Physiological sensing for thermal comfort assessment

Dragos-Ioan Bogatu*[1], Jun Shinoda[1], José Joaquín Aguilera[2], Bjarne W. Olesen[1], Futa Watanabe[3], Yosuke Kaneko[3], and Ongun B. Kazanci[1]

1 International Centre for Indoor Environment and Energy – ICIEE, Department of Environmental and Resource Engineering, Technical University of Denmark
Nils Koppels Allé, Building 402
2800 Kgs. Lyngby, Denmark
**Corresponding author: drabo@dtu.dk*

2 Section of Thermal Energy, Department Civil and Mechanical Engineering, Technical University of Denmark
Nils Koppels Allé, Building 403,
2800 Kgs. Lyngby, Denmark

3 Mitsubishi Electric Corporation
5-1-1 Ofuna, Kamakura
Kanagawa 247-8501, Japan

ABSTRACT

Accounting for inter- and intra-personal differences requires individual and cohort comfort models. For their development, emulators for thermal sensation of occupants are needed. Physiological signals can be acquired using both wearable and contactless devices. However, due to the widespread availability of sensing methods it is difficult to select the proper measuring method for the application. The objective of this study is to provide an overview of the capabilities of contemporary devices that measure physiological indicators used in literature and identify their capabilities and limitations. The analysis was made on a dataset of reviewed thermal comfort research studies that employed physiological sensing devices in experimental and field test campaigns. The physiological indicators investigated in literature were derived from the human thermoregulation mechanism. The physiological indicators measured were neural activity (brainwave frequency bands), heartbeat (heart rate and heart rate variability), blood flow (blood pressure, blood oxygen saturation, skin blood flow), activity (metabolic rate, activity, calorie consumption), temperature (core and skin), sweat (relative humidity, skin conductance, skin hardness, and amount of sweat). The wrist is the most investigated body part as it is a convenient area for acquiring multiple physiological indicators i.e., all physiological measurements except for ECG and EEG measurements. However, most devices are not "plug-and-play" solutions for thermal comfort assessment. As contact devices, smartbands acquire an extensive set of indicators but present 3rd party data privacy protocols which may limit their applicability. Cameras (RGB and infrared) can only be used to acquire skin temperature and heart rate but can be deployed in the space by the building owner. Further studies are required on the sensing accuracy and signal variability as a function of thermal sensation to determine the optimal measurement method.

KEYWORDS

Thermal comfort, sensing strategies, physiological indicators, wearable/contactless, sensing performance

1 INTRODUCTION

In order to deal with inter- and intra-personal differences, personal and cohort thermal comfort models were proposed (Kim, Schiavon, and Brager 2018; Quintana et al. 2022). However, these models require input from or representative of the occupant in question (Deng and Chen 2020; Laftchiev and Nikovski 2017). As thermal comfort is a function of thermoregulatory aspects, emulators such as physiological signals could be used to distinguish between thermal sensation of different people and for the same person over time (Bogatu et al. 2023; Lee and Ham 2021).

Further studies are though required on the set of indicators and their variability as a function of thermal sensation across people with different anthropometric characteristics and behaviour.
With economically feasible physiological sensing methods emerging, wearable sensing devices become widespread and monitoring physiological indicators becomes simpler in both experiments and field studies. However, with a market under constant change it is difficult to select the proper measuring method for the application. The objective of this study is to provide an overview of the capabilities of current physiological indicator measuring devices used in literature and identify their benefits and limitations.

2 METHODS

The objective was to identify current physiological indicator measuring techniques in thermal comfort studies. The analysis was made on an existing dataset (Bogatu et al. 2023) where the objective was to determine relevant indicators for data driven thermal comfort prediction for HVAC control. The dataset was generated using Google Scholar, Scopus, and Web of Science, and the "reference by reference" method.
For finding relevant research studies permutations, combinations, and specific keywords such as physiological, physiology, wearable, contactless, smart control, control, smart building, thermal comfort, sensing were used. The database consisted of 94 articles that measured physiological indicators, used either physiological, environmental, behavioural, or anthropometric measurements in personal comfort model development, or integrated occupant feedback or physiological indicators in the HVAC control.

3 RESULTS

3.1 Physiological indicators

Physiological indicators used in thermal comfort studies are derived from human thermoregulation mechanism (Bogatu et al. 2023). Thermoregulation is controlled by the central nervous system, which sends nerve impulses based on signals received at skin level. The nervous system regulates blood flow through the heart and through the constriction and dilation of vessels, perspiration, and metabolic rate to regulate body temperature. Therefore, physiological indicators can be obtained from:

- Neural activity: brainwave frequency bands.
- Heartbeat: heart rate (HR) and heart rate variability (HRV).
- Blood flow: blood pressure (BP), blood oxygen saturation (SpO_2), skin blood flow (BF).
- Activity: metabolic rate (MET), activity, calorie consumption.
- Temperature: core (T_{CORE}), skin temperature (T_{SK}).
- Sweat: skin relative humidity (RH_{SK}), skin conductance (SC), skin hardness, and amount of sweat.

3.2 Physiological indicator sensing

Figure 1 shows the frequency of investigated body parts and the corresponding indicators. Most measurements were made at the wrist level, followed by the forehead, hand, upper arm, cheek, chest, forearm, thigh, ankle, neck, abdomen, waist, ankle, and calf. A collection of the sensors employed in literature and their characteristics can be found in the Appendix.
Neural activity can be recorded at the head level by an electroencephalogram (EEG) instrument consisting of electrodes which measure brain electrical activity (Pigliautile et al. 2020). Advanced instruments are available where the electrodes are attached to a headset (Kim and Hong 2020; Pigliautile et al. 2020). Although portable, these devices must be in contact with

the subject during the measurement and require dedicated software to analyse the obtained information. The analysis of the brainwaves power spectrum is made with a fast Fourier transform method to obtain the distribution of the magnitude of signals within particular frequency bands, such as Alpha, Beta, Delta, Theta, and Gamma ranges (Shan and Yang 2020). Recent devices are convenient, becoming light and easy to set up but highly intrusive if intended for long term use (Pigliautile et al. 2020; Shan and Yang 2020).

HR can be derived from HRV which can be obtained by measuring the heart's electrical activity (Chaudhuri et al. 2018; Nkurikiyeyezu, Suzuki, and Lopez 2018). **Error! Reference source not found.**The HRV is usually measured at the chest level or a combination of chest, arm, wrist, thigh, and ankle through electrodes placed on the skin (Gwak et al. 2016; Zhu et al. 2018). Since the electrodes are in contact with the skin, electrocardiogram (ECG) devices must be in occupant proximity. Although intrusive, wearable devices (medical and commodity sensors) for chest placement are available (Liu et al. 2019; Pigliautile et al. 2020). If other indicators than HR must be obtained, these devices are no longer "plug and play" and may require additional data processing.

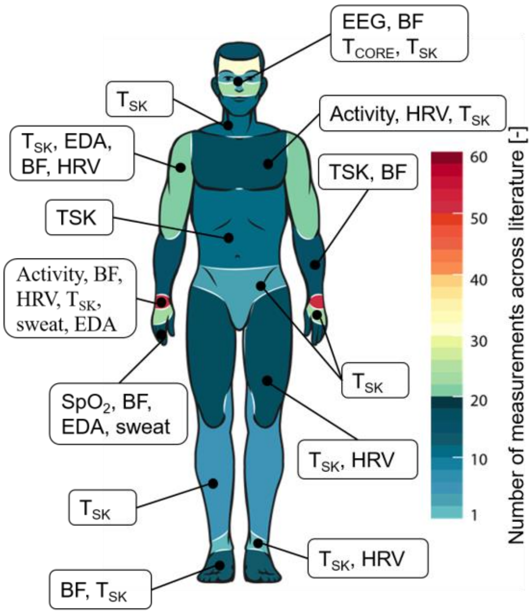

Figure 1. Frequency of physiological measurements across the human body.

Photoplethysmography (PPG) measures blood volume changes in the vessels, where light transmitted from a source onto the skin tissue is being either absorbed or reflected. The increase in blood volume is obtained based on the relative change in the light captured by the photodetector (Jung and Jazizadeh 2018b). PPG measurements can be made at the skin level, e.g., on the face where there is a high density of blood vessels (Ghahramani et al. 2016), at the wrist (Laftchiev and Nikovski 2017), or finger (Chaudhuri et al. 2020). Wrist measurements usually make use of smartbands or smartwatches equipped with a PPG sensor (Lee and Ham 2021). Blood volume changes measured at the face level are usually contactless and are obtained using Red Green Blue (RGB) cameras that track tiny colour changes in the reflected light of the region of interest (Dabiri and Jazizadeh 2014; Jung and Jazizadeh 2018a). Blood flow can be measured through laser Doppler flowmeters - similar principle to PPG using different light frequencies (Cheng, Lee, and Huang 2018). This technology was mainly used for measuring the microvascular blood flow at the finger (Cheng et al. 2018) or foot (Song et al. 2016) level. Blood pressure was measured by using a sphygmomanometer (inflatable cuff coupled to a manometer) and was rarely employed most likely due to the difficulty of obtaining a continuous measurement. SpO_2 can also be obtained through PPG at the finger level (Chaudhuri et al. 2018, 2020). An indirect measurement of blood oxygen intake, respiration,

was measured contactless using Doppler radar sensors through the motion of the chest and abdomen areas (Jung and Jazizadeh 2018a). BF, BP, and SpO_2 were investigated using medical and research grade sensors where devices were placed in contact with the skin.
The MET can be measured with a cardiopulmonary tester (Song et al. 2016). This involves a spiroergometer device where a mask is used to analyse the oxygen and carbon dioxide in the inhaled and exhaled air. Although portable products exist, they cannot be worn in daily life due to their intrusiveness. Activity level, representative of the MET, is usually measured instead (Lee and Ham 2021). Motion-based activity was measured using either wrist or chest connected tri-axial accelerometer devices. These sensors are relatively cheap and are usually integrated in smartwatches and smartbands (Laftchiev and Nikovski 2017). Other approaches involved the use of weight and calorie consumption estimation (Huang, Yang, and Newman 2015).
T_{CORE} is approximately measurable from the oesophagus, rectum, gastro-intestinal tract, mouth, tympanum, auditory canal regions (CEN 2021). Other options are radio-pills (Wang et al. 2007) or predicting it from heart rate measurements with high accuracy (Nazarian et al. 2021). The inner eye is also a suitable measurement point, obtainable using thermal cameras (Metzmacher et al. 2018). However, certain studies considered the eye temperature as the T_{SK} (Cosma and Simha 2019a, 2019b). A wireless non-invasive thermometer which estimates T_{CORE} based on T_{SK} and heat flux is also available, though costly (Ajčević et al. 2022).
T_{SK} can be obtained using both wearable and contactless devices (Hwang et al. 2019; Salehi, Ghanbaran, and Maerefat 2020). Except for measurements on the eye, T_{SK} represents the most investigated indicator for each human body part. The standard way of measuring T_{SK} involves the use of low-cost thermocouples (Jung and Jazizadeh 2018b; Liu et al. 2020) and resistance temperature detectors (Lopez et al. 2016) which are wired to a logging system. This method is highly intrusive and makes it difficult to perform daily activities. Wireless T_{SK} sensors are also available, consisting of button sized devices (Liu et al. 2019), which can be attached to the skin through e.g., medical tape. These devices cannot transfer data in real-time though, making them impractical for smart system integration. Smartwatches and smartbands were previously reported throughout literature as useful for measuring T_{SK} in the wrist area due to the convenient placement of the sensors (Barrios and Kleiminger 2017; Deng and Chen 2020; W. Li, Zhang, and Zhao 2019; Yoshikawa et al. 2019). Still, few newer smartwatch/smartband devices make available T_{SK} as a signal. The facial area has also drawn extensive attention due to the appearance of low-cost contactless monitoring technologies (Ranjan and Scott 2016; Warthmann et al. 2018). T_{SK} was obtained through thermal infrared cameras generally pointed at the face, a feasible non-intrusive method (Cosma and Simha 2019b; Li et al. 2020; Lu et al. 2019; Pavlin et al. 2017), or through infrared lasers which must be close to the skin level for a continuous measurement of the point of interest (Luo et al. 2018). An innovative solution was found in literature where infrared sensors were attached to a pair of glasses (Ghahramani et al. 2016). The main advantage of contactless T_{SK} measurements is that the measurement is not influenced by the sensor covering the skin area under investigation (Metzmacher et al. 2018).
Skin relative humidity (RH_{SK}) was measured using button sized sensors in studies involving high physical activity (Priego-Quesada et al. 2020). Sweat rate was also directly measured with an innovative sensor (watch-type device with a capacitive humidity sensor) with low operation power and weight (Sim, Yoon, and Cho 2018). SC, or electrodermal activity (EDA), can be obtained through electrodes connected to the fingers (Pigliautile et al. 2020) or at the wrist level through smartbands (Lee and Ham 2021). Only one mention of skin hardness was found in the literature measured using a durometer (not designed for skin hardness measurements) which was placed at the skin level of the arm or wrist (Yoon et al. 2018).

3.3 Capabilities and limitations of current sensing strategies

A summary of capabilities and limitations of the physiological measurement strategies are given in Table 1. The analysis was made by comparing wearable and contactless devices.
Wearable devices represent relatively cheap and mature products. They can be wired or wireless. Device examples are probes, telemetry devices, smartwatches/smartbands, and headsets. Contactless examples found in literature are RGB cameras, infrared thermal cameras, and devices employing laser Doppler velocimetry.

Table 1: Capabilities and limitations of measuring devices for physiological indicators.

Device	Capabilities	Limitations
Wearable	• May be integrated in a device attached to an occupant • May measure multiple parameters • Clothing does not interfere with the measurement • Mature products • May be relatively cheap • Can be placed directly on the skin • Can be placed on different and multiple body areas • Can be connected via cloud-based solutions	• Measurement length dependent on the battery life and data storage capacity of the equipment • Could be intrusive and invasive (e.g., chest strap) • Accuracy issues (improper use, movement, fastening option) • Sensor accuracies may be unknown • Covers body area where measurement is made • Narrow operating ranges • Single point measurement • Influenced by physical pressure, insulation from fitting material and thermal inertia of the sensor • Inconvenient if wired
Contactless	• Can gather data on body areas not covered by clothing, e.g. face • Non-invasive and non-intrusive • Can capture a bigger surface area • Can detect changes from the skin naturally and directly impacted by the surrounding environment	• May require a complex system consisting of multiple nodes (e.g. depth and thermal image camera) • Privacy concerns • Little flexibility regarding placement • Correction regarding clothing might be required • May not be suitable for multi-occupancy spaces due to the limited field of view • Error in detecting area of interest for measurements • Can be difficult to implement in building due to size and compatibility issues (e.g. in Building Management Systems). • Higher cost compared to wearable sensors

4 DISCUSSION

As wearables, devices designed for measuring certain physiological indicators, e.g., HRV, brainwave frequency bands, SpO_2, can be found though lacking wireless connectivity. Few commodity health monitoring telemetry devices designed to acquire multiple physiological indicators were observed (Chaudhuri et al. 2018). Smartbands/smartwatches were the most complete devices, being able to measure multiple indicators, such as T_{SK}, HR, SpO_2, and activity simultaneously. However, just as chest bands, they are commodity devices lacking standardized datasheets with information on the device's accuracy, resolution, and range. Extracting real-time data from these devices may also not be possible or would require specific knowledge. On the other hand, medical and research-grade devices are costly and usually designed for measuring specific physiological indicators, e.g., SC and brainwave sensors.
For quantifying physiological indicators in real-time, RGB and infrared thermal cameras could be feasible. RGB cameras are cheaper and usually available at the workspace. Although privacy measures such as discarding images after data collection must be taken into account when employing cameras (D. Li, Menassa, and Kamat 2019), these systems also enable pose tracking (Qian et al. 2020; Yang et al. 2019), age, and clothing estimation (Rida et al. 2023), which may complement T_{SK} and HR measurements. Infrared thermal cameras present a wider working range than contact measurements (e.g., thermocouples) but have a slightly worse correlation with the thermal sensation (Wu et al. 2019). When compared to resistance temperature sensors (usually with an accuracy of ±0.2 °C) only a maximum of 0.5 to 0.7 K difference was observed (Metzmacher et al. 2018). Low-cost options present low image resolution, which may lead to difficulties in detecting the human profile, but information from the surrounding pixels

surrounding could reduce noise and thus improve stability. Combining RGB and infrared thermal cameras may even increase measurement accuracy as the influence of light is reduced generating clearer contours (Metzmacher et al. 2018). However, both solutions require additional data processing for obtaining the desired parameters (Dabiri and Jazizadeh 2014).
From a practicality point of view, wearable devices are connected to the occupant which makes it difficult to determine ownership, operation, and maintenance responsibility. Contactless devices are deployed in the space. Although requiring the consent of the occupants, ownership, operation, and maintenance can be performed by the building owner.

5 CONCLUSIONS

Acquiring physiological indicators in real-time still represents a difficult task and thus further development of current sensing devices is required. Not all devices measuring physiological indicators present real-time data access while "plug-and-play" solutions specifically designed for thermal comfort assessment are lacking.
Contactless devices (e.g., RGB and infrared cameras) can only be used to acquire skin temperature and heart rate and require extensive data processing. Wearable devices can be used to acquire an extensive range of indicators, with the wrist area being the most versatile. Smartwatches and smartbands are mature devices used to acquire multiple physiological indicators (T_{SK}, HR, SpO_2, and activity) simultaneously. Since they are mostly consumer products protected through 3rd party data privacy protocols, these devices cannot be deployed in buildings with ease. Measurement accuracy represents a limitation for low cost contactless solutions, which requires further investigation.

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APPENDIX

Table 2. Characteristics of sensors employed in literature (T: temperature, RH: relative humidity, HR: heart rate, EDA: electrodermal activity, SC: skin conductance, ACC: accelerometer, ECG: electrocardiogram, SpO_2: blood oxygen saturation, EEG: electroencephalogram).

Type	Model	Measurable parameters	Details
Smartwatch or Smartband	Microsoft Band 2	HR, T, EDA, ACC	Smartwatch
	LG Watch R (W110)	HR	Smartwatch
	Hesvit S3	HR, T (Acc. ±0.3 °C, Res. 0.1 °C), RH_{SK}	Smartband
	Empatica E4	HR, T (Range -40 to +85 °C), ACC (± 2g), EDA (Range 0.01 to 100 µS)	Smartband
Temperature sensor or probe	Exacon D-S18JK	T (Acc. ±0.1 °C, Range 0 to 50 °C)	Temperature probe
	TT-K-30-SLE	T (Acc. ±1.1 °C or ±0.4 %, Range 0-350 °C)	Thermocouple
	iButton DS1923	T (Acc. ±0.5 °C, Res. 0.5 °C, Range -10 to 65 °C), RH (Acc. ±5%, Range 0 to 100%, Res. 0.6% or 0.04%)	Temperature and RH probe
	muRata NTC	-	Thermistor
	WZYCH4	T (Sens. 0.1 °C)	Temperature probe
	SBS-BTA	T (Acc. ±0.5 °C, Res. 0.03 °C)	Thermistor
	Gigarise SG900	T (Acc. ±0.2 °C, Range -50 to +180 °C)	-
	MLX90614	T (Acc. ±0.5 °C, Res. 0.02 °C)	Infrared sensor
	Beurer FT70	T: ear (Acc. ±0.2 °C, Range 34-43 °C), forehead (Acc. ±0.2 °C, Range 34-43 °C), object (Acc. ±1.5 °C, Range 0-100 °C)	Medical device
	CORE	T (Acc. ±0.05 °C from 20 °C to 42 °C), T_{CORE} (± 0.28 (1σ) ± 0.21 (MAD) – chest)	Body temperature sensor
Heart rate sensor	Zephyr HXM-08L	HR (Acc. ±3%, Range 0-200 bpm)	Telemetry device
	Polar H7	ECG, HR (Acc. ±4%)	Chestband
	HER-BTA	HR (Freq. 5 kHz ±10 %)	
	HRV101	ECG (SRate 250 Hz and 400 Hz, BW 0.05-40Hz)	ECG Holter
	BioHarness 3.0	HR (Acc. ±1 bpm, Range 25-240 bpm), ECG, respiration rate, body orientation, ACC	Physiological monitoring telemetry device
Health monitoring device	MySignals, Libelium CO.	HR (Acc. ±5%, Range 25 to 250 bpm), SpO_2 (Acc. ±2%, Range 35 to 100%, SC (Acc. ±5%, Range 0-20 µS), BP (Acc. ±3 mmHg, Range 0 – 300 mmHg)	Pulse oximeter, Sphygmomanometer
Laser Doppler	moorVMS-LDF1	Blood flow (Acc. ± 10%, Range: 0-1000AU)	Deeper tissue blood flow and temperature monitoring
Neural headset	EPOC+	14 ch. EEG (Res. 14 bits, DRange 8400 µV, BW 0.2-45 Hz, BL 12 h)	14 channel EEG
	B-Alert X10, ABM	9 ch. EEG (Res. 16 bit, DRange ±1000 µV, BL 8+ h)	9 channel EEG
Camera	Yukai USB	Sweat area/sweat pore diameter	Digital camera with microscope
	Microsoft Kinect	RGB-DT camera (Acc. ±4 cm at 5 m, depth range 0.8-5 m, $48)	RGB-Depth Temperature
	FLIR A35	T_{SK} (Acc. ±5 °C or ±5 % of reading, Range -23 to 135 °C/-40 to 550 °C, Sens. < 0.05 °C)	Infrared
	FLIR A655sc	T_{SK} (Acc. ±2 °C or ±2 % of reading, $22000)	Infrared
	FLIR T540	T_{SK} (Acc. ±2 °C or ±2% of reading, Range -20 to 120 °C, Res. 464x348 px)	Infrared
	FLIR B8400	TSK (Range -20 to 120 °C)	Infrared
	FLIR Lepton	TSK (Acc. ±0.5 °C, Res. 0.1 °C, $250)	Infrared

FLIR Lepton 2.5	TSK (Acc. ±5 °C or ±5 % of reading, Range -10 °C to 65 °C, Sens. < 50 mK, $200)	Infrared