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Off-the-shelf wearable sensing devices for personalized thermal comfort models: A systematic review on their use in scientific research

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ABSTRACT

Human thermal comfort depends on objective variables -related to the environment- and to subjective variables, related to physiological conditions. While the former are relatively easy to be measured, the latter are difficult to be investigated since differ from person to person and they are characterized by sudden variations over time. The recent spread of off-the-shelf wearable devices for monitoring bio-signals has considerably facilitate this challenging task. The aim of this work is to provide a detailed framework about the use of off-the-shelf wearable devices for thermal comfort investigations. A systematic review of 35 scientific papers -selected over 302 results from the initial database query- was performed. The results highlight that wristbands (mainly, Empatica E4 and Fitbit), headbands (i.e., Muse 2), chest bands (mainly, BioHarness 3.0 and Polar H7), miniature data loggers (i.e., iButton), and activity sensors (i.e., Move 3) were the off-the-shelf devices whose use is predominant in thermal comfort investigations. Those devices were adopted for different purposes, namely finding correlations between physiological signals and thermal sensations, training and/or validating thermal comfort models, improving data acquisition, and controlling HVAC systems. The proposed framework could represent a solid background for future investigations which should focus on two main research streams. The first one should aim at strengthening the knowledge about statistical correlations between thermal sensations and physiological signals, as well as defining standardized procedures for the model development and validation. The second research stream should aim at integrating off-the-shelf wearable devices and personalized thermal comfort models into HVAC control systems.

List of abbreviations

ACC	Acceleration
AI	Artificial Intelligence
ANN	Artificial Neural Network
BVP	Blood Volume Pulse
ECG	Electrocardiography
EDA	Electrodermal activity

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EEG	Electroencephalogram
GPS	Global Positioning System
HF	High Frequency of heart rate variability
HR	Heart Rate
HRV	Heart Rate Variability
HVAC	Heating, Ventilation, and Air Conditioning
LED	Light-Emitting Diode
LF	Low Frequency of heart rate variability
MET	Metabolic Equivalent of Task
ML	Machine Learning
PMV	Predicted Mean Vote
PPG	Photoplethysmography
RH	Relative Humidity
RR	Respiration Rate
SRH	Skin Relative Humidity
ST	Skin Temperature

1. Introduction

1.1. Motivations

The historical period we are living in sees a global effort to develop and implement new solutions in the energy field. The reduction of greenhouse gas emissions, the diminution of the use of fossil fuels, and a transition toward cleaner energy sources are key pillars of future development plans of most countries. Energy efficiency of buildings plays a key role in this framework and its goal is to minimize the energy consumption while maintaining high comfort levels for building occupants, to ensure their health, wellbeing, and productivity [1]. Comfort requirements affect considerably the building energy demand, as also envisioned by the latest recast of EU directive 844/2018 [2] which relates the energy efficiency of buildings to their ability to optimize "health, indoor air quality and comfort levels" while guaranteeing their cost optimality [3]. Considering that the principal purpose of a HVAC system is to provide indoor climate conditions that are adequate for the thermal comfort [4], therefore driving the transition from optimal design to operation of highly performing buildings [5], it is evident that the very own thermal comfort is the driver for space heating and cooling energy demands.

Human thermal comfort is a complex "*condition of mind that expresses satisfaction with the thermal environment*" [6]. It is widely recognized that this perception process depends on objective variables -related to the environment- and to subjective variables, related to human physiological conditions. If the objective variables related to the indoor environment, such as air temperature and air velocity, are relatively easy to be measured [7], subjective variables are much more difficult to be investigated. This since the subjective variables differ person to person and are characterized by sudden variations over time. However, latest research has highlighted that studying the variations of these physiological variables could have a great potential in improving occupants' thermal comfort [8]. To monitor physiological signals, specialized sensors and medical equipment can be used. Nevertheless, they are not convenient for longtime monitoring [9] due to, for example, their dimensions and wiring. In the very last few years, the acquisition of physiological signals has considerably improved because of the development and spread of various wearable devices for the measurement and monitoring of bio-signals. According to various definitions present in literature, wearable devices are electronics apparatuses that can be worn or mated with human skin (i.e., by tattooing or implanting) to monitor biometric and environmental variables continuously and closely, without interrupting or limiting the user's motions [10,11]. As shown by Salamone et al. [11], Google Trends highlights a remarkable rise of interest for the keyword "wearable" during the last decade, especially from 2014. An exceptional push for the spread of wearable devices was COVID-19 pandemic that boosted the R&D of wearable devices due to the increasing awareness of personal health monitoring. Evidence of that is the market size of wearable medical devices that, in 2021, achieved 21.3 billion USD at a global level. The interest in these wearable devices does not seem to be fleeting since the global market size of those devices is expected to have a compound growth rate by around 28% between 2022 and 2030 [12]. Consequently, wearable devices are expected to spread even more in the coming feature and they can play an essential role in thermal comfort studies. These devices are currently used in different domains (e.g., physics, sports, and medicine), but they can be used to better characterize the indoor environment from the perspective of the user perception. The acquired physiological signals may be extremely useful for increasing the awareness of comfort of building occupants and optimizing the energy use in buildings. Thus, it appears fundamental to investigate the current state of the art about the use of those devices for thermal comfort investigations with the aim of providing researchers and manufacturers with a detailed and updated framework about this topic. Such framework could represent a solid starting point for future research, especially in wide-scale investigations where off-the-shelf wearable devices could be a valuable solution.

1.2. Definition of aim and scope of the work

The aim of this work is to provide a detailed framework about the use of off-the-shelf wearable sensing devices in thermal comfort studies. To this aim, a systematic and critical review is performed by considering recent scientific studies that have already experimented the use of off-the-shelf wearable sensing devices for the purpose of thermal comfort investigations. Detailed information about obtainable physiological signals, technical features, and limitations are reported and critically compared for different devices. The potentialities of their adoption for advanced thermal comfort experimental studies are highlighted.

The scope of this review is limited to “off-the-shelf” wearable devices only. Thus, only ready-to-use devices available directly on the market are considered in this review, while *ad-hoc* prototypes are excluded. This choice is since off-the-shelf wearable devices are considered the novel approach to thermal comfort investigations for their readiness to use and relatively low cost that allow their massive implementation for large-scale studies in the real world. In fact, they are ready-to-use devices characterized by a high level of standardization that guarantees a high replicability of the application procedures. So, off-the-shelf devices can be used without any additional skills and efforts needed for their design, development, and validation. Moreover, off-the-shelf devices are usually compact and convenient to be worn even 24/7. Including only off-the-shelf devices in the scope of this review may lead to the exclusion of experimental methods for thermal comfort investigations based on prototypes. Nevertheless, this exclusion is not considered a bias because the use of those experimental methods and prototypes cannot be suitable for large-scale studies in real world.

1.3. Differences with previous researches and novel key contributions of this review

This review fills a gap in literature since, according to the Authors’ knowledge, the use of off-the-shelf wearable sensing devices in thermal comfort investigations has ever been the target of a systematic review. By contrast, reviews about personalized comfort models [13] and physiological indices [14] are present in literature. It is worth to be mentioned that previous review works investigated the use of wearable devices for environmental monitoring, but with substantial differences. Dong et al. [15] performed a review focused on smart building sensing systems to explore their applications. The main difference with the present review is the scope of the work that is considerably broader but less detailed and not focused on thermal comfort. Dong et al. [15], in fact, analyzed a wide range of sensors, without a specific focus on off-the-shelf wearable devices for thermal comfort investigations. The review work of Abboushi et al. [16] investigated the use of wearable devices but with a different focus. That work, in fact, was targeted on the acquisition of health performance indicators and on the data accessibility from wearable devices. Moreover, the analysis was limited only to wristbands and chest bands. Wearable devices, such as headbands and miniature data loggers, were not included in that review. Finally, the systematic review of Salamone et al. [11] was specifically focused on the environmental monitoring in the built environment using wearable devices. The main difference with the present work is its broader area of interest which encompasses all the domains of the indoor environmental quality. Consequently, the use of wearable devices for the acquisition of thermal, air-quality, visual, and acoustic factors was analyzed, without a specific and detailed focus on the thermal comfort assessment.

Given this framework, the following novel key contributions can be identified for this review:

- A detailed view about the use of off-the-shelf wearable sensing devices in thermal comfort studies with a focus on their strengths, weaknesses, and technical features.
- An analytical evaluation on the actual feasibility of using off-the-shelf wearable sensing devices for investigating, monitoring, and controlling the human thermal comfort in the real world and not only in small-sized controlled environments -as they are laboratories or test rooms- but in large-scale studies.
- A critical discussion on the approaches adopted in thermal comfort studies that adopt off-the-shelf wearable sensing devices and on the possible research streams which could be expected in the coming future.

This paper is structured as it follows. After this introductory discussion about the motivations at the basis of this work (section 1), a concise background about the main physiological signals obtainable through wearable devices is provided in section 2. Then, the methodological framework adopted in this systematic revies is described (section 3). The results of this review are presented in section 4, where the off-the-shelf sensing wearable devices are classified according to the typology. Insights about their use in the analyzed papers are provided. In section 5, the obtained results are discussed and the main insights about where the current research is heading, which are the main issues that attract significant research, and which may be possible developments in the coming future are provided. The final remarks are provided in section 6. In Annex A, a comparative analysis amongst the datasheets of the mostly adopted off-the-shelf wearable devices is performed through summary tables.

2. Background

2.1. Overview on physiological signals

Off-the-shelf wearable devices can monitor different physiological activities. A broad range of physiological signals can be acquired by using various sensor technologies coupled to algorithms to derive additional signals and parameters. Even though this review focuses on the devices, a concise background about the main physiological activities, the signals that can be monitored through these devices and their potential implication in thermal comfort studies is here provided.

- **Heart activity**: it provides a lot of information about how heart is working and the human stress condition. Heart activity can be monitored in two different ways. The first way is the Electrocardiography (ECG) that provides information about the duration and the amount of the electrical waves passing through the heart using electrodes placed on subject’s chest and limbs. The second way is the optoelectronic technology of Photoplethysmography (PPG) which measures the Blood Volume Pulse (BVP) that is the volume of blood pushed by the heart through body tissues [17]. To do so, a light source -usually a LED- emits light and a photodetector registers the amount of light absorbed and reflected at the skin level [14]. Several features can be extracted from ECG and PPG

signals, such as the Heart Rate (HR) that is the frequency of a complete heartbeat -usually expressed in beats per minute (bpm)- and the Heart Rate Variability (HRV) that is related to the fluctuation of the amount of time between heartbeats.
- **Skin activity**: skin is a sensory organ that works as a physiological bridge between human body and the surroundings due to the presence of cutaneous blood vessels and sweat glands used for thermoregulation. Two main skin parameters can be monitored, namely the Electrodermal Activity (EDA) and the Skin Temperature (ST). EDA is a measure of the continuous changes in the skin electroconductivity due to the modification of sweat gland activity. When humans are under stress, the sympathetic nerve activation increases the sweat gland activity causing the increase of moisture on the skin and, consequently, its electroconductivity [12]. EDA, also known as Galvanic Skin Response or Skin Conductivity, is acquired by measuring the variation of a low voltage current applied between two electrodes and is usually expressed in μS. ST -usually expressed in °C- can be measured through various sensor technologies, such as resistance thermometers, infrared thermometers, or thermocouples [14].
- **Brain activity:** during each state of human emotion, brain has a spontaneous electrical activity that can be monitored through the Electroencephalogram (EEG). By placing electrodes on the subject's scalp, the voltage changes caused by the movement of ions in the brain's neurons can be monitored and a raw EEG signal -in the range of μV- can be acquired. After a preprocessing, the EEG can be segmented into epochs and different brain waves -e.g., Alpha, Beta, Delta, Theta, and Gamma waves- can be obtained through specific analyses, such as spectral ones [14].
- **Respiratory activity:** respiration is an essential physiological task in living organisms. In humans, it consists in the movement of respiratory gases into (oxygen) and out (carbon dioxide) of the lungs. The main signal related to the respiratory activity is the Respiration Rate (RR) expressed in breath per minute (bpm) that is often measured through the strain gauge method. In a strain gauge sensor, the electrical resistance of a conductor increases when the area of the conductor itself increases [18]. Thus, a strain gauge sensor made of extendible conducting material is embedded in a pad mounted on to a chest strap of the subject's left-hand side. During the respiratory process, the thoracic expansion and contraction cause variations in pad dimensions and the area of the conductor, with consequent variation of its electrical resistance [19].
- **Physical activity:** it is a factor that remarkably affects the subject metabolic rate, that is the rate of internal energy produced through the oxidation reaction of glucose molecules [20]. Physical activity can be monitored by wearable devices through different strategies. A first one is the monitoring of the subject's Acceleration (ACC) –expressed in g (1 g = 9.83 m s^{-1})- using a 3-axis accelerometer. Steps and distance are estimated through specific algorithms and with the aid of a GPS, when present. Moreover, if a barometric pressure sensor is embedded in the device, the barometric pressure changes can be used in combination to the steps to calculate the floors climbed. Finally, if the HR -in resting condition and during the activity- and subject's physical data -e.g., height, weight, gender, and age- are available, they can be used to estimate the activity level, the burnt calories, and the metabolic rate, also expressed as Metabolic Equivalent of Task (MET).

2.2. Relations between physiological signals and thermal comfort assessment

The monitoring of the above-mentioned physiological activities and the measurement of related parameters can be directly implemented in existing comfort models to provide accurate estimation of the different quantities involved in the thermal balance of human body. Parameters related to respiratory activity can be related to sensible and latent heat losses due to respiration, while monitoring the skin activity can be related to the estimation of evaporation and conductive, convective, and radiative heat exchanges between the human body and the surrounding ambient. As mentioned, parameters related to hearth and physical activities are directly involved in the determination of the metabolic rate, which is essential for thermal comfort assessment in the framework of existing models. Together with the accurate monitoring of ambient conditions (air temperature, velocity, relative humidity, and mean radiant temperature), a detailed estimation of such personal factors is essential for accurate thermal comfort evaluation, especially when conductive in-field studies aimed to evolve from the traditional PMV-based approach (estimating the average thermal sensation of a large samples of individuals) to advanced approaches based on individual thermal sensation and responses, for which personalized comfort models may be derived [21]. Monitoring parameters related to brain activity is crucial to include psychological parameters towards novel multi-physics and multi-domain comfort models [22].

Further, the great potential of large-scale monitoring of such physiological parameters through off-the-shelf devices can be seen not

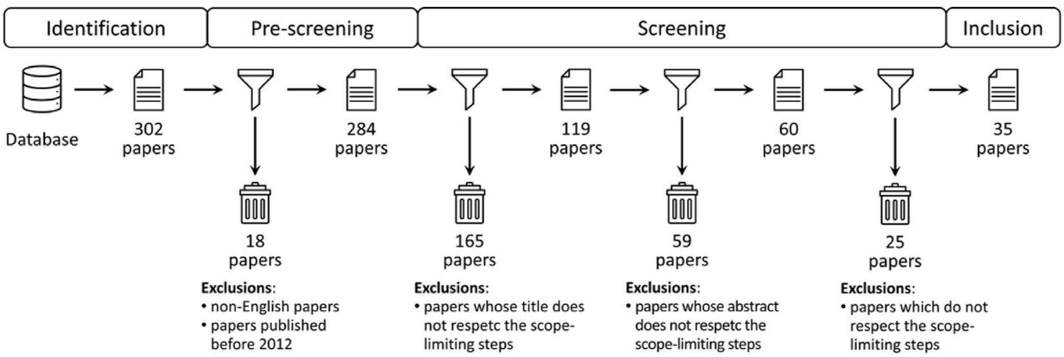

Fig. 1. Schematization of the systematic selection of the scientific papers considered within this review.

only in the context of validation and application of existing and new comfort models, but also in large-scale big-data gathering for the development of data-driven comfort models supported by artificial intelligence-based techniques [23].

3. Review methodology

3.1. Definition of the literature to review

An extensive literature research was performed through Scopus® database in September 2022 by considering the selected keywords "thermal", "comfort", and "wearable". To limit the number of results to the publications in which wearable devices are used for studies related to thermal comfort, the three keywords were combined using the Boolean variable "AND" only. The research was carried out by considering titles, abstracts, and keywords. Thus, the "TITLE-ABS-KEY (thermal AND comfort AND wearable)" query was introduced in the database.

This extensive literature search yielded 302 papers that were systematically selected with the PRISMA methodology, similarly to Song et al. (2022) [24]. The selection process is reported in Fig. 1 with a visual schematization derived from the PRISMA flowchart.

After the identification of the papers ($n = 302$), a pre-screening selection was performed to exclude non-English papers and papers published before 2012. These criteria were adopted to focus this work only on international literature published in the last 10 years. This exclusion could have been integrated directly in the search query through additional Boolean operators. Nevertheless, this exclusion was performed in a second step (i.e., the pre-screening stage) to provide additional information about the excluded papers. Six papers ($n = 6$) were excluded since non-English ones. Twelve papers ($n = 12$) were excluded due their publication prior to 2012. Please note that 7 of the 12 papers excluded due to their publication year were published in 2009 and 2011. The provided information shows the recent publication years of most of all the papers and, consequently, highlights the novelty of the investigated topic.

The third stage showed in Fig. 1 is the screening activity that was performed using the scope-deliming steps presented in Fig. 2, as previously done in other systematic reviews [13]. To consider a paper in this review, it has to accomplish all the four drop-down steps presented in Fig. 2. First, papers should be focused on thermal comfort in indoor or outdoor conditions. Thus, visual, acoustic, or ergonomic comfort is excluded. Second, the study should adopt wearable devices. Consequently, all the studies that adopt fixed devices or wearable devices connected through a wired network to acquisition or logging systems are excluded. Third, the wearable devices should acquire physiological parameters. Hence, papers in which devices are worn by participants to measure other parameters, such as the climate conditions around them, are excluded. Similarly, studies focused on wearable heating or cooling devices for improving thermal comfort are excluded. The last step presented in Fig. 2 regards the market availability (off-the-shelf) of the adopted devices. Consequently, papers in which prototypes are adopted or developed were excluded too.

As visible in Fig. 1, the presented scope-delimiting steps are applied consecutively to the titles, the abstracts, and the entire papers. At the end of this screening process, 35 papers are considered suitable and included in this review.

3.2. Included papers

The 35 papers that are included in this work are presented in Table 1, sorted descending by year as they appear in the Scopus® database. Moreover, the types of wearable sensing devices that are used in each one of the considered papers are shown. As visible from the table, three main types of wearable sensing devices are used in the considered papers, namely wristbands, headbands, and chest bands. If further types of wearable sensing devices are used in the included papers, such as miniature data loggers, these devices are included in the "others" type.

Wristbands are wrist-worn devices that are used to acquire physiological signals, such as HR and wrist ST, depending on the features of the considered off-the-shelf device. Commercially, wrist-worn devices are denominated using different terms, such as wristband, smartwatch, smart band, and smart bracelet, depending on their features (e.g., dimensions and functions) and manufacturers' commercial strategies. In the framework of this research, the term "wristband" is used to indicate all the previous mentioned types of wrist-worn devices. The second type of wearable sensing devices that is presented in Table 1 is the headband. This device is

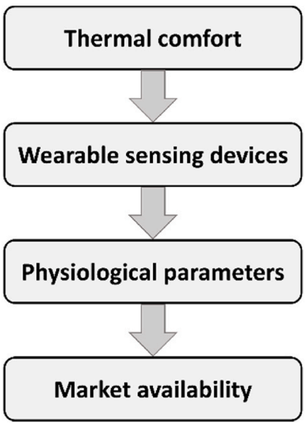

Fig. 2. Schematization of the scope-delimiting steps for screening the scientific papers considered within this work.

Table 1
List of the scientific papers included in this review and type of wearable sensing devices that are adopted in each one of them.

Paper	Wristband[a]	Headband	Chest band	Others[b]
Čulić et al. (2022) [25]	✓			
Gao et al. (2022) [26]	✓			
Kim et al. (2022) [12]	✓			
Mansi et al. (2022a) [8]	✓	✓		
Abdelrahman and Miller (2022) [27]	✓			
Mansi et al. (2022b) [28]	✓	✓		
Barone et al. (2022) [29]	✓			✓
Cosoli et al. (2022) [30]	✓	✓		
Galarretta et al. (2022) [31]	✓			
Park and Park (2022) [32]	✓			
Morresi et al. (2021) [33]	✓			
Mansi et al. (2021) [34]		✓		
Lee and Ham (2021) [35]	✓			
Nižetić et al. (2020) [36]				✓
Alsaleem et al. (2020) [37]	✓			
Pigliautile et al. (2020) [38]			✓	
Deng and Chen (2020) [9]	✓			
Salamone et al. (2020) [39]	✓			
Pivac et al. (2020) [40]				✓
Feng et al. (2020) [41]	✓			
Razjouyan et al. (2020) [42]			✓	
Jayathissa et al. (2019) [43]	✓			
Yoshikawa et al. (2019) [44]	✓			
Kobiela et al. (2019) [45]	✓		✓	
Liu et al. (2019) [46]			✓	✓
Youssef et al. (2019) [47]			✓	
Calvaresi et al. (2018) [48]			✓	
Salamone et al. (2018a) [49]	✓			
Salamone et al. (2018b) [50]	✓			
Liu et al. (2018) [51]			✓	✓
Li et al. (2017) [52]	✓			
Hasan et al. (2016) [53]	✓			
Abdallah et al. (2016) [54]	✓			
Huang et al. (2015) [55]	✓			
Gauthier and Shipworth (2014) [56]			✓	

[a] The term "wristband" includes different types of wrist-worn devices, such as smartwatches and smart bands.
[b] Devices such as activity sensors and mini data loggers are included.

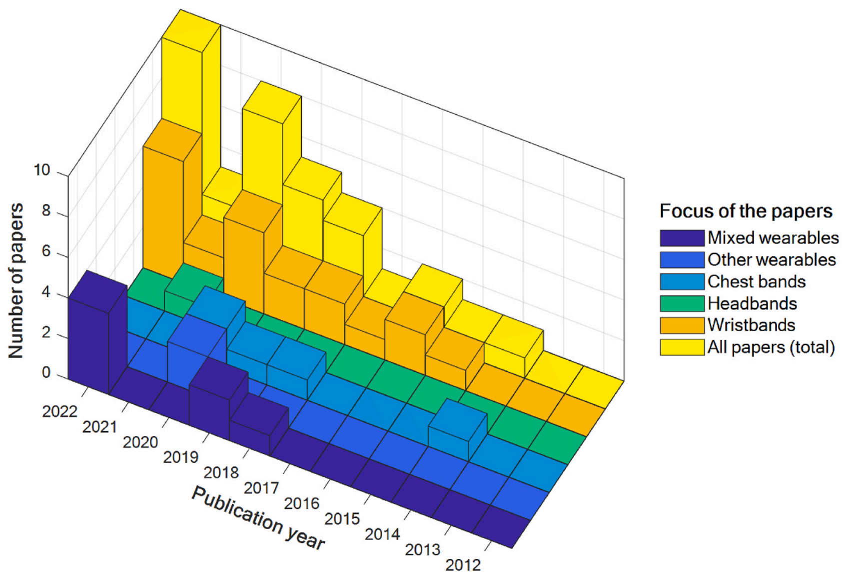

Fig. 3. Analyzed papers divided per year of publication (2012–2022) and per type of wearable sensing devices adopted.

usually adopted to obtain the EEG of the involved participants. The chest band is the third type that is considered in Table 1. This type of wearable device is usually adopted to monitor the heart activity, by acquiring HR or ECG, and the respiratory activity. The "others" type includes all those wearable devices which use in scientific literature is minor, such as activity sensors and mini data loggers.

From the table, it stands out that wristband is the sensing wearable device that is mainly used to acquire physiological signals in studies related to thermal comfort. This device is adopted alone in 20 papers and in combination with other devices in 5 more papers. Hence, wristbands are used in 70% ($n = 25$) of the analyzed papers. Another remarkable element that stands out from Table 1 is that chest bands were widely used mainly between 2018 and 2020. Later, their adoption considerably decreased. This decrease in the use of chest bands may be attributed to an increase of the reliability of wristbands in monitoring the HR, the main signal that is usually acquired by chest bands. Hence, wristbands have become preferred to chest bands in the last years.

In the 3D bar chart of Fig. 3, the 35 analyzed papers are divided per year of publication and type of adopted device. While in 2012 and 2013 no papers were published, an increasing trend of published papers can be appreciated between 2014 and 2022. The use of wristband in this type of study can be considered the driver of this increasing trend that reached its peak in 2022, when 10 scientific papers were published in literature. It is worth of mentioning that the publication trend remarkably fell in 2021, when only 3 papers were published. This dramatic decrease can be attributable mainly due to the spread of COVID-19 that limited considerably the experimental activities involving participants.

4. Results

In this section, the main contributions of the selected papers are analyzed according to the classification reported in the columns of Table 1. Each sub-section analyzes a different type of wearable devices (wristbands, headbands, chest bands, and others) by highlighting the adopted off-the-shelf device, the acquired signals, and the main insights about their use. Moreover, the mostly adopted off-the-shelf devices are analyzed from a technical point of view by comparing their datasheets. The result of this comparison is summarized in the Annex A through summary tables that highlight their hardware features, operating conditions, data management, and main measured signals.

4.1. *Wristbands*

The off-the-shelf wristbands adopted in the papers considered in the framework of this review are presented in Table 2. As visible from the table, various off-the-shelf wristbands are used for investigations related to thermal comfort. Empatica E4 and Fitbit (different models) wristbands are the devices which use is mostly spread in scientific literature. Among all the listed devices, Empatica E4 is the only that was specifically developed for professional research applications. The other devices were developed mainly for not-professional usages. Table 2 also shows the physiological signals that were acquired by the considered off-the-shelf wristbands in

Table 2
Considered scientific papers that adopt off-the-shelf wristbands for thermal comfort studies.

Paper	Off-the-shelf wristband	Acquired physiological signals
Čulić et al. (2022) [25]	E66	HR, ST[d]
Gao et al. (2022) [26]	Empatica E4	ACC, EDA, HR, ST[d]
Kim et al. (2022) [12]	Empatica E4	EDA, HR, ST[d]
Mansi et al. (2022a) [8]	Empatica E4[a]	EDA, HR, ST[d]
Abdelrahman and Miller (2022) [27]	Fitbit Versa/Ionic	HR, ST[d]
Mansi et al. (2022b) [28]	Empatica E4[a]	EDA, HR, ST[d]
Barone et al. (2022) [29]	Empatica E4[b]	HR, ST[d]
Cosoli et al. (2022) [30]	Empatica E4[a]	EDA, HR, ST[d]
Galarretta et al. (2022) [31]	Huawei GT2e	HR
Park and Park (2022) [32]	Empatica E4	BVP, EDA, HR, ST[d]
Morresi et al. (2021) [33]	Galaxy Watch	HR
Lee and Ham (2021) [35]	Empatica E4	ACC, EDA, HR, ST[d]
Alsaleem et al. (2020) [37]	Microsoft Band 2	HR, MET, ST[d]
Deng and Chen (2020) [9]	Hesvit S3	HR, SRH[d,e], ST[d]
Salamone et al. (2020) [39]	Empatica E4	ACC, EDA, HR, ST[d]
Feng et al. (2020) [41]	Empatica E4	ACC, EDA, HR, ST[d]
Jayathissa et al. (2019) [43]	Fitbit Versa/Ionic	HR
Yoshikawa et al. (2019) [44]	Empatica E4	EDA, HR, ST[d]
Kobiela et al. (2019) [45]	Empatica E4[c]	BVP, ST[d]
Salamone et al. (2018a) [49]	Empatica E4	ACC, EDA, HR, ST[d]
Salamone et al. (2018b) [50]	Empatica E4	ACC, EDA, HR, ST[d]
Li et al. (2017) [52]	Microsoft Band 2	Activity level, HR, ST[d]
Hasan et al. (2016) [53]	Fitbit Charge HR	MET
Abdallah et al. (2016) [54]	Basis	EDA, HR, ST[d]
Huang et al. (2015) [55]	Basis B1	EDA, MET, ST[d]

[a] Adopted in combination with a head band.
[b] Adopted in combination with a miniature data logger.
[c] Adopted in combination with a chest band.
[d] Measured at the wrist.
[e] Skin Relative Humidity.

the framework of the analyzed papers. As visible from the table, the considered wristbands are mainly used to acquire wrist ST, EDA, and HR. Please note that the third column of the table reports the signals acquired in the related work. From each signal, various features can be extracted to be used in the thermal comfort studies.

In the following subsections, the use of each off-the-shelf wristband for thermal comfort studies is analyzed.

4.1.1. Empatica E4

Empatica E4 wristband is a wearable device specifically designed for a continuous real-time data acquisition in daily life for research purposes. This wristband is a class II medical device according to the FDA 21 CFR Part 860.3 regulation [49] and is equipped with four sensors, namely a photoplethysmogram, an EDA sensor, a 3-axis accelerometer, and an infrared thermopile. A specific software was developed by the manufacturer to transfer and manage the acquired data [57]. The technical features of Empatica E4 wristband are reported in Table A1.

Empatica E4 wristband was used in Gao et al. (2022) [26] to collect physiological signals of students and teachers in a school for creating a dataset useful for future studies focused on the relationships between indoor climates and students' behaviors/mental states.

Kim et al. (2022) [12] adopted the Empatica E4 wristband in their study aimed at proposing an advanced thermal comfort-prediction model that achieves an accuracy of around 68% when using nine physiological features. When blood glucose and salivary cortisol are added to the model, the accuracy rises at around 78%. According to the results, EDA and ST are between the features of the Machine Learning (ML) model that mostly contribute to the correct prediction, especially in the case of female subjects.

Mansi et al. (2022a) [8] adopted Empatica E4 wristband in a study aimed at experimentally demonstrating the use of physiological measurements for thermal comfort decoding. In that study, several features were extracted from the signals retrieved through Empatica E4 wristband and their significant differences between different thermal sensations were statistically evaluated. The results show that the considered features are especially suitable to distinguish between cold and warm thermal sensations. A similar approach was used by Mansi et al. (2022b) [28] to evaluate the workers' thermal comfort through a ML model based on different features extracted from the signal retrieved by Empatica E4 wristband. The maximum ML model accuracy was 76% achieved using a Random Forest classifier.

The approach adopted in Barone et al. (2022) [29] was quite different if compared to the previous mentioned works. The signals monitored by Empatica E4 wristband, in fact, were used for validating a new direct thermal comfort model that discretizes the human body into three nodes.

Cosoli et al. (2022) [30] adopted Empatica E4 wristband to acquire physiological signals to be used together with EEG to predict thermal sensations using different ML algorithms. Even though the use of all the acquired signals maximizes the prediction accuracy (80%), the use of EDA plus EEG or wrist ST plus EEG provides a good accuracy too, being 78% and 76% respectively.

The signals collected by Park and Park (2022) [32] using Empatica E4 wristband were used to develop a prediction model for thermal comfort based on ensemble transfer learning. The proposed model was considered suitable to overcome the weak generalization performance that occurs when the dataset of each subject is insufficient.

Lee and Ham (2021) [35] developed a thermal comfort model using signals acquired by Empatica E4 wristband. The results highlighted the importance of a real-time estimation of change in activity and the issues related to the prediction of a neutral thermal state. This is because the Authors observed a weak predictive performance of the model when the subject's thermal sensation is within a neutrality range.

Salamone et al. (2020) [39] compared the thermal comfort perception in both real and virtual environments, even considering light color, using ML models. In both real and virtual reality scenarios, ST resulted to be the physiological variable that mostly contribute to improve the model accuracy.

Feng et al. (2020) [41] adopted Empatica E4 wristband and other sensors to develop a framework for an individualized comfort monitoring system to be later integrated in the HVAC control system of healthcare facilities. No specifications about the ML model and the use of monitored physiological signals are provided.

Yoshikawa et al. (2019) [44] used Empatica E4 wristband in combination with a low-cost thermal camera for estimating subjects' thermal comfort. Empatica E4 wristband was used to acquire wrist ST, HR, and EDA, while the low-cost thermal camera was used to acquire various temperatures in different regions of the face, such as nose, lip, and cheek through a face-detector algorithm. The results show that the accuracy of the ML model is 73% when using the wristband-based features, while it rises up to 78% by including the thermal camera-based features. The combination of all the features improves the classification accuracy up to 80%.

Kobiela et al. (2019) [45] used Empatica E4 wristband in combination with a chest band for training and validating a personal thermal perception model. As better described in section 4.3, the results demonstrated that ML models trained of wristband-based features performed worse than the ones trained with chest band-based features.

Empatica E4 wristband is also used in the works of Salamone et al. (2018b) [50] and Salamone et al. (2018a) [49] that are strictly related between them because the former is propaedeutic to the latter. While in Salamone et al. (2018b) [50] the main variables for a ML model aimed at assessing thermal comfort are identified, in Salamone et al. (2018a) [49] the ML model is trained and validated. According to the results, when only physiological features are used, the accuracy achieved by the ML model ranges between 50% (Logistic Regression) and 81% (Classification and Regression Trees), depending on the adopted algorithm. When environmental features, such as operative temperature and relative humidity, are included in the model, the accuracy increases in the range between 81% (Logistic Regression) and 99% (Classification and Regression Trees). According to the results of Salamone et al. (2018a) [49], HR is a feature that can be excluded from the ML models when evaluating thermal comfort in sedentary activities.

4.1.2. Fitbit

Fitbit wristbands are a series of wearable devices that can be used to monitor different users' parameters, including the metabolic rate which is estimated by the devices' algorithms as a function of the basal metabolic activity and the estimated energy requirement [53]. The main technical features of one example of Fitbit series device (i.e., Fitbit Versa 4) are reported in Table A2. One of the main advantages of this series of devices is its spread. Around 25 million of Fitbit users were registered in 2019 [43], making this off-the-shelf device especially suitable for large and remote studies on the population, such as "The Fitbit Heart Study" that aimed at detecting cardiac arrhythmia among Fitbit users and, contemporarily, validating Fitbit algorithms on large scale [58]. The reliability of Fitbit measurements was previously evaluated by various small-scale experimental validations focused on child [59] and adult physical activities [60,61].

From the point of view of thermal comfort studies, Fitbit wristbands represent a flexible tool because they embed the possibility of integrating customized apps and clockfaces specifically developed for research purposes [62]. This opportunity was seized by Jayathissa et al. (2019) [43] who used Fitbit wristband in a different and novel way to perform thermal comfort studies if compared to the previously presented research works. Fitbit wristband was used in combination with *cozie*, an app developed for Fitbit that is available for download from *cozie* website [63]. This app is a Fitbit clockface that can collect subjective comfort feedbacks from the users. The default status of the clockface is a binary question to the user that could choose between two icons representing a comfort or a discomfort thermal sensation. By clicking on the icons, the information regarding the location, HR, steps walked since the last log and the comfort feedback are sent to a database. If the user is feeling discomfort, additional questions can be configured by using the mobile phone paired with Fitbit wristband. Using this application, the Authors of that work were able to obtain 1460 responses from 15 users during a month, with minimal administrative overhead. *Cozie* application was then used by Abdelrahman and Miller (2022) [27] in an investigation focused on the improvement of the subjective data sampling for thermal comfort studies. The main idea of that work is to perform a targeted occupant survey -a concept introduced by Duarte Roa et al. [64]- that consists in exactly determining *where* and *when* collecting data from occupants. Abdelrahman and Miller (2022) [27] used the HR acquired by Fitbit wristband, the outdoor temperature, and the personality to create triggering conditions to start the data acquisition. Thus, Fitbit is not only a passive device for the signal acquisition, but it also contributes to determining when that signal has to be acquired.

Finally, Fitbit wristband was used by Hasan et al. (2016) [53] to acquire the actual metabolic rate of two users for estimating their Predicted Mean Vote (PMV) and comparing it to the PMV calculated assuming a constant MET value of 1.0. The results showed that occupants' MET varies remarkably over time, even though they were performing comparable activities. These results highlighted that the assumption of a constant MET represents a limitation for the correct estimation of occupants' thermal comfort.

4.1.3. Other wristbands

In addition to Empatica E4 and Fitbit, further off-the-shelf wristbands were adopted to perform thermal comfort studies. Table 2 shows that Microsoft Band 2, Basis, E66, Huawei GT2e, Galaxy Watch, and Hesvit S3 were also adopted, although their use can be considered minor compared to Empatica E4 and Fitbit.

Microsoft Band 2 -now discontinued- was a wrist-worn device equipped with various sensor for monitoring several physiological parameters. Alsaleem et al. (2020) [37] adopted Microsoft Band 2 to develop a wearable-based personalized thermal comfort model integrated in an intelligent comfort controller based on particle swarm optimization. Microsoft Band 2 was used in combination to a designed app to allow the user to enter the clothing conditions and feedback about the thermal sensation. The results show that metabolism, wrist ST, and especially the EDA are the features that mostly contribute to improve the prediction accuracy of the ML model. By contrast, the use of cloth insulation and HR as prediction features provides less accuracy. A similar investigation was performed by Li et al. (2017) [52]. They used Microsoft Band 2 to acquire physiological signals for training a ML model for developing a personalized HVAC control framework. The developed model integrates a decision algorithm that can switch between either the activation and control of the HVAC system or the window opening for natural ventilation. The results show that the inclusion of physiological parameters in the ML model considerably increases its accuracy. Moreover, this personalized HVAC control was estimated to decrease by over 50% the number of uncomfortable reports regarding discomfort conditions collected from the occupants.

Basis is a wristband that is equipped with sensors for monitoring the triaxial acceleration and various heat-related variables, such as ST, ambient temperature, and EDA to estimate the energy expenditure. The accuracy of Basis B1 in the estimation of physical activity were evaluated by a specific study [65] that highlighted a bad accuracy of this device when compared to similar ones and a portable metabolic system. Basis wristband was adopted in the studies of Abdallah et al. (2016) [54] and Huang et al. (2015) [55]. Both those works are among the oldest ones considered in this literature review. Thus, their approach seems to be more explorative than the one adopted in the next works. The aim of Abdallah et al. (2016) [54] was to investigate the feasibility of adopting wearable devices to measure and monitor occupants' thermal comfort by using Artificial Neural Network (ANN). Similarly, Huang et al. (2015) [55] used Basis B1 wristband to acquire physiological signals with the final aim of inferring thermal comfort. The results showed that the incorporation of physiological quantities increases considerably the prediction accuracy. Moreover, Huang et al. (2015) [55] identified the main situations that pose challenges for inferring occupants' thermal comfort at home, such as local heat sources (e.g., a laptop on the lap), short terms effects (e.g., a cold/hot beverage), and extra covers (e.g., a puppy on the lap).

E66 wristband was adopted by Čulić et al. (2022) [25] to investigate personal thermal comfort indicators and introduce a personal thermal comfort evaluation framework. The results of this work showed that thermal comfort is not very sensitive to HR and wrist ST.

Galarretta et al. (2022) [31] designed and developed an automatic HVAC control system based on occupants' body temperature. The improved performance of the proposed control system was evaluated by assessing the occupants' thermal comfort based on the stress level -a function of HR- measured through a Huawei GT2e wristband.

Galaxy Watch was the off-the-shelf wristband used by Morresi et al. (2021) [33] in their work aimed at measuring thermal comfort in response to the variation of the environmental conditions using ML classifiers. The results showed that frequency-domain quantities of HRV are especially suitable to be used as indicators to distinguish whether a user is thermally comfortable or in discomfort.

The last analyzed off-the-shelf wristband is Hesvit S3 that was used by Deng and Chen (2020) [9] to develop a HVAC control strategy for offices using an ANN model based on the use of wristbands to monitor HR. This control strategy was then validated through experimentations and simulations. The results show that the proposed control system improves the office thermal comfort, but it was not effective from an energy point of view. The control of the set point temperature using the ANN model, in fact, does not show remarkable differences in terms of heat load, in comparison to a HVAC control that maintains a constant set point temperature. Moreover, the proposed control strategy increases by 7% the cooling load compared to a control strategy based on a constant set point temperature. The most energy-efficient solution resulted to be coupling the wristband control using HR to an occupancy-based control that can be performed using the Bluetooth of the same wristbands.

4.2. Headbands

In Table 3, the papers in which off-the-shelf headbands were adopted to perform investigations on thermal comfort are reported. Moreover, the adopted off-the-shelf headbands and the acquired physiological parameters are also presented. As visible from Table 3, only four papers adopted headbands for performing analyses related to thermal comfort and all of them used Muse 2 devices for the EEG monitoring.

4.2.1. Muse 2

According to the manufacturer [66], the Muse series headbands are multi-sensor meditation devices that provide real-time feedback on the user's brain activity, HR, breathing, and body movements. These headbands are equipped with a reference electrode (FPz) placed on the forehead and four more input electrodes. Two of them are silver-made front electrodes (AF7 and AF8), while the remaining ones are posterior electrodes (TP9 and TP10) made in conductive rubber. Please note that the electrode positions and the nomenclature refer to the 10–20 international system for scalp electrodes for EEG [67]. Muse headband can acquire the EEG signal with a sampling frequency of 256 Hz [28], as reported in Table A3.

Muse devices were primarily developed for helping the meditation practice [66]. Nevertheless, the recent rising interest for portable low-cost EEG devices has led to extend the use of Muse headband also for research purposes, mainly in neuroscience field. For example, Youssef et al. [68] used Muse headband for developing a ML-dependent lie detector, while Karydis et al. [69] adopted Muse to classify brain states corresponding to the experience of "pain" or "no pain" associated with cold. Muse devices, in fact, are characterized by a reduced time for the application to users, a minimum intrusiveness during the measurements, and a lower cost if compared to professional equipment. Indeed, the limited number of electrodes and their low adjustability to different head shape and size may question the Muse reliability for research use. Nevertheless, the experimental validation against a professional equipment for laboratory EEG recordings performed by Krigolson et al. [70] proved the reliability of Muse.

A first study involving a Muse 2 headband for thermal comfort evaluation was performed by Mansi et al. (2021) [34]. This study is preliminary to the others presented in Table 3 because sets the data processing -noise removal and power spectrum analysis- and feature extraction procedures. Starting from the signal acquired through the Muse headband, the five major brain waves in the different frequency ranges were extracted, namely Delta, Theta, Alpha, Beta, and Gamma brain waves. The extracted features were then used to find statistical correlations with thermal sensations. The results showed that brain activity was altered by the occupants' thermal sensation. Most of the EEG features can be used to distinguish between warm and cold thermal sensations. Nevertheless, the considered features cannot be used to distinguish between neutral and cold thermal sensations. Similar analyses were performed by Mansi et al. (2022a) [8] who used Muse 2 headband with Empatica E4 wristband. The performed analyses confirmed the results obtained in Mansi et al. (2021) [34], especially regarding the correlation between the increase/decrease of power of brain waves as a function of the user thermal sensation.

While the previously presented two works were focused on finding correlations between thermal sensations and EEG features, the investigations presented in Mansi et al. (2022b) [28] and Cosoli et al. (2022) [30] adopted a different approach. This is since the signals acquired by Muse 2 headband and Empatica E4 wristband were adopted for developing ML models aimed at predicting the occupants' thermal sensation. The work of Mansi et al. (2022b) [28] was mainly focus on workplaces and the developed ML model was characterize by an accuracy of 76% when the Random Forest Classifier was adopted. Moreover, a Thermal Comfort-Related index was developed for assessing thermal sensations based only on features extracted from physiological signals acquired by the adopted off-the-shelf wearable devices. Cosoli et al. (2022) [30] demonstrated that the combinations of EEG with EDA or ST provide high accuracies -up to 78% and 76%, respectively- for the estimation of thermal sensation through ML algorithms.

Table 3
Considered scientific papers that adopt off-the-shelf headbands for thermal-comfort studies.

Paper	Off-the-shelf headbands	Acquired physiological signals
Mansi et al. (2022a) [8]	Muse 2[a]	EEG
Mansi et al. (2022b) [28]	Muse 2[a]	EEG
Cosoli et al. (2022) [30]	Muse 2[a]	EEG
Mansi et al. (2021) [34]	Muse 2	EEG

[a] Adopted in combination with a wristband.

Table 4
Considered scientific papers that adopt off-the-shelf chest bands for thermal-comfort studies.

Paper	Off-the-shelf chest bands	Acquired physiological signals
Pigliautile et al. (2020) [38]	BioHarness 3.0	HR
Razjouyan et al. (2020) [42]	EcgMove 3	Activity level, HR
Kobiela et al. (2019) [45]	RespiBan[a]	HR, ST
Liu et al. (2019) [46]	Polar H7[b]	HR
Youssef et al. (2019) [47]	Polar H7	HR
Calvaresi et al. (2018) [48]	BioHarness 3.0	ACC, Activity level, Body posture, HR, RR
Liu et al. (2018) [51]	Polar H7[b]	HR
Gauthier and Shipworth (2014) [56]	Kalenji CW 300	HR

[a] Adopted in combination with a wristband.
[b] Adopted in combination with miniature data loggers.

4.3. Chest bands

In Table 4, the papers in which off-the-shelf chest bands were adopted to perform investigations on thermal comfort are reported. As visible from the table, BioHarness 3.0 and Polar H7 are the chest bands that are mainly used in this type of investigations. The use of other chest bands -e.g., RespiBan- is minor. Between the considered chest bands, BioHarness 3.0, EcgMove 3, and Respiban can be considered as wearable devices intended for a professional use also for in- or out-of-the-lab research applications. By contrast, Polar H7 and Kalenji CW 300 were developed mainly for not-professional sport usages.

In the analyzed papers, the off-the-shelf wearable devices reported in Table 4 were mainly adopted to acquire HR. Nevertheless, in some studies, these chest bands were also used to acquire further parameters, such as ST, RR, and activity level.

4.3.1. BioHarness 3.0

As reported in the user manual [71], the BioHarness 3.0 chest band is a physiological monitoring telemetry device intended for monitoring of adults in the home workplace and alternate care settings. The chest band consists of a chest strap and an electronic device that allows the user to acquire five physiological and physical quantities, namely HR, RR, ACC, activity level, and body posture. The main technical features of this off-the-shelf wearable device are reported in Table A4. The metrological characterization performed by Casaccia et al. [72] highlighted a good accuracy in the estimation of HR and RR. Additional analyses regarding BioHarness validity and reliability were performed in the works of Johnstone et al. [73,74].

The HR signals acquired by BioHarness 3.0 was used by Pigliautile et al. (2020) [38] to extract features to be correlated with thermal comfort. The results showed a good correlation especially between Low (LF) and High Frequency (HF) components of HRV and indoor air temperature, Relative Humidity (RH), and CO_2 concentration, in both summer and winter experiments. Lower correlations were also found between LF/HF and PMV. The features extracted from BioHarness 3.0 signals were used to predict the thermal sensation vote through ML algorithms. When LF/HF were considered together with time-domain and frequency-domain features, an accuracy of 84% was achieved by using the Support Vector Machine algorithm.

In Calvaresi et al. (2018) [48], BioHarness 3.0 was adopted for a different purpose. The aim of that work was the dynamic estimation of the metabolic rate of users through mathematical relationships between the monitored signals, such as HR and RR. The proposed methodology enabled an accurate estimation of the metabolic rate with an uncertainty of ± 0.2 met. Through Simulink simulations, the Authors demonstrated that a climate control system based on a dynamic estimation of occupants' metabolic rate could save around 30% of the energy if compared to a constant value of metabolic rate during a 8-h working day in wintertime.

4.3.2. Polar H7

Polar H7 is a HR chest band that is used in investigations focused on thermal comfort due to is reliability in the HR signal acquisition when compared to ECG signal acquired through the standard electrode placement of torso-mounted limb leads [75]. The main technical features of Polar H7 are reported in Table A5.

Liu et al. (2018) [51] used Polar H7 to collect HR signal to be used with other parameters to develop a ML model based on the Random Forest algorithm for predicting the occupants' thermal preferences. The results showed that the model had a good average accuracy (74% $\pm$ 13%) that increases when occupants are satisfied with the thermal environment. This study is preliminary to the one of Liu et al. (2019) [46], where the same methodology was used. The results showed a low correlation between thermal sensation and HR (0.184). Moreover, Liu et al. (2019) [46] also pointed out useful information about the performance of Polar H7 chest band in the HR monitoring. The Authors, in fact, decided to adopt Polar H7 chest band after a comparison of the HR acquisition with Empatica E4 wristband. This comparison showed a low Spearman correlation ($r_s = 0.242$) between the signals and it was attributed to the inaccuracy of the Empatica E4. The wristband, in fact, can loosen the contact with the body, while Polar H7 chest band can be damped and slightly tight on the chest, increasing the reliability of the measurements.

Polar H7 chest band was also used by Youssef et al. (2019) [47] in the development of a personalized adaptive modeling algorithm to predict the individuals' thermal sensation based on features extracted from signals acquired by several sensors. The accuracy of the model was 57% and the confusion matrix shows that the maximum confusion is observed between adjacent classes of thermal sensations. The proposed solution is to reduce the number of considered classes by merging them. Different configurations were evaluated and the accuracy rose up to a maximum of 85%.

4.3.3. Other chest bands

The remaining chest bands that are reported in Table 4 are EcgMove 3, RespiBan, and Kalenji CW 300.

EcgMove 3 is a psycho physiologic ambulatory measurement system for the assessment of ECG and physical activity [76]. The associated software makes it possible to calculate features such as HR, HRV, activity classes, and energy expenditure. EcgMove 3 was used by Razjouyan et al. (2020) [42] to analyze the role of RH in thermal comfort in the context of office workers' health and wellbeing. The Authors performed this investigation because since ASHRAE 55–1989 standard [77] there has been no lower limit to RH in thermal comfort or ventilation standards [42]. The results suggested that a lower RH limit may contribute to improve workers' wellbeing. This is because the workers that spend most of their time in environment with 30%–60% of RH show a 25% lower stress response compared to those who spend most of their time in drier conditions.

Very few information is currently available in literature regarding RespiBan chest band. According to Schmidt et al. [78], RespiBan is a chest band that embeds sensors for measuring ACC and RR. Moreover, this device can work as a hub by using four analog ports to acquire ECG, EDA, electromyography, and ST with sampling frequency of 700 Hz. Kobiela et al. (2019) [45] used RespiBan together with Empatica E4 for investigating the feasibility of ML models to predict the individuals' thermal sensation. This work showed that the ML model presented an accuracy up to 83%, using only the chest belt device, and up to 80% when only the wristband is used. Moreover, the investigation showed that the features related to distal ST are those that most improve the model accuracy. Thus, in the future, the detection of an individual's thermal perception may be remarkably improved by using new wearable devices worn on more distal body regions, such as smart rings [45].

Finally, Gauthier and Shipworth (2014) [56] adopted Kalenji CW 300 chest belt and the Kalenji Cardio Connect logger to acquire HR. The aim of the work was to improve the evaluation of the metabolic rate and the clothing insulation as quantitative variables. Nevertheless, no information about the use of the monitored HR were provided.

4.4. Other wearable sensing devices

In addition to wristbands (sub-section 4.1), headbands (sub-section 4.2), and chest bands (sub-section 4.3), other off-the-shelf wearable devices were used in literature to perform analyses related to thermal comfort. Even though their use is minor compared to other devices, they are worth to be presented for highlighting the opportunities they can provide in thermal comfort studies. In Table 5, the works in which those devices were adopted are presented. As visible from the table, these wearable devices are classified as miniature data loggers and activity sensors, mainly used to acquire ST and MET, respectively.

4.4.1. DS1923 iButton

iButton is a small (16 × 6 mm^2), rugged, self-sufficient system that measures temperature and RH and records the results in a protected memory section [79]. The main technical features of iButton are reported in Table A6. The main advantages of this miniature data logger are its small size and the absence of wiring. These features make it particularly suitable for different long-term monitoring activities. iButton was used in animal research through its implantation into rats to monitor their core body temperature [80]. When attached to clothes or accessories, iButton can be adopted to measure air temperature and RH around the individual, as done by Gnecco et al. (2022) [81] and Liu et al. (2019) [46] that pinned iButton to backpacks and pants, respectively. Moreover, iButton can be directly fixed at human epidermis using medical tapes to monitor ST for research on metabolism, circadian rhythms, and human thermal physiology [79]. The use of this device for the monitoring of human ST is supported by positive results obtained in experimental validations [79,82]. Different models of iButton are available on market, as visible from the manufacturer website [83]. The selection of the most adequate model depends on the necessity of including the RH in the monitoring activity and on the needed accuracy range. Some models, in fact, guarantee an accuracy of ±0.5 °C between +20 °C and +75 °C, which is adequate for ST acquisition. By contrast, the models that guarantee the same accuracy but in the range from −10 °C to +65 °C can be also adopted for monitoring air temperature.

iButton was used by Barone et al. (2022) [29] to acquire ST for the validation of the direct thermal comfort model previously mentioned in sub-section 4.1.1. To this aim, the ST was acquired by applying iButton DS1923 Hygrochron on the participants' body through medical tape, according to the 10-point method [84].

Liu et al. (2019) [46] and Liu et al. (2018) [51] used iButton with a chest band for the purposes previously described in in sub-section 4.3.2. In both the works, the ST was acquired at wrist and ankle. In addition, an iButton device was pinned at the individuals' lower pant with the sensing side facing outside to monitor the air temperature of the environment. The results Liu et al. (2019) [46] showed that ankle ST seems more sensitive to thermal preferences than wrist ST and HR in intermediate ranges of thermal sensations. Finally, Liu et al. (2019) [46] also compared the accuracy of iButton with the ST measured by two wristband, one equipped

Table 5
The considered scientific papers that adopt other types of wearable devices.

Paper	Type of device	Off-the-shelf device	Acquired physiological signals
Barone et al. (2022) [29]	Miniature data logger	DS1923 iButton[a]	ST
Nižetić et al. (2020) [36]	Activity sensor	Move 3	MET
Pivac et al. (2020) [40]	Activity sensor	Move 3	MET
Liu et al. (2019) [46]	Miniature data logger	DS1923 iButton[b]	ST
Liu et al. (2018) [51]	Miniature data logger	DS1923 iButton[b]	ST

[a] Adopted in combination with a wristband.
[b] Adopted in combination with a chest band.

with a resistance thermometer and the other with an infrared thermopile (Empatica E4). The results showed a spearman correlation of 0.918 between iButton and the resistance thermometer and of 0.572 between iButton and infrared thermopile. Hence, data acquired using iButton are considered more reliable because they are acquired using a device directly taped on the skin, while wristbands can provide inaccurate data since they loosen the skin contact.

4.4.2. Move 3

Move 3 is a scientific research instrument designed to capture the physical activity and other secondary parameters of a person. The main technical features of this device are reported in Table A7. The best fixation of this device is on chest, using a strap, or at the hip, by clipping it at the belt. These fixations maximize the number of obtainable outputs, but alternative fixations can be at wrist, thigh, and ankle. By acquiring the 3D ACC and the atmospheric air pressure, the algorithms of the software associated to Move 3 provide elaborated data about the individual's physical activity, such as activity class, body position, energy expenditure, and MET [85]. Specific experimental validations showed a good accuracy of previous Move models in comparison with indirect calorimetry measurements -the gold standard- and other similar technologies [86,87].

Move 3 was adopted by Pivac et al. (2020) [40] to monitor the MET of four office workers during cooling periods. The results highlighted that the MET dynamically changes during the day, even though all the monitored participants have similar daily activities. This work was preliminary to the one of Nižetić et al. (2020) [36], where Move 3 was used to monitor the MET of office workers with the final aim of validating a new model of metabolic response based on ANN. The model provided acceptable results since the validation showed an overlapping of 90%. Moreover, the analysis of the acquired MET data demonstrated the inapplicability of a static MET value in the calculation of PMV indexes. This is since the METs of the monitored workers dynamic change during working hours, with variations in the range 1.0–2.0 met.

5. Discussion

As just shown, off-the-shelf wearable devices provide several opportunities for performing thermal comfort investigations. From the analysis of the considered papers, four different approaches regarding the use of off-the-shelf wearable devices in thermal comfort investigations can be identified, namely:

a) Finding correlations between physiological features and thermal sensations;
b) Training and/or validating thermal comfort models;
c) Controlling HVAC systems;
d) Improving data acquisition.

Approaches a) and b) represent the current core of the research on thermal comfort using wearable devices, being the approaches adopted in most of the considered works. Purpose a) is characterized by the acquisition of physiological signals and the following feature extraction aimed at assessing possible correlations between their variations and the subjects' thermal sensations. The work of Mansi et al. [8] is an example of investigation carried out with this purpose. Purpose b) is characterized by the use of extracted features from physiological signals for training and validating indirect prediction models of thermal comfort, an activity that is mainly based on ML algorithms, as done by Kin et al. [12]. This purpose can concern direct thermal comfort models too. In this case, the acquired signals are used only for the model validation, as done by Barone et al. [88].

While purposes a) and b) are very widespread and consolidated in literature, purpose c) and d) represent novel promising perspectives in the use of off-the-shelf wearable devices for thermal comfort investigations. Purpose c) aims at using the signals obtained from off-the-shelf wearable devices to develop models to be integrated in the control of HVAC systems, as done by Deng and Chen [9] and Alsaleem et al. [37]. This purpose originates from the previously described purpose b), but takes a step forward to the application of thermal comfort models in buildings by facing practical issues related to the control of HVAC systems. Finally, works focused on purpose d) represent a remarkable opportunity offered by wearable devices to improve the data acquisition. On the one hand, off-the-shelf wearable devices make it possible to define trigger conditions, that is deciding *where* and *when* data are acquired. On the other hand, the combination of wearable devices with apps or clockfaces (in the case of smartwatches) can facilitate the collection of subjects' feedbacks, with a consequent reduction of the subjects' survey fatigue and the increase of accuracy in their responses. Examples of research working in this direction are the ones of Jayathissa et al. [43] and Abdelrahman and Miller [27]. It has to be remarked that the opportunity of defining trigger conditions could also represent a significant advance in studies related to the broader topic of indoor environmental quality, by including aspects of visual and acoustic comfort, and indoor air quality.

From this analysis two different research streams can be expected for the future.

The first research stream will be focused on the previously mentioned purposes a) and b). It will aim at strengthening and widening the current knowledge about statistical correlations between thermal sensations and physiological signals, as well as the development and validation of thermal comfort models. The analyzed papers, in fact, showed that there is not a common agreement on which physiological features are the main drivers for predicting thermal sensations, with significant uncertainties in the model development stage. Thus, future analyses should clearly define the most significant physiological features driving the prediction of thermal sensations and they must be integrated in personalized thermal comfort models. This aspect should be deepened especially considering that, currently, weak predictive performances were highlighted for thermal sensations within a neutrality range. This issue seems to be the real challenge for decoding the human thermal comfort.

Another issue that should be faced by this research stream is the standardization of the methodology for the model development and validation. Currently, the models presented in the literature are characterized by a wide range of accuracies, different subject samples, and different validation procedures. It is evident that strongholds in the methodology for the model development and validation are needed. The setting of standard procedures is an essential step toward the definition of more reliable models that are propaedeutic for the second research stream.

The second research stream should be focused mostly on approach c), that is the integration of off-the-shelf wearable devices and personalized thermal comfort models into HVAC control systems. This integration would represent the real innovation in the control of HVAC systems. It has emerged that, until now, very few investigations have worked to achieve this integration and they mainly adopted a numerical approach, without experimental validation. For this purpose, several issues should be faced, such as the introduction of optimization algorithms to search for the optimal values of control parameters to maximize thermal comfort. Moreover, future investigations should clarify how the integration of off-the-shelf wearable devices and personalized thermal comfort models into HVAC control systems would actually affect the perceived occupants' thermal comfort and, especially, its impact on energy consumption, mainly primary energy consumption [89]. This last issue, in fact, has not been clearly assessed until now. For example, Calvaresi et al. (2018) [48] estimated a reduction by about 30% in winter energy consumption by adopting a control of set-point temperature based on a dynamic calculation of the metabolic rate. By contrast, Deng and Chen (2020) [9] estimated an increase by 7% of the cooling load when using an HVAC control system based on the occupants' physiological data and an ANN model. It means that integrating personalized comfort models in HVAC systems may not entail an overall decrease of the energy consumption, as it was supposed by several works in literature. By contrast, HVAC systems based on personalized thermal comfort models may increase the energy consumption. This possible increase is in contrast with the goals of several national and international guidelines and directives -such as the previously mentioned EU directive 844/2018 [2]- which primary objective is precisely the reduction of energy consumption. It means that additional analyses are essential to find a trade-off between the possible increase of energy consumption, the improvement of thermal comfort, and positive impacts on occupants' activities and wellbeing, such as the increased productivity in workplaces and improvements in patients' health in healthcare facilities.

Given these perspectives, insights about the use of the off-the-shelf wearable devices for future research are provided. In Table 6 the main off-the-shelf wearable devices for each one of the types analyzed in this review are reported together with the main physiological signals they can acquire. Amongst the wristbands, Empatica E4 and Fitbit Versa 4 are included in the comparison since they resulted to be the most adopted wristbands and the most reliable ones, as mentioned in sections 4.1.1 and 4.1.2. For the same reason, BioHarness 3.0 and Polar H7 were selected for the comparison between chest bands. By contrast, less alternatives are currently present on the market for headbands, miniature data loggers, and activity sensors. Thus, Muse 2, DS1923 iButton, and Move 3 are all included in the comparison of Table 6. Please note, that additional off-the-shelf wearable devices are present on the market and they could be used in the framework of thermal comfort investigations. Nevertheless, they are not included in Table 6 since they were not present in the paper analyzed in this review.

A remarkable element that stands out from Table 6 is that certain physiological signals can be acquired by different types of off-the-shelf wearable devices. For example, HR can be acquired by Empatica E4, BioHarness 3.0, Polar H7, and Muse 2. The main difference is how this signal is obtained. Empatica E4, Polar H7, and Muse 2 derive the HR from the BVP monitored through PPG. By contrast, BioHarness 3.0 monitors the HR through the ECG. Moreover, BioHarness 3.0 is a chest band that can be damped and tight on the chest, with a consequent decrease of measurement uncertainty due to the loosen of contact with the body, as pointed out by Liu et al. [46].

Table 6
Main off-the-shelf wearable devices and acquirable physiological signals.

Acquirable signals	Off-the-shelf wearable devices						
	Empatica E4	Fitbit Versa 4	Muse 2	BioHarness 3.0	Polar H7	DS1923 iButton	Move 3
Heart rate	✓[a]	✓[a]	✓[a]	✓	✓[a]		
Heart rate variability		✓[a]		✓	✓[a]		
Blood volume pulse	✓						
Respiration rate		✓	✓[b]	✓			
Electroencephalogram			✓				
Electrodermal activity	✓						
Skin temperature	✓[c]	✓[c]				✓	
Acceleration	✓		✓	✓			✓
Activity level		✓		✓			✓[d]
Body posture			✓	✓			✓[d]
GPS		✓		✓[e]			
Steps		✓					✓
Distance		✓					
Floors climbed		✓					
Calories burnt		✓					
Oxygen saturation		✓					
Energy expenditure							✓[d]
Metabolic Equivalent of Task							✓[d]

[a] Derived from plethysmograph measurements.
[b] Derived from plethysmograph, accelerometer, and gyroscope measurements.
[c] Only wrist skin temperature is obtainable.
[d] Acquisition dependent on device position on the body.
[e] Available as a supplementary module.

Those features could make the use of BioHarness 3.0 especially suitable when the HR and the derived futures (i.e., HRV and heartbeat interval) are the core of the analyses. In a similar way, ST can be acquired by wristbands (i.e., Empatica E4 and Fitbit) and miniature data loggers (iButton). The main difference is that the measurement of wristbands is limited to the wrist ST, while iButton can be taped directly on the subjects' skin and can be used to monitor ST in various body regions. Probably, if the target of the work is the acquisition of ST, the use of miniature data loggers is more flexible. By contrast, headbands are the only wearable devices that enhance the acquisition of EEG. Even though this physiological signal seems promising for decoding thermal comfort, it could be expected that head bands may not find a wide application in this field in the future. Despite its relevance in decoding thermal comfort, EEG is quite hard to be acquired in real conditions for controlling HVAC systems. This is since a tradeoff between technical aspects and wearability is needed. Chest bands, miniature data loggers, and headbands, in fact, are devices that subjects would not traditionally wear in their day-to-day life, especially in working environments [43]. A good compromise can be found considering the previously mentioned two research streams for future investigations. For the first research stream -the one focused on purposes a) and b)- high reliability in the measurements is needed to find statistical correlations and develop models. So, the use of chest bands and miniature data loggers seem a proper solution. By contrast, the second research stream, based on purpose c), needs devices characterized by a high wearability since this stream aims at practical applications in real environments. For this reason, wristbands seem more adequate for the second research stream. Moreover, wristbands are characterized by the acquisition of multiple parameters that could be used to define the HVAC control strategies. Specifically, Empatica E4 -maybe coupled with an activity sensor- could be considered a good solution for this aim. This is since Empatica E4 is a class II medical device that was specifically developed for research purposes. Furthermore, the main specifications (e.g., range, resolution, and accuracy) of the embedded sensors are provided in the datasheet of the product. By contrast, this information is confidential for Fitbit wristbands, as it stands out by comparing Table A1 and Table A2. This lack of sensor specifications is an issue that could hinder its use in future scientific investigations and makes the metrological characterization essential for those devices.

Please note that all the previous considerations should be evaluated bearing in mind that the market of off-the-shelf wearable devices is in constant evolution. New devices may be developed, representing a further contribution in decoding the thermal comfort. A striking example is the smart ring, as underlined by Feng et al. [41], that may contribute to the acquisition of the ST from distal body regions in a simpler way if compared to skin-taped miniature data loggers. Moreover, the possible adoption of off-the-shelf wearable devices in scientific research could push the manufacturers to further improve their products, increasing and stating their accuracies, or even creating new commercial lines for this specific application.

The last element that could be pointed out is that off-the-shelf wearable sensing devices may contribute also to assessing and improving the ergonomics of working environments where thermal comfort cannot be maintained. In certain workplaces, such as steelworks [90], cold storage warehouses [91], livestock houses [92,93], and greenhouses [94], productive requirements prevent workers from being in indoor climate conditions suitable for their comfort, with consequent exposure to heat or cold stress. Currently, the ergonomics of such workplaces and their thermal-related risks are assessed through specific indicators, as defined by international standards, such as ISO 11079 [95] and ISO 7933 [96]. In the coming future, a real-time thermal stress prediction for workers based on wearable devices -that are also compatible with their working tasks- can be expected, as highlighted by various works in literature [97,98]. The use of off-the-shelf wearable devices may lead to the development of more reliable indicators and predictive models that could help defining strategies and solutions to mitigate heat/cold stress and, thus, improving worker safety and productivity.

6. Conclusions

In this work, a detailed framework about the use of off-the-shelf wearable sensing devices in thermal comfort studies is provided. For this purpose, a systematic review of 35 scientific papers -selected out 302 resulting from the initial database query-) was performed considering the last ten years as time span (2012–2022). The results show that the use of off-the-shelf wearable sensing devices has remarkably increased in the last years and the most adopted types of devices are wristbands, headbands, chest bands, and other devices, such as miniature data loggers and activity sensors. Those devices are adopted in investigations related to thermal comfort with different purposes, that are finding correlations between physiological signals and thermal sensations, training and/or validating thermal comfort models, improving data acquisition, and controlling HVAC systems. Empatica E4 and Fitbit are the off-the-shelf wristbands that are mostly adopted for thermal comfort investigations. Those devices are mainly used to monitor the electrodermal activity, the heart rate, and the wrist skin temperature. Muse 2 is the off-the-shelf headband that was used in various work to acquire the electroencephalogram. Amongst chest bands, BioHarness 3.0 and Polar H7 are the most adopted to acquire the heart rate. Finally, DS1923 iButton and Move 3 are adopted to monitor the skin temperature and activity level, respectively.

The analysis of the considered papers and the highlighted research gaps show that two main research streams can be expected for the coming future. On the one hand, future investigations could aim at strengthening the knowledge about statistical correlations between thermal sensations and physiological signals, as well as defining standardized procedures for the model development and validation, also supported by AI-based techniques. On the other hand, future investigations could aim at integrating of off-the-shelf wearable devices and personalized thermal comfort models into HVAC control systems.

Author statement

Andrea Costantino: Conceptualization; Methodology; Software; Validation; Formal analysis; Investigation; Data Curation; Writing – Original Draft; Writing – Review & Editing; Visualization. **Maria Ferrara**: Conceptualization; Validation; Investigation; Writing – Review & Editing; Supervision. **Marco Arnesano**: Conceptualization; Writing – Review & Editing; Funding acquisition. **Enrico Fabrizio**: Conceptualization; Writing – Review & Editing; Supervision; Project administration; Funding acquisition.

Declaration of competing interest

The Authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A

Table A1
Technical specifications of Empatica E4 wristband.

		Empatica E4 wristband
HARDWARE	*Description*	A wearable wireless device designed for comfortable, continuous, real-time data acquisition in daily life.
	Case dimension	44 mm, 40 mm, 16 mm
	Case weight	25 g
OPERATING CONDITIONS	*Temperature*	−10 °C — 40 °C
	Relative humidity	20%–95% of relative humidity
	Battery	260 mAh with 3.7V output
	Battery duration	Streaming mode 20+ hours Recording mode 36+ hours
	Charging time	<2 h
DATA MANAGEMENT	*Software*	Empatica Manager (PC), Empatica E4 real-time app
	Data storage	60+ hours
	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	View data and graph and download raw data in CSV format from Empatica cloud platform for analyses in third party applications.
MEASURED SIGNALS	*Electrodermal activity*	• Sampling frequency: 4 Hz (Non customizable). • Resolution: 1 digit ~900 pS. • Range: 0.01 μS – 100 μS. • Alternating current (8 Hz frequency) with a max peak to peak value of 100 μA (at 100 μS). • Electrodes: Placement on the ventral (inner) wrist. Snap-on silver (Ag) plated with metallic core. Electrode longevity: 4–6 months
	Blood volume pulse	• PPG sensor: sampling frequency 64 Hz (Non customizable). • Sensor output resolution 0.9 nW/Digit. • The heart rate is derived from this measurement.
	Skin temperature	Infrared thermopile: • Sampling frequency: 4 Hz (Non customizable). • Range: 40 °C–85 °C for ambient temperature (only available with custom engineering work), −40 °C — 115 °C for skin temperature. • Resolution: 0.02 °C. • Accuracy ±0.2 °C within 36 °C–39 °C.
	Acceleration	Sampling frequency: 32 Hz (Non customizable). • High sensitivity motion detection across 3 axes: X,Y, and Z. • Default range ±2 g. • Ranges of ±4 g or ±8 g are selectable with custom firmware. • Resolution: 8 bits of the selected range.
MAIN REFERENCES	*User manuals*	Empatica E4 User Manual [99]
	Product webpages	Get started with your new E4 wristband [100]

Table A2
Technical specifications of Fitbit Versa 4 wristband.

	Fitbit versa 4 wristband	
HARDWARE	*Description*	NA
	Bracelet Dimensions	Small: 140 mm–170 mm of wrist circumference Large: 180 mm–220 mm of wrist circumference
	Bracelet weight	NA
OPERATING CONDITIONS	*Temperature*	−10 °C — 45 °C
	Relative humidity	NA
	Battery	Rechargeable lithium-polymer battery
	Battery duration	6+ days
	Charging time	1–2 h
DATA MANAGEMENT	*Software*	Fitbit app
	Wireless	Bluetooth 5.0 and NFC chip
	Data storage	7 days
	Data transfer	Data can be exported from active Fitbit accounts through the webpage. Recent data (up to 31 days) are immediately available, while lifetime data are available upon request.
	Data format and analysis	Data can be exported in.csv format
MEASURED SIGNALS	*Heart Rate*	NA
	Respiration rate	NA
	Acceleration	NA
	Skin temperature	NA
	Oxygen saturation	NA
MAIN REFERENCES	*User manuals*	Fitbit Versa 4 – User Manual Version 1.1 [101]
	Product webpages	How do I export my Fitbit account data? [102]

Table A3
Technical specifications of Muse 2 headband.

	Muse 2 headband	
HARDWARE	*Description*	A multi-sensor meditation device that provides real-time feedback on your brain activity, heart rate, breathing, and body movements
	Dimension	Between 30 and 35 cm from ear to ear
	Weight	38.5 g
OPERATING CONDITIONS	*Temperature*	NA
	Relative humidity	NA
	Battery	Rechargeable Li-ion
	Battery duration	5 h
	Charging time	3 h
DATA MANAGEMENT	*Wireless*	Bluetooth 5.0
	Software	Muse: EEG Meditation & Sleep app
	Data storage	None
	Data transfer	Through Bluetooth and Micro USB protocol
	Data format and analysis	Data can be exported in.csv format through a third-party apps, such as Mind Monitor
MEASURED SIGNALS	*Electroencephalography*	• 4 EEG channels +2 amplified Aux channels • Sampling rate (per channel): 256 Hz • Resolution: 12 bits per sample
	Acceleration	• Three axes • Range: ±4 g • Sampling rate: 52 Hz • Resolution: 16 bits
	Photoplethysmography	• 3 LEDs: infrared, infrared, red • Sampling rate: 64 Hz • Resolution: 16 bits
MAIN REFERENCES	*Product webpages*	Muse 2 presentation webpage [103] Muse 2 product comparison [104]

Table A4
Technical specifications of BioHarness 3.0 chest band.

	Bioharness 3.0 chest band	
HARDWARE	*Description*	A physiological monitoring telemetry device intended for monitoring of adults in the home workplace and alternate care settings
	Transmitter dimension	28 mm (diameter), 7 mm (thickness)
	Transmitter weight	18 g
OPERATING CONDITIONS	*Temperature*	−30 °C–60 °C
	Relative humidity	NA
	Battery	3.7 V lithium-polymer rechargeable battery
	Battery duration	12–28 h in active mode (logging + transmitting data), 35 h in standby mode (logging)
	Charging time	3 h
DATA MANAGEMENT	*Wireless*	Bluetooth and 802.15.4 frequencies simultaneously
	Software	Zephyr configuration tool, Zephyr's OmniSense software, Software Developer's Kit (SDK) provided
	Data storage	500+ hours (general), – 140 h (general + heart rate), 280 h (general + accelerometer)
	Data transfer	Bluetooth, ECHO (802.15.4 transmitting mode), Configuration cradle (USB protocol).
	Data format and analysis	• .csv format. • .dat/.hed file pairs. These are data files design for input of large data sets into a 3rd party data processing application. • .kml files, if used in conjunction with a supported Bluetooth GPS device.
MEASURED SIGNALS	*Heart rate*	• Range: 25–240 bpm (±1 bpm) • Sampling frequency: 250 Hz
	Respiration rate	• Range: 3–70 bpm (±1 bpm) • Sampling frequency: 25 Hz
	Acceleration	• Range: (±) 16 g on any axis • Sampling frequency: 100 Hz
	Activity	• Vector Magnitude Units (VMU): 16 g • Sampling frequency: 125 Hz
	Posture	• Dynamic range: ±180° • Reporting frequency: 1 Hz
MAIN REFERENCES	*User manuals*	BioHarness 3.0 User Manual [71] BioHarness 3.0 Log Data Description [105]

Table A5
Technical specifications of Polar H7 chest band.

	Polar h7 chest band	
HARDWARE	*Description*	NA
	Dimension	NA
	Weight	NA
OPERATING CONDITIONS	*Temperature*	−10 °C–50 °C
	Relative humidity	NA
	Battery	CR 2025 lithium battery
	Battery duration	200 h
	Charging time	Non-rechargeable battery
DATA MANAGEMENT	*Wireless*	Bluetooth
	Software	Polar Beat app
	Data storage	None
	Data transfer	To the Polar Beat app (smartphone or PC) via Bluetooth.
	Data format and analysis	.csv and.xls formats.
MEASURED SIGNALS	*Heart rate*	NA
MAIN REFERENCES	*User manuals*	Polar H7 User Manual [106]

Table A6
Technical specifications of iButton DS1923 miniature data logger.

	Ibutton ds1923 miniature data logger	
HARDWARE	*Description*	A rugged, self-sufficient system that measures temperature and/or humidity and records the result in a protected memory section.
	Dimension	17.35 mm (diameter), 5.89 mm (thickness)
	Weight	5 g
OPERATING CONDITIONS	*Temperature*	−20 °C–85 °C
	Relative humidity	0%–100% relative humidity
	Battery	3 V Lithium coin cell battery, size BR 1225
	Battery duration	Depending on use, 8-bit logging at 20 °C: 300 days at 30 s interval, 5.5 years at 10 min interval
	Charging time	Non-rechargeable battery, quite hard to replace
DATA MANAGEMENT	*Wireless*	Not present
	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 storage	512 Bytes. A total of 8192 8-bit readings or 4096 16-bit readings taken at equidistant intervals ranging from 1 s to 273 h 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	NA
MEASURED SIGNALS	*Temperature*	• Range: 20 °C — 85 °C • Accuracy: ±0.5 °C (in range: 10 °C–65 °C) with software correction • Resolution: 0.5 °C (8 bit), 0.0625 °C (11 bit) • Sampling rate: 1 s up to 273 h
	Relative humidity	• Range: 0–100% • Accuracy: ±5% with software correction • Resolution: 0.6% (8 bit), 0.04% (12 bit) • Sampling rate: 1 s up to 273 h
MAIN REFERENCES	*User manuals*	iButton DS1923 datasheet [107] iButton catalogue [108]
	Product webpages	iButton DS1923 webpage [109]

Table A7
Technical specifications of Move 3 activity sensor.

	Move 3 activity sensor	
HARDWARE	*Description*	A scientific research instrument designed to capture the physical activity and other secondary parameters of a person. It is designed and optimized for research applications
	Dimension	62.3 mm, 38.6 mm, 11.5 mm
	Weight	25 g
OPERATING CONDITIONS	*Temperature*	−20 °C–60 °C (0 °C–45 °C during charging)
	Relative humidity	0–75%
	Battery	3 V Lithium-Polymer battery
	Battery duration	9 days (recording), 2 months (maximum recording capacity with a 15-min daily charge)
	Charging time	It is recommended a daily recharging of about 15 min to achieve the 2-month maximum battery duration
DATA MANAGEMENT	*Wireless*	Bluetooth Smart
	Software	SensorManager (sensor configuration), UnisensViewer (to view the stored data)
	Data storage	NA
	Data transfer	Micro-USB, Bluetooth Smart
	Data format and analysis	.csv and unisens format (an open data format, .xml + .bin). The stored data can be analyzed through DataAnalyzer
MEASURED SIGNALS	*Acceleration*	• Range: ±16 g • Output rate: 64 Hz • Noise: 4 mg
	Barometric pressure	• Range: 300 hPa — 1000 hPa • Output rate: 8 Hz • Noise: 0.03 hPa
MAIN REFERENCES	*User manuals*	Move 3 User Manual [110]
	Product webpages	Move 3 webpage [111]

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