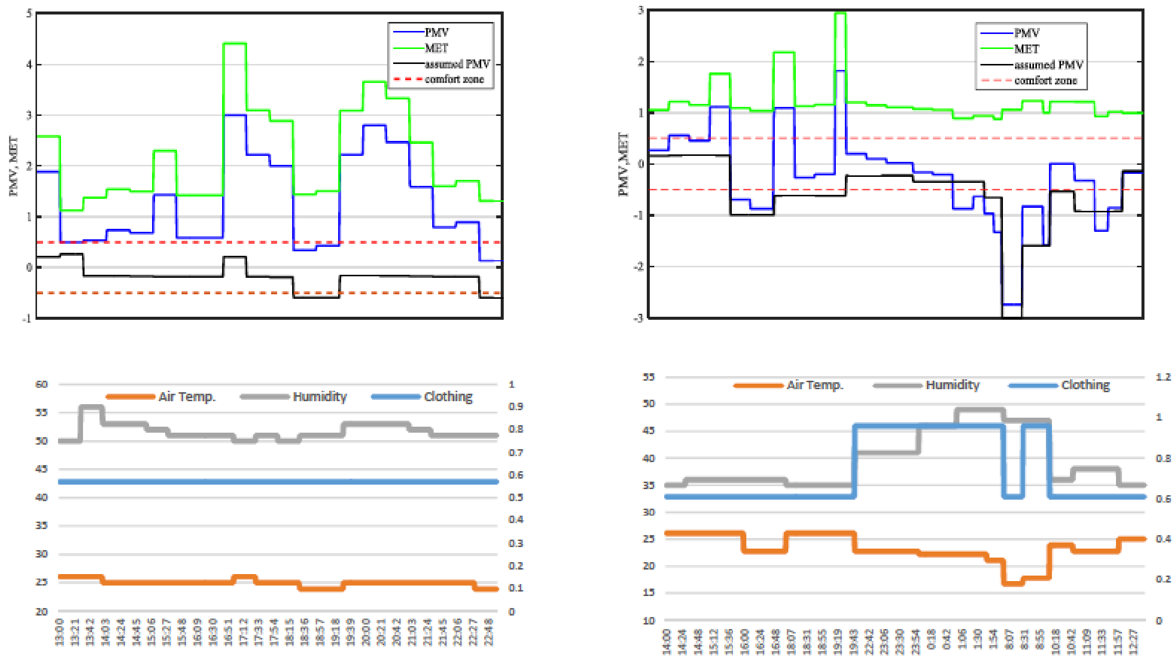


Figure 21 – Trends of PMV in the two simulations

The dynamic simulation also led to an energy consumption of 5.8 kWh compared to 8.6 kWh in the second test.

Given the results obtained from this study, it is highlighted that a real time and a more truthful assessment of the metabolism can reduce the systematic error introduced by the use of constant activity values assigned to the building, leading to an improvement in internal comfort as well as a better energy management of the building itself.

- Fitbit Charge HR: also in this article by Hasan et al. [8] (previously described), the attention is placed on the metabolism assessment and on the effect it has on the calculation of the PMV index. In this study we compare the PMV value calculated using the metabolic rate assessed through the Fitbit Charge HR device and the PMV value obtained considering the constant metabolism value equal to 1.0 MET.



(a) 22-year-old male student

(b) 35-year-old male student

Figure 22 – MET and PMV values, clothing, and indoor environmental conditions recorded for two students [8]

From the results obtained by the authors, it is noted that considering a constant value of the metabolism during the whole experiment is not correct, since the activity and the metabolic rate vary continuously.

The variation of the metabolism leads to the variation of the PMV index, leading to discomfort. For example, the value of the metabolism for one of the occupants was always higher than 1.0 MET for the whole duration of the experiment, even at its lowest value it was however higher than the constant value chosen. Therefore, most of the time the occupant felt thermally unsatisfied, feeling hot, with an average PMV value of 2.5, while instead, according to the calculation made with the constant value of the metabolism, the person would have had to feel right comfortable with a PMV value of approximately -0.2. From here it's possible to understand the sensitivity of the PMV to the metabolic rate and also explain the great difference between the value obtained from the actual calculation and the presumed one.

- Comfort Eye: in the study of Arnesano et al. [41], this sensor, capable of evaluate the internal temperature of a room and the mean radiant temperature in multiple positions in the space, was integrated with a sensor for the continuous monitoring of the heartbeat to evaluate thermal comfort through Fanger's model. The continuous estimate of the metabolic rate obtained by monitoring the heartbeat presented advantages and improvements to the thermal comfort assessment: the system is able to identify the different activities carried out by the occupant by itself, allowing to take into consideration the real perception of the subjects involved (taking into account that the same activity can be carried out differently from person to person, with a different perception of comfort). This measurement of the metabolism shows a deviation of $\pm 7\%$ compared to the values found within the ISO 8996 standard with a resulting ± 0.05 in the PMV computation. Consequently, the proposed methodology is able to bring an improvement in the measure of thermal comfort.

From the results obtained from these studies, it is well understood how the metabolism is actually one of the parameters that most influences the PMV and how its more accurate evaluation can improve the calculation of the PMV index, not only in order to better evaluate the thermal comfort but also in order to intervene on the energy management of a building.

3.2 New models of thermal comfort

This category includes the studies that used: the iButtons and Polar H7 devices [30] and the Body Area Network [39].

- Polar H7 and iButtons: in this study [30] Liu et al. developed a personal thermal comfort model for each participant through machine learning methods. These models use information and data relating to the individual occupant and not average information: in this way it is possible to better understand the needs and preferences of the individual occupants and better satisfy their thermal comfort.
  The authors have shown that these models of personal thermal comfort that they developed have the maximum prediction precision towards the extremes of the scale of thermal sensations, unlike the PMV model which, instead, has maximum precision in the neutral thermal zone.
  These new models therefore exhibit significantly greater median prediction power than conventional PMV.

- BAN: in this research [39] the author used the data acquired by the body area network to estimate individual thermal comfort through a model based on Markov's hidden hierarchical model (HHMM). The comfort level of this model has been sized as the PMV index from -3 (cold) to +3 (hot) as shown in the table below:

Scale of comfort level	Comfort state
0	comfort
+1, -1	a little comfort
+2, -2	a little discomfort
+3, -3	discomfort

Table 16 – Comfort level [39]

> Using this model and the data obtained, a better control of the temperature inside a building is obtained, preventing excessive cooling or overheating, taking into account the personal conditions of each individual occupant. It consequently also allows better energy management than a PMV-based model. This detection system and the model that was derived from it has the potential to be used in many applications, being able to manage both physiological and environmental information.

These new models are actually promising and show an improvement compared to the standard PMV model. They obviously present critical issues that can certainly be overcome in future studies: for example the quantity and quality of the data collected could be improved to obtain more predictive comfort models such as in the case of the study by Liu et al [30] in which, although the 14 subjects had participated in the research for several weeks, the average number of votes was only 275, to prevent their daily activities from being influenced by the measurement campaign. The data set may also be incomplete, there may be missing data due for example to unstable measurements (loss of internet connection or problems with the sensor batteries). Moreover, the algorithm chosen for the creation of personal comfort models could adapt very well to one subject but not to another, therefore the choice of calculation algorithms must also be studied and possibly adapted to the subject.

CONCLUSION

In this work the limitations of Fanger's comfort model were presented, in particular the one concerning the calculation of the metabolic rate. In order to overcome these drawbacks, many researches experimented the use of wearable sensors capable of measuring physiological parameters of the subject involved, such as heart rate, breathing, skin temperature etc.

The characteristics of all the sensors used in the studies under consideration were review, explaining how they were used in each research. The analyzed studies use these sensors both to improve the estimate of the PMV index, above all by making the estimate of the metabolic rate more precise, and for the creation of new personal comfort models based on the collected physiological and environmental data.

The use of these sensors is actually able to improve the prediction of comfort of the Fanger's model and also to develop new alternative personal thermal comfort models.

These wearable sensors represent, given the results obtained, a decisive step forward in the ability to evaluate all those physiological parameters that contribute to determining the state of well-being of the occupants. New research can be carried out using new combinations of sensors, trying to make them as less invasive as possible without losing the accuracy of the measurement.

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