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Modeling local thermal responses of individuals: Validation of advanced human thermo-physiology models

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ABSTRACT

Human thermo-physiology models (HTPM) are useful tools to assess dynamic and non-uniform human thermal states. However, they are developed based on the physiological data of an average person. In this paper, we present a detailed evaluation of two sophisticated and well-known models, JOS3 and ThermoSEM, with the objective to evaluate their capabilities in predicting the local skin temperature of individual people as both models use individual parameters such as sex, height, weight, and fat percentage as input. For the purpose of validation, controlled experiments were conducted with six human subjects (3 males, 3 females) at different environmental conditions (22–28 °C). The measured core temperature and the local skin temperature at 14 locations were used to evaluate the predicted values. Outputs from both HTPMs followed the dynamic trend of the experiments, with a root mean squared error (RMSE) of 0.9–0.3 °C for core temperature and 1.3–0.9 °C for mean skin temperature from both ThermoSEM and JOS3 correspondingly. However, the main errors came from the body extremities. The RMSE was different for each subject, and both models showed lower errors in the warmer environment. The average RMSE for the hands of all subjects was 2 °C from ThermoSEM and 1.9 °C from JOS3, while it was 0.8 °C for the forehead in both models. The paper highlights the capabilities and limitations of the selected HTPMs and, furthermore, discusses the application of HTPMs in the field of personalized thermal comfort.

1. Introduction

1.1. Local thermal sensation and thermal responses of individuals

Thermal comfort can be affected by physical, psychological, and behavioral aspects of individuals. Physical parameters consideration is the foundation of the Predicted Mean Vote-Predicted Percent Dissatisfied (PMV-PPD) comfort model [1], while the importance of human psychological and behavioral adaptation is considered in the adaptive comfort model [2]. As the human body continuously generates metabolic heat distributed throughout the body via blood circulation and transferred to the body and clothing surface, the heat balance between the human body and the environment is the main physical mechanism influencing thermal comfort. Thus, physiological factors such as thermal responses of the human body can be somewhat related to the thermal sensation of a person. For instance, Zhang et al. [3] and Choi and Loftness [4] have investigated the factors that influence the prediction of thermal sensation, where skin temperature was the most correlated physiological parameter that accounts for the influence of the environmental factors, the internal thermoregulation, and the individual characteristics. Bulcao et al. [5] reported that thermal comfort in humans can be linked to the skin temperature, whereas changes in both skin and core temperature are responsible for physiological reactions. Zhang et al. [3,6] developed a mathematical model that can predict the local thermal sensation and comfort of 19 body parts, as well as overall thermal sensation and comfort. The model was built upon experimental data from 109 individuals, where specific body areas were subjected to independent heating or cooling while the remaining body was exposed to a warm, neutral, or cool environment. The logistic function to predict local thermal sensation relied on the local skin temperature and its deviation from the neutral set point temperature (i.e., local skin temperature at which the thermal sensation of that particular body part feels neither warm nor cold, local thermal sensation index is 0). For the transient effect, the model also considered the derivation of core and mean skin temperature. In this regard, *human thermo-physiology models* (HTPMs) predict all the necessary physiological information that is needed to determine thermal sensation based on the models such as proposed by Zhang et al. [6].

Different occupants may perceive the same thermal environment differently, or they may achieve the same thermal comfort in different

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temperature conditions [7,8]. According to a number of studies, the perception of the indoor environment can be influenced by sex. There are studies reporting that females are more sensitive to the cold environment and prefer warmer conditions compared to males. Karjalainen [9] in a quantitative survey showed significant gender differences in thermal comfort, temperature preference, and use of thermostats. Indraganti and Humphreys [10] reported that females are more sensitive to temperature compared to males in a study conducted in conditioned office environments in different Asian countries. Yang et al. [11] in a controlled experiment showed that females tend to have lower metabolic rates than males at all temperatures and that they tend to be cooler and less comfortable than males at cool temperatures. Furthermore, the thermal neutral temperature of elder people can be different from that of young people, which can be due to health issues and the variation of muscle and blood circulation system deficiency. van Hoof et al. [12] and Giamalaki and Kolokotsa [13] showed how elderly perceive thermal comfort differently compared to young adults. Schellen et al. [14] in a controlled comparative experiment between young (22–25 y.o.) and elderly (67–73 y.o.) showed that during a constant temperature exposure, the elderly preferred a higher temperature in comparison with the young adults. Therefore, defining thermal sensation using a generalized approach is insufficient.

The thermoregulatory mechanisms of the human body can be considerably influenced by individual characteristics such as age, fitness, sex, body fat percentage, body mass index (BMI), and basal metabolic rate (BMR) variations. van Marken Lichtenbelt et al. [15] stated that considering individual characteristics and personal metabolic rate can improve the predictability of HTPM. Davoodi et al. [16] showed the effects of individual parameters such as age, gender, body mass index, and BMR in improving the prediction in a two-nodes thermophysiology mode. Rida et al. [17] and Novieto [18] implemented the physiological body characteristics of elderly in human thermo-physiology models to get a better prediction of thermal responses in elderly people. Therefore, it can be advantageous to use advanced HTPMs to consider complex thermal environments, local thermal states (i.e., body part temperature at a given time), and the physiological differences between people to evaluate the thermal responses of building occupants in a personalized way.

1.2. Overview of human thermo-physiology models

Mathematical models of human thermoregulation vary in their level of detail, complexity, and applicability [19]. The first attempt at modeling the human body's heat exchange with the environment started by Lefèvre in 1911 when the whole human body was modeled as a sphere [20]. With the advancement of computers, a synergy between physiology and mathematical modeling led to the development of complex HTPMs [21]. The representation of the human body by models ranges from a single cylindrical element with a core and skin shell [22] to a more detailed series of cylindrical and spherical elements [23–27], and, finally, to three-dimensional complex shapes of organs in the body parts [28]. The typical inputs used in HTPMs are environmental parameters (local air temperature, radiant temperature, air speed, relative humidity) and personal parameters (metabolic rate, local clothing insulation and sometimes body characteristics). A more detailed model requires the knowledge of the composition and thermal characteristics of local tissues, which are difficult to measure [29]. As an output, the models can predict local skin temperature $T_{skin,i}$ and the body's core temperature T_{core}. Accurate environmental data must be provided as input to the physiological model in order to obtain an accurate prediction of the person's thermal state.

In the built environment application, the HTPMs have been used in research accounting for the environmental parameters, clothing and metabolic rate variation, aiming to improve the prediction of human thermal comfort and for preliminary assessments of new designs of HVAC systems [21]. In recent years, there has been increasing interest in evaluating the thermal comfort of building occupants using computational fluid dynamics (CFD) [30,31]. In such studies, HTPMs can provide dynamic environmental boundary conditions and also reflect the thermal state of the occupant in the simulation. Furthermore, there were several attempts in the literature to couple an HTPM with an HVAC controller with an aim to reduce the use of energy in buildings while maintaining people's thermal satisfaction [32,33]. Simple models were adopted in standards, e.g., the two-node model in ASHRAE [34] used for transient thermal comfort prediction. However, the two-node model could not be applicable in non-uniform, asymmetric environments where local body parts are usually exposed to heterogeneous environments. Since a multi-segment model accounts for the local thermal environment, this allows modeling the effect of localized heating and cooling environment on human thermal perception.

The first multi-node model developed by Stolwijk [35] is considered a foundation for different multi-node models available these days. The model divides the body into 6 segments (including the head, trunk, 2 arms, and 2 legs), and each body part has 4 lumped nodes (core, fat, muscle, and skin) plus a central blood flow compartment connected to all the other nodes. The thermoregulatory control system such as shivering, sweating, vasodilation and vasoconstriction in the Stolwijk model was based on the two temperature signals, cold and warm, which reflected the change in the temperature of each node. Various thermophysiological models evolved from the Stolwijk model to improve the prediction of human thermal responses in transient and non-uniform environments. Examples of the most known and developed lumped models are Fiala [24], Tanabe (JOS1–JOS3) [27], the Berkeley Comfort Model [25], the AUB model [26] and ThermoSEM [23,36]. The well-established HTPMs are summarized in Table 1, improvements in each model over the years and their blood circulation models are also highlighted. The models are normally divided into a controlled passive part and an active control part [24,25,37,38]. The passive part determines the properties of the body, heat transfer within the body, and heat transfer between the body and the environment. The active part determines the temperature control system. Based on the literature, some models have been more widely accepted and validated than others. Table 1 presents whether the developers validated their models with their own experiments or with third-party experiments, and the number of references used for validation. Mean skin temperatures and core temperature are always used for validation; however, other researchers presented a comparison of local skin temperatures' prediction [21]. Despite the fact that many of these models can take into account physiological variations between individuals, they are usually generalized and use data from a typical young male. van Marken Lichtenbelt et al. [39] concluded that body composition is an important factor in physiological response differences. Some researchers considered individual characteristics and applied them in a two-node thermophysiology model [16,40], and others considered them in multi-segment models [27,41]. The majority of those models did not consider the individual differences between subjects; their validation is mainly done by comparing the model outputs for a young male with the averaged data from all experimental participants. However, there are several attempts to obtain a personalized thermoregulation model that can be scaled to an individual [15,27,29,39,42]. Just recently the use of HTPM to model individual people has started to develop, for example, the two models that reported individual comparison using personalized data are ThermoSEM and JOS3 [27,41]. Thus, this research investigates if ThermoSEM and JOS3, which use individual body parameters as input, and are capable of predicting the local thermal responses of individuals.

Table 1
Overview of human thermo-physiology models.

Model name	Pub. year	Body parts	Nodes	Features/Improvements	Blood circulation model	Validation
Stolwijk [35]	1971	6	25	First to describe local effects due to non-uniform environments and non-uniform clothing coverage	Central blood pool	Experiment previously conducted by authors [43]
Gagge [44]	1972	1	2	Consideration of relative humidity and skin wettedness	Central blood pool	Own experiments [45]
Fiala [24]	1999	15	187	Multi-regression model of shivering, sweating, and peripheral vasomotion	Central blood pool + regression model	Third-party experiments [43,45–57]
UCB [25]	2001	v*	v*	Variable number of body parts and nodes	Central blood pool	Third-party experiments [43,47,57,58]
Tanabe [38]	2002	16	65	Increased number of body parts	Central blood pool + setpoints	Own CFD simulation [38]
JOS2 [59]	2013	17	83	Modification of different nodes structure in Tanabe model [38], improved blood circulation model	Local artery and vein blood pool	Third-party experiments [60,61]
JOS3 [27]	2021	17	83	Consideration of personal characteristics, brown adipose tissue activity, aging effects, shortwave solar radiation	Local artery and vein blood pool	Third-party experiments [43,47,60,62,63]
ThermoSEM [15]	2004	19	262	Based on [24], the extremities were split into upper and lower parts, the skin perfusion was corrected for tissue volume	Central blood pool	Own experiments [15,39]
ThermoSEM [23]	2012	19	262	Thermoregulation is based on neurophysiology model	Central blood pool + neurophysiological skin blood flow model	Own experiments [36,64,65]
ThermoSEM [42]	2022	19	262	Improved Skin Blood Flow (SBF) model for the feet, and representation of local clothing insulation	Central blood pool	Own experiments [41]
AUB [66]	2007	15	60	Detailed blood flow circulation based on the exact physiological data	Local artery and vein blood pool	Third-party experiments [43,58,67,68]
AUB [26]	2014	25	124	Extending the artery tree to include the arterial branching to five fingers; modeling of Arterio-Venous Anastomoses (AVA) of fingers	Local artery and vein blood pool	Third-party experiments [43,68–70]

v* (variable) authors claimed an unlimited number of body parts with no constraints.

1.3. Modeling details of ThermoSEM and JOS3

The mathematical model ThermoSEM [23,42] is a direct descendent of the multi-segment model of Fiala [24]; however, it is a more comprehensive model that considers additional physiological and environmental factors that can affect thermoregulation. It was developed with the direct involvement of thermo-physiologists and has multiple differences compared to other existing models [36]. For example, the number of body parts was increased by splitting arms and legs into upper and lower parts compared to Fiala's model. It is able to take individual body characteristics (height, weight, and fat percentage) into account. The human body is defined as a concentric semi-sphere for the head and a series of concentric cylinders for the rest of the body parts. Each body part is composed of several tissue layers and each layer has its specific density, conduction, heat capacity, basal blood perfusion, and basal metabolic heat production. The model further splits each body part into multiple sectors; some body parts have two sectors (dorsal and ventral) and others have three (anterior, posterior, inferior). Fig. 1(a) presents a schematic of the ThermoSEM model that shows the body parts, section, nodes, and overview of heat transfer. ThermoSEM is known for its advanced method called *neurophysiological skin blood flow model* that simulates five phases of the thermoregulatory tract [37]. Also, the model does not rely on the traditional setpoint temperature approach as in models like Fiala and JOS3 [37]. The skin blood flow in the model is regulated by the sympathetic branches of the autonomic nervous system. The model incorporates thermal reception data and the neural pathways to model the control of skin blood flow [23,41,42,71]. In addition, ThermoSEM proved its validity in predicting the human thermal state under a transient and non-uniform environment [23,41,42,71]. The sympathetic nervous system increases the blood flow to the skin in response to a rise in core body temperature, while the parasympathetic nervous system decreases the blood flow to the skin in response to a drop in core body temperature.

The model JOS3 is based on the same underlying physiological principles as the ThermoSEM model, but it has a smaller number of body parts and a simpler mathematical structure. JOS3 is a direct advancement of Tanabe's 65-node model [27]. Compared to Tanabe's 65-node model, the number of concentric layers (e.g., fat, muscle) in some body parts is reduced in JOS3, and they were merged with either core or skin node; however, they introduced the vein and artery nodes. The model has an advanced connected blood flow system, it includes the artery and vein nodes in each body part and a superficial vein in the extremity. The arteries and veins are distributed in each of the body parts, according to the formulation in the work of Smith [68]. JOS3 also included the modeling of arteriovenous anastomoses (AVA) blood circulation phenomena in hands and feet to improve the overall model predictability. Fig. 1(b) shows the different body parts and nodes that

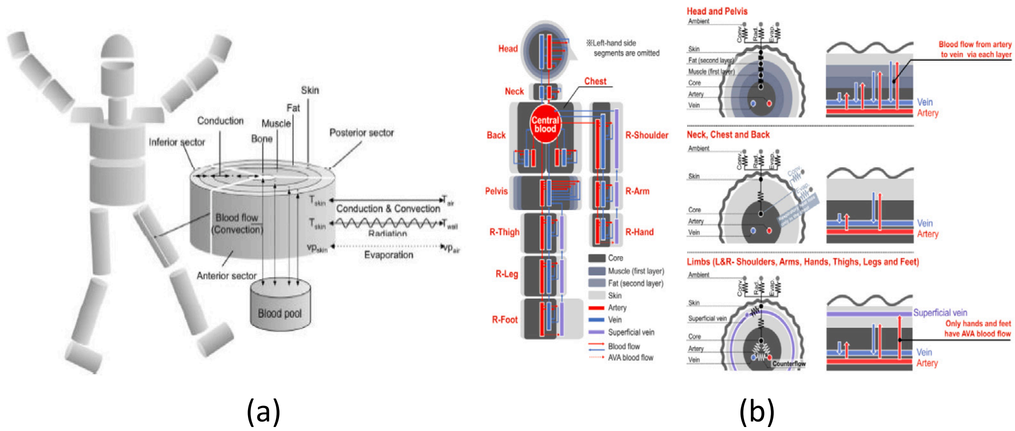

Fig. 1. Schematic of models: (a) ThermoSEM [23], (b) JOS3 [27].

Table 2
Personalized input parameters in ThermoSEM and JOS3.

Model	Personalized input parameters					
	Height	Weight	Fat %	Sex	Age	Cardiac index
ThermoSEM	+	+	+	+	−	−
JOS3	+	+	+	+	+	+

JOS3 is constituted of and an overview of heat exchange considered between all nodes.

Both models require some specific individual input listed in Table 2 to re-scale the model to fit the person (i.e., to build the personalized model). In ThermoSEM, the individual input parameters are used to generate the length and radius of local body parts, from which the volume of each compartment in each of the body parts is calculated. All physiological characteristics including local basal metabolic rate (BMR) are computed within the model based on the new local volumes. In JOS3, the rate of change in the total surface area and weight, and total BMR are first calculated and applied to local values. The coefficient of fat distribution in JOS3 is categorized based on the total body fat percentage, and it is used in the calculation of thermal conductance. The sex in JOS3 is considered in the basal metabolic rate calculation and the age effect (young adult 20–30 y.o. or older adult above 60 y.o.) is considered in adapting the shivering threshold, sweating, and the computation of basal blood flow. The total BMR is calculated from a selected set of equations based on the height, weight, age, and sex of the person, and then it is multiplied by the BMR distribution fraction to get the local values. The physiological parameters that are affected by the individual changes are surface area, conductance, thermal capacity, basal blood flow, basal metabolic rate, shivering, and sweating thresholds. The thermoregulation control system in ThermoSEM does not require pre-defined set-points [37]. However, JOS3 requires set points that describe the neutral body temperatures from which the thermoregulatory control system calculates the deviation from neutrality. There is a possibility to pre-calculate set-points for each individual, but the method is purely based on simulation using the PMV model to define the operative temperature of thermal neutrality [27].

To sum up, the current advanced thermo-physiology models consider individual specifications such as height, weight, sex, and fat percentage in order to rescale the average calibrated model by changing characteristics of body parts such as volume, fat distribution, and basal metabolic rate distribution. In this paper, the performance of ThermoSEM and JOS3, two advanced models considering individual inputs, is evaluated by comparing the local skin temperature prediction with our own (independent) experimental data. The main objective of the work is to identify the limitations of those models in predicting the local thermal state of individuals and to outline the ways forward.

2. Methodology

The research methodology consists of two parts: (i) the experimental part conducted to collect local skin and core temperatures from different human subjects, and (ii) the simulation part where modeling of experimental conditions was performed to evaluate the selected thermo-physiology models. The experimental part of the study was approved by the Cantonal Ethics Commission for Research on Human Beings (CER-VD) in Switzerland under the project ID 2022-00561.

2.1. Experimental part

Experiments were performed in the climatic chamber of the ICE laboratory at the EPFL-Fribourg site. The thermally insulated facility has a 20 m^2 floor area (height of 2.5 m), and the ability to provide a stable indoor environment in the range of 15–35 °C, 20%–80% of relative humidity, and 1–15 air change rate. Thermal conditioning in experiments was achieved using the all-air conditioning system. The experiments consisted of four protocols and each subject had to undergo all of them. The protocols differed by environmental temperatures and the clothing type worn where the relative humidity was kept at 50%:

- **Protocol (a)**: 22 °C, thick clothing
- **Protocol (b)**: 24 °C, thick clothing
- **Protocol (c)**: 26 °C, light clothing
- **Protocol (d)**: 28 °C, light clothing

The timeline of the protocols is shown in Fig. 2, where the starting and ending times, and the different physical activities undertaken by a subject are highlighted. In each 135-min long protocol starting at 8:00 in the mornings, a participant performed four different standardized activities starting with 45 min of *relaxed sitting* when a subject watched an emotionally-neutral documentary in front of a laptop (Fig. 3a). The sitting relaxed activity was followed by 30 min of *standing sorting papers* into alphabetic/numeric orders (Fig. 3b). Then, it was followed by another 30 min of *sitting typing*, and a participant was provided with the same standard text in each protocol. The subject then had 15 min of rest while sitting in a relaxed state, followed by 15 min of *walking* on a walking pad at a speed of 2 km/h (Fig. 3c).

Two sets of clothing ensembles were used in the experiments according to the thermal exposure. Light (summer) clothing consisted of a cotton T-shirt (regular fit), underpants, cotton trousers (regular fit), and plastic flip-flops. Heavy (winter) clothing consisted of a cotton T-shirt (regular fit), long-sleeve cotton sweater, underpants, jeans (regular fit), cotton ankle socks, and sneakers. The total insulation of the light clothing was 0.354 clo and 0.649 clo for the heavy clothing. The clothing insulation was measured using a thermal manikin, details of measurements and local clothing insulation values are provided in Appendix A.1.

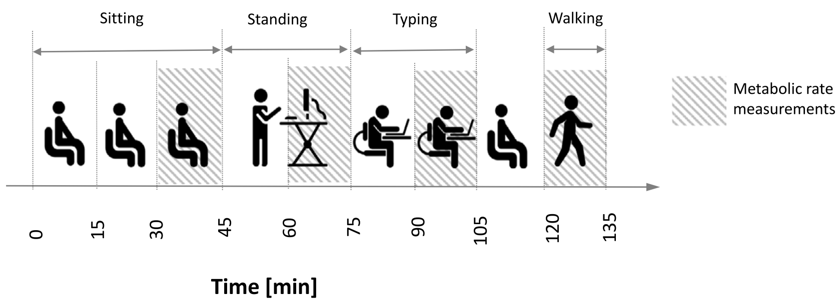

Fig. 2. Timeline of experiments and the activities performed by participants.

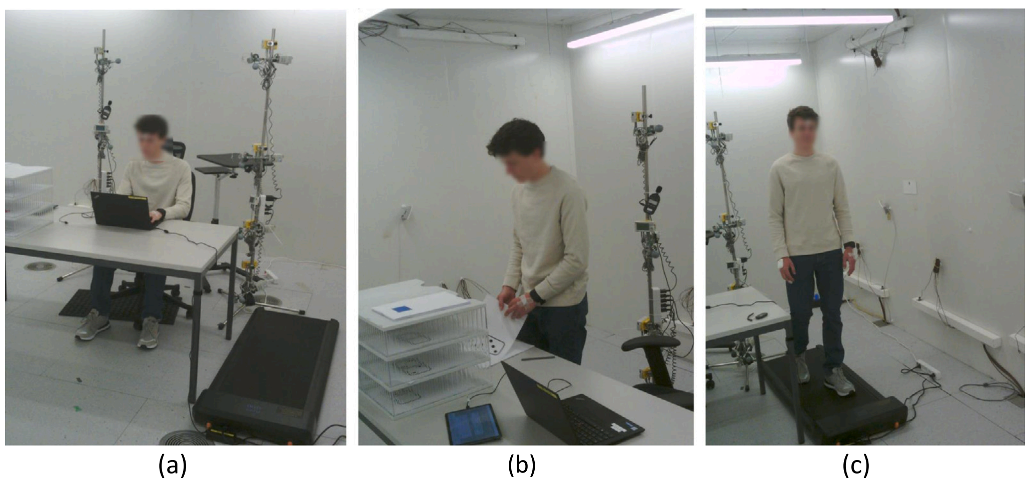

Fig. 3. Experimental setup in the climatic chamber and overview of activities: (a) relaxed sitting, (b) standing sorting papers, (c) walking.

Table 3
Participant's body characteristics.

ID	Sex	Age [Y]	Height [cm]	Weight [kg]	BMI [kg/m^2]	Body fat [%]	Fat free mass [%]
M1	M	29	175	70.6 ± 0.2	23.0 ± 0.1	14.3 ± 0.3	60.5 ± 0.3
M2	M	21	178	67.7 ± 0.3	21.3 ± 0.1	9.4 ± 0.2	61.3 ± 0.3
M3	M	34	185	73.8 ± 0.4	21.5 ± 0.1	16.9 ± 0.3	61.3 ± 0.5
F1	F	24	162	61.2 ± 0.4	23.3 ± 0.1	35.5 ± 0.6	39.4 ± 0.6
F2	F	27	170	63.5 ± 0.4	21.9 ± 0.2	23.5 ± 0.4	48.6 ± 0.3
F3	F	29	168	73.4 ± 0.5	25.9 ± 0.2	39.3 ± 0.8	44.5 ± 0.8

2.1.1. Human participants

Six subjects, 3 men and 3 women, participated in the study meeting the following inclusion criteria of the age between 20 and 35 years old, BMI between 18 and 28 kg/m^2, healthy with no active diseases, non-smoker, and non-competition athlete. The selection criteria were set to limit the variables that affect thermoregulation, particularly the age corresponding to young adults for the purpose of the comparable validation of JOS3 and ThermoSEM models (ThermoSEM was developed for young adults only).

All subjects were asked to fast with a last meal not later than 19:00 the night before the experiment and to avoid drinking water from 7:15 the morning of the experiment to exclude the dynamic effect of food on metabolic rate. Subjects reported to the facility at 07:00, and during the preparation period, changed into standard clothing, completed the arrival survey, underwent anthropological measurements, and finally put on all the wearable sensors with the help of a research assistant. Every morning the body composition (weight, body fat, and fat-free mass) was measured using the body analyzer InBody 770, the height was measured using a stadiometer. Table 3 presents the mean body compositions of six participants based on 4 measurements.

2.1.2. Experimental measurements

Multiple environmental sensors and personalized (wearable) sensors were used in the experiments. Two stands, A (on the right side) and B (on the left side), were used to place sensors for measuring environmental factors around the subject (Fig. 3a), each of which had measurements at four different heights (0.1, 0.6, 1.1, and 1.7 m). The following environmental factors were measured:

- Air (dry bulb) and globe temperatures at 8 locations on two stands using PT100 sensors (accuracy ±0.15 °C) connected to dataloggers UX120-006M (ONSET). The operative temperature was calculated using the measured air temperature, globe temperature, and air speed per standard ISO 7726:1998.
- Air speed at 8 locations on two stands using omnidirectional anemometers SensoAnemo 51CONSF (range of 0.05–5 m/s, accuracy ±0.02 m/s, Sensor Electronic)
- Relative humidity and CO_2 concentration using the datalogger MX1102A (ONSET) at one location closer to the subject

As physiological measurements, the following parameters were measured:

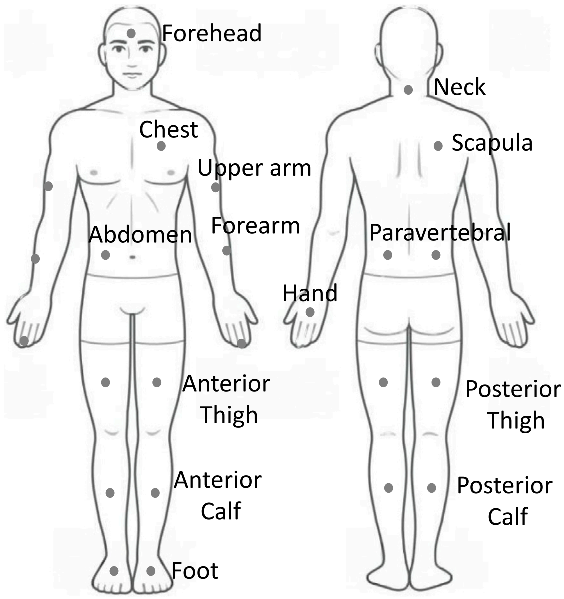

Fig. 4. Locations of skin temperature sensors and body parts analyzed.

- Skin temperature was measured at 24 different locations using iButton (Maxim Integrated) sensors, including the 14 locations according to standard ISO 9886 [72] to calculate the mean skin temperature. The frequency of measurements was 10 s Fig. 4 shows the location of iButton sensors and the body parts used for the analysis. The sensors were calibrated in-house, and their accuracy was ±0.2 °C, details of the calibration process are provided in Appendix A.2.
- Core body temperature was continuously measured every minute during the experiments using a gastrointestinal telemetry capsule eCelsius Performance (accuracy ±0.1 °C) from BodyCAP. The capsule was ingested by subjects 45 min before each protocol under the supervision of the research assistant
- Energy expenditure of participants in [kcal/min] was measured breath-to-breath during the last 15 min of each activity using a portable indirect calorimeter K5 (COSMED) (accuracy of O_2 sampling ±0.3%, and ±1% for CO_2 sampling).

2.2. Modeling part

Both ThermoSEM and JOS3 use individual anthropological data as input, as explained in Section 1.3. From the four sets of measurements, the averaged values of weight, height, and fat percentage according to Table 3 were taken to create the body construction file that described each subject in ThermoSEM. The same data were used in JOS3 to describe the body composition of each subject. The measured environmental parameters in each protocol were used in the simulation for each subject. The environment was considered transient but uniform, which means that all body parts were exposed to the same air temperature and mean radiant temperature since the variation in temperature at different heights was less than 0.3 °C. Environmental measurements were considered according to the different activities: (i) average data from stands A and B for *sitting*, (ii) data from stand A for *standing*, and (iii) data from stand B for *walking*. For each subject, an environmental input file was prepared, each file constituted of a minutely variable air temperature, mean radiant temperature, relative humidity, and air speed. The simulated experiment lasted for 135 min, however, for initialization purposes, the simulation started 60 min before the use of the actual measured values at a uniform fixed temperature (22, 24, 26 or 28 °C, according to the experiment), 50% relative humidity, and 0.1 m/s air speed.

The measured energy expenditure was used to calculate the subject's physical activity ratio during the experiment. The energy expenditure measurements were conducted for 15 min at the end of each activity, the averaged value over the 15 min was used and generalized toward the whole corresponding period. For example, during the 45 min of resting, the activity rate used in the simulation for the whole 45 min was the one measured during the last 15 min. Both models take the activity ratio as input, which is the actual energy expenditure divided by the basal metabolic rate (BMR) that was measured by the body analyzer. In addition, both HTPMs were adjusted to take the posture (e.g., sitting or standing) as a variable input; posture in both models was used to determine radiant heat transfer. The local clothing insulation values measured (Appendix A.1) were used as an input to both simulation models.

3. Results

The results section is divided into two main parts. The first part shows experimental results of environmental parameters, human energy expenditure, and clothing insulation; while the second part presents the averaged error of local skin, mean skin, and core temperatures from both models compared to the experimental data.

3.1. Experimental results

The variation of operative temperature during each experiment is presented in Fig. 5. The dynamic plot shows the mean value of the averaged temperature at four heights on stands A and B in addition to the standard deviation bars. The differences in operative temperature with height and between the stands were small. The temperature slightly deviated from the set points, with a maximum offset of 0.5 °C. Only during the experiment at 24 °C with the subject M3 the temperature around 4 °C lower than the set point due to a fault in the control system.

The energy expenditure of each participant per type of activity and experimental protocol is presented in Table 4; the data represent the averaged values of 13 min out of the 15 min of measurement, excluding the first and last minute. As shown, the energy expenditure during the sorting activity increased in male subjects on average around 34% compared to sitting relaxed and an average increase of 45% for female subjects. For the typing activity, the energy expenditure of all subjects decreased compared to the previous activity (i.e., the standing posture) on an average of 18% for males and 19% for females. However, the energy expenditure increased again during walking; males had an average increase of 81% and females had an increase of 89%. The results show that participants had different energy expenditure even though they were performing the same kind of standardized activity.

3.2. Averaged skin and core temperature values per activity

To compare outputs of ThermoSEM and JOS3, the experimental results were separated by activity type (e.g., sitting relaxed, standing sorting, sitting typing, and walking), and several representative body parts shown in Fig. 4 were selected for the comparison. The difference in skin temperature between the simulated and measured values $\Delta T = T_{sim} - T_{exp}$ were computed for the last 15 min of each activity, and reported as violin plots. Example plots for a male subject M1 and a female subject F1 are shown in Fig. 6; the rest of the results are shown in Figs. A.11–A.14 in Appendix. Skin temperature variability is reflected in the length of the violins. When the skin temperature difference ΔT is close to zero, it indicates that the model is in good agreement with the experimental results.

For the sitting activity, the variation in skin temperature was minimal in most of the body parts, indicating that the subjects reached a steady state. However, hands and feet had the highest temperature

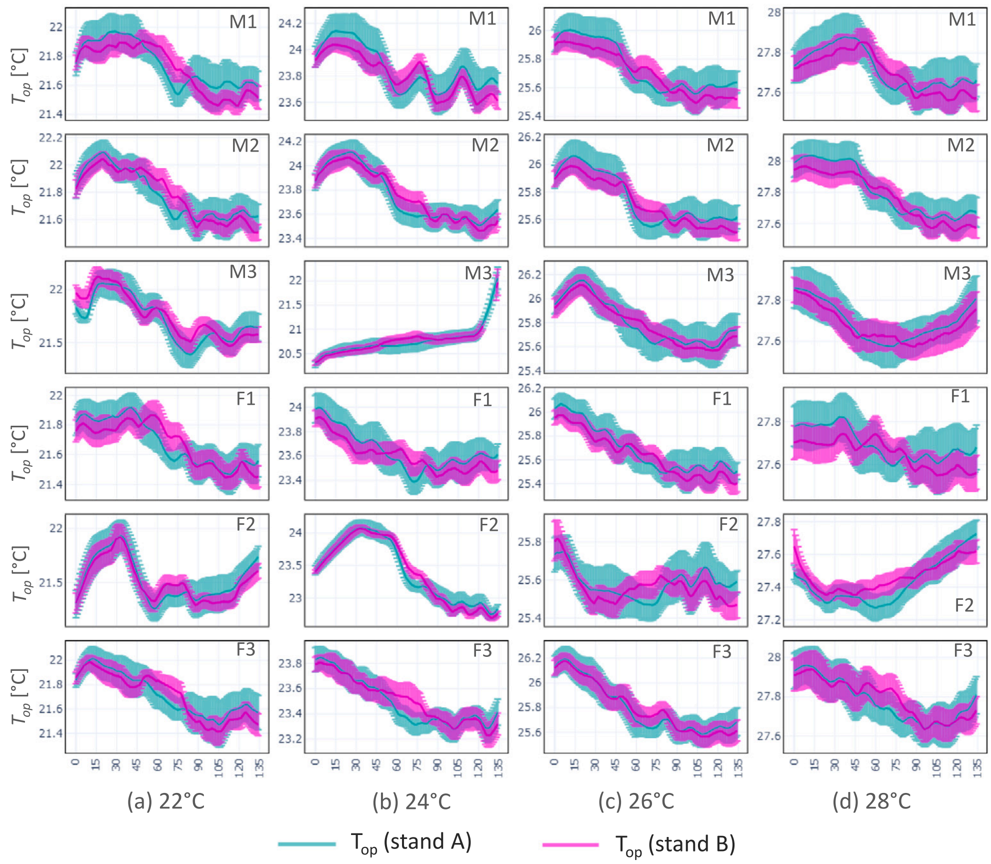

Fig. 5. Mean operative temperature variation measured on stands A and B across all environmental cases with subjects M1–M3 and F1–F3.

Table 4
Energy expenditure of participants per activity and thermal exposure type.

Activity type	Subject ID	EE [kcal/min]			
		22 °C	24 °C	26 °C	28 °C
Sitting	M1	1.26	1.26	1.37	1.33
	M2	1.51	1.37	1.45	1.28
	M3	1.43	1.12[a]	1.57	1.7
	F1	1.00	1.19	1.08	1.11
	F2	1.12	1.15	1.06	1.16
	F3	1.23	1.14	1.28	1.04
Sorting	M1	1.67	1.68	1.57	1.51
	M2	1.85	1.9	2.09	2.14
	M3	1.95	1.87[a]	1.91	2.12
	F1	1.50	1.66	1.91	1.65
	F2	1.38	1.55	1.39	2.02
	F3	1.65	1.92	1.8	1.63
Typing	M1	1.45	1.41	1.28	1.39
	M2	1.45	1.5	1.48	1.47
	M3	1.35	1.52[a]	1.87	1.92
	F1	1.22	1.24	1.42	1.37
	F2	1.24	1.24	1.3	1.42
	F3	1.25	1.28	1.22	1.44
Walking	M1	2.58	2.63	2.79	2.22
	M2	2.64	2.36	2.65	2.79
	M3	2.77	2.73[a]	3.11	3.05
	F1	2.26	2.47	2.89	2.09
	F2	2.01	2.15	2.12	2.81
	F3	2.78	2.83	2.78	2.44

[a]Subject M3 was actually exposed to 20 °C during a 24 °C protocol due to a system error.

variation within 15 min of interest. In the colder environment, the error in average temperature was greater at the extremities, especially in the feet, compared to the core and central body parts. For sitting activity, simulation results of both models for all subjects had less error in the majority of body parts in the warmer environments (26 and 28 °C) compared to colder environments (22 and 24 °C). However, the accuracy of prediction by both models varied between subjects; for example, simulation results for subject M2 showed better agreement with experiments compared to M1 (Fig. A.11). Regarding the female subjects, the output of the simulations for subject F1 showed less error compared to the other two females. The results of simulation at 28 °C show that ThermoSEM was overpredicting in males and underpredicting in female subjects. The results of the hand and feet skin temperature of the subject M3 in Protocols (a) and (b) were underpredicted by JOS3, while ThermoSEM results were slightly overpredicted. Similarly, the results show a larger variation in the skin temperature of the hand during the standing activity compared to the sitting relaxed activity. Based on Fig. A.12, the warm environment cases (c) and (d) showed fewer prediction errors and more occurrences of ΔT values closer to zero. In Protocol (d), ThermoSEM slightly underpredicted the female skin temperatures, while JOS3 overpredicted them. For males, the results of both models were close. The results from typing activity presented in Fig. A.13 show that the hands continued to have the larger deviation of skin temperature during the 15 min, with a variation of around 0.8 °C. The overprediction and underprediction patterns of models were also valid for the typing activity since simulations were dynamic. However, the rate of error decreased compared to standing activity; for example, the prediction error in chest skin temperature for subject M1 was improved by an average of 0.7 °C in ThermoSEM and 0.5 °C in JOS3. In case (d) shown in Fig. A.13, the local skin temperatures for the females were slightly overpredicted by JOS3 and slightly underpredicted by ThermoSEM. The temperature differences

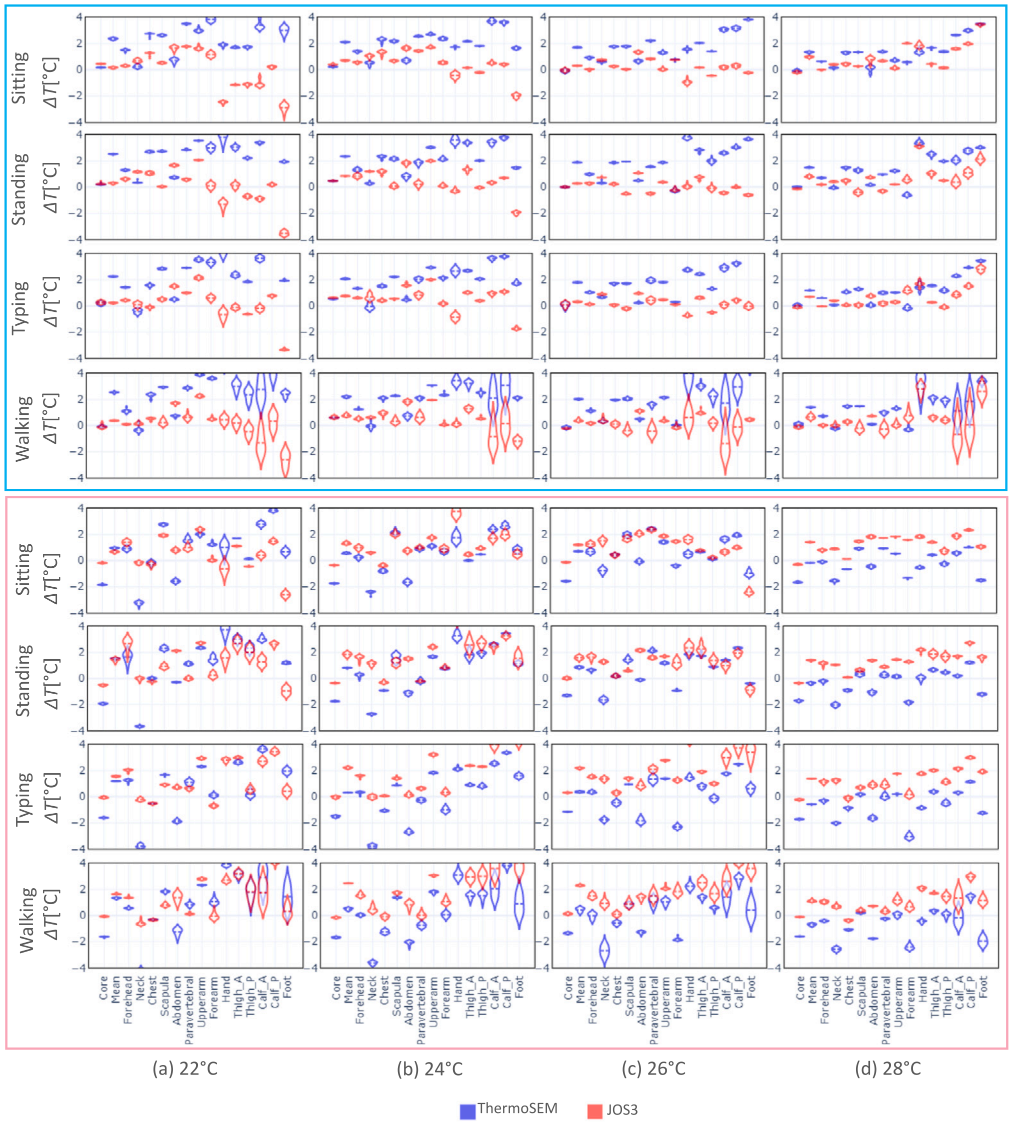

Fig. 6. Selected temperature difference between the experimental data and ThermoSEM and JOS3 models prediction for a male subject M1 (in a blue frame) and a female subject F2 (in a pink frame), the mean value is shown in the middle of each violin. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for the males were similar in both models. During the walking activity, the measured skin temperature in the majority of body parts showed a larger variation. The prediction error increased compared to previous activities, especially during the cold environment cases (a) and (b). Large fluctuations were observed in the calf and feet in all 4 protocols. In general, the error in the prediction of core temperature by ThermoSEM was low in male subjects but increased in female subjects. Contrarily, the error in the prediction of mean skin temperature in JOS3 was low in male subjects and increased in female subjects.

To have a better insight into the performance of ThermoSEM and JOS3, the root mean square error (RMSE) was calculated based on the difference between the experimental and simulation results, and the results are presented in Fig. 7 for selected parameters: (a) core and the mean skin temperature, (b) forehead and chest skin temperature, (c) forearm, arm, and hand skin temperature, (d) thigh, calf, and foot skin temperature. The RMSE of mean skin temperature predicted by ThermoSEM was lower at 28 °C compared to 22 °C. However, the RMSE was the lowest, according to JOS3, at a near-neutral environment of 24 and 26 °C. These observations indicate the limitations of HTPM models in being applied to various environments without any caution.

3.3. Dynamic variation

The dynamic prediction behavior of both models along the course of experiments is shown in Fig. 8 for the mean skin temperature and in Fig. 9 for the core temperature. The figures show the comparison for all six subjects (M1–M3, F1–F3) and for all four experimental protocols. The calculation of the mean skin temperature using experimental and simulation data was based on 14 points according to the weighting method by ISO 9886 [72]. By time zero, all simulations were run for an hour during initialization under the same indoor conditions as those in the corresponding protocols. Thus, by the beginning of the actual experimental time, the models reached a steady state in most cases. During the first 45 min, when people were sitting relaxed, the mean skin temperature prediction was steady; however, experimental data showed a decrease during that period, especially in the cold

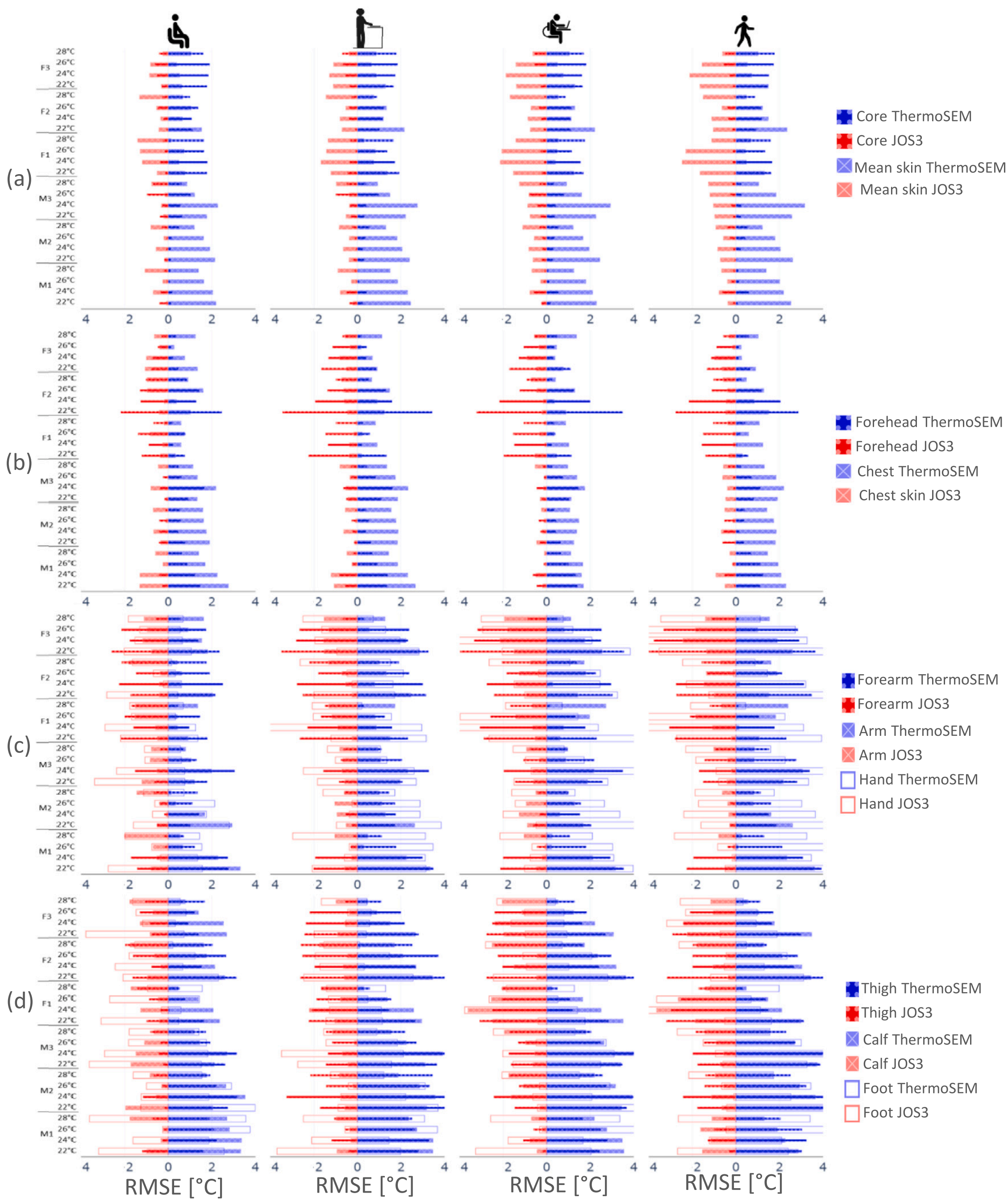

Fig. 7. Root mean square errors of ThermoSEM and JOS3 for different body parts.

environment cases (a) and (b), indicating that subjects were not fully in thermal steady-state. The mean skin temperature predicted by JOS3 was closer to the experimental data in the majority of cases. Fig. 8 shows that the calculated mean skin temperature by ThermoSEM was higher compared to the prediction by JOS3. However, the mean skin temperature computed by ThermoSEM for female subjects were often closer to the measured values than in males. The dynamic variation and the pattern of change in the mean skin temperature were clearer in the JOS3 prediction.

The predicted core temperature of male subjects by both models was in good agreement with experiments, with a deviation within 0.3 °C. However, the prediction by ThermoSEM for female subjects was low compared to the experimental data, while the average error of prediction by JOS3 remained within 0.3 °C. The error by ThermoSEM was in the range of 1.4 °C. The change in core temperature due to the change in activity was not very noticeable in the experimental results. In particular, for the case of the female F1, there was a slight increase in core temperature after switching to standing activity, a slight decrease after sitting typing, and another increase during the walking activity due to the higher metabolic rate.

To detail the changes in local values, the box plots in Fig. 10 present the skin temperature of the forearm and the hand at the end of sitting (S) and walking (W) activities. Two specific body parts are chosen as the difference between the hand and the forearm temperature

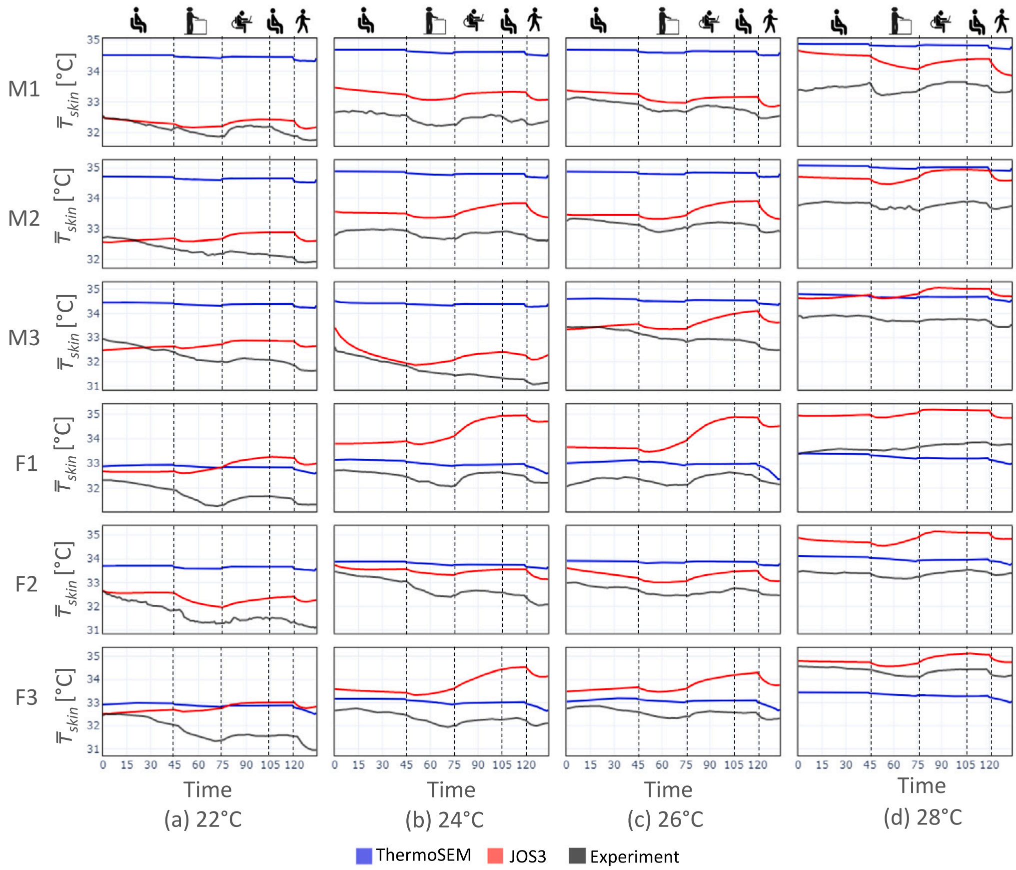

Fig. 8. Dynamic variation of predicted and measured mean skin temperature.

is an important indication for vasomotion [19]. Two activities are chosen to highlight how local skin temperature changes from the first activity (sitting relaxed) to the last activity (walking), after two hours of exposure to a certain environment. The experimental results were presented together with the prediction from both HTPM models. To show the underlying relation, the variation between the beginning and the end of the experiment can be seen in Fig. 10. Results show that there is a strong relation between the thermal response of the body parts to the thermal environment. As experimental results in Fig. 10 show, the temperature of both forearm and hand drops in the walking activity, this could be due to the time the subject spent in the environment and to the movement of the hands. Also, at the end of the experiment (walking activity), the temperature of the hands was lower compared to the temperature of the forearm. The magnitude (marked with an arrow on Fig. 10) between hand skin temperature and forearm is higher in the cold environments (a) and (b) compared to warm environments (d) and (c). Based on the experimental observation, the difference ($T_{forearm} - T_{hand}$) was in the range of 4 °C in the cold environment case of Protocol (a) and that reduced to around 2–3 °C in Protocols (b) and (c). However, the difference was lower than 2 °C in the case of a warm environment, as in the case of Protocol (d).

4. Discussion

The discussion combines observations of physiological changes between individuals from experiments and the comparison of ThermoSEM and JOS3 simulation results with the experimental data.

4.1. Sensitivity of skin temperature to activity variation

During each experimental protocol, subjects performed consecutive standardized activities, starting from sitting relaxed, standing sorting paper, sitting typing, sitting relaxed, and walking at a pace of 2 km/h. Although the metabolic rate increased in the standing sorting and walking, the mean skin temperature decreased during these activities. The decrease in mean skin temperature shown in Fig. 8 can be explained by subjects moving hands while sorting papers that might increase the air speed around the upper body leading to the increase in heat losses. To consider the movement of the subject in the simulations, the air speed was manually modified, as it was difficult to measure the air speed close to the body parts of the subject while moving. The individual's core temperature was adapting to the change in activity. A slight increase in core temperature was noticed in some participants after standing and walking (Fig. 9). Both models showed better performance with lower error at the beginning of the simulation for the sitting relaxed activity, while the error increased in the later activities. Longer sitting duration could bring the body to a steady state condition leading to less error. These findings can also be confirmed when compared to the validation performed by the developers of both models in studies [27,41].

4.2. Sensitivity of skin temperature to environmental temperature variation

The results showed that ThermoSEM had better performance in warmer environments at 26 °C and 28 °C; however, JOS3 showed a consistent performance across all protocols. Comparing the skin temperature of the forearm and hand in Fig. 10 between the four different environments (a)–(d), we found that the hand is more sensitive to

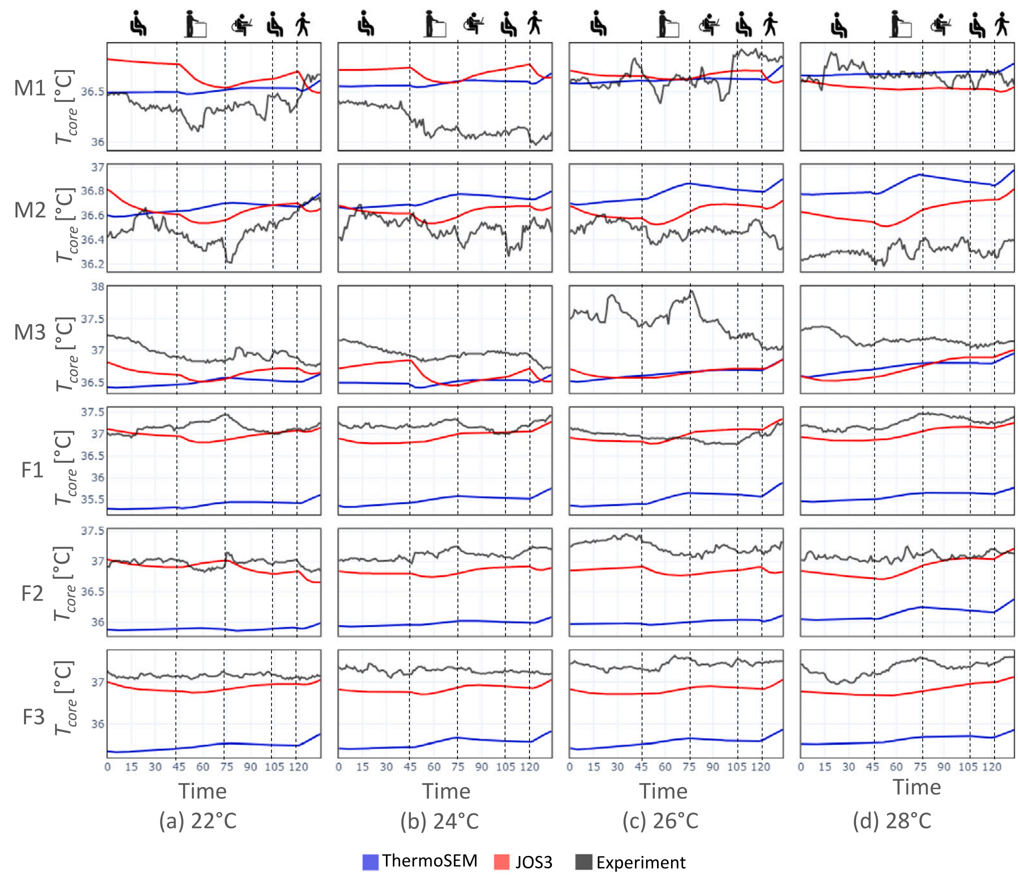

Fig. 9. Dynamic variation of predicted and measured core temperature.

the environment since it is nude and sensitive to the movements that increase the convection heat loss. In a cold environment, during the walking activity, the hand skin temperature was much lower compared to the forearm, and in a warmer environment, the hand temperature became closer to the forearm temperature. During the sitting activity for the first 45 min, the hand temperature was closer to the forearm temperature in most of the cases.

The difference in temperature between the extremities (hands and feet) and their preceding body parts increased during the exposure to 22 °C and 24 °C environments. At 22 °C, the deviation between the skin temperature of the hand and the forearm gradually increased with time and reached the maximum at the end of the experiment. Generally, as HTPMs require initialization, accurate information about the environmental factors the subject is exposed to before starting the experiment can lead to a better prediction. In our case, the preparation of participants was conducted in a different room, and its temperature was slightly affected by the outdoor conditions (the experiments were carried out during May–June with an outdoor maximum temperature of 15–25 °C). Thus, the exact environmental exposure of participants prior to the controlled experiments was accounted for with less accuracy compared to the experimental time.

The RMSE presented in Fig. 7 is the most common metric to evaluate the prediction accuracy of HTPMs, and it indicates in this study how well the models performed for individuals at local levels. RMSE results from ThermoSEM simulations were lower at a warmer environment of 28 °C compared to a cooler environment of 22 °C. The validation of ThermoSEM presented by Veselá et al. [41] had the absolute error for the core temperature of 0.5–1.4 °C, for mean skin temperature of 0.5–1.8 °C, and for the foot skin temperature of 1.8–6 °C. Takahashi et al. [27] reported RMSE for JOS3 outputs for core temperature between 0.17–0.63 °C, for mean skin temperature between 0.17–1.1 °C, and for foot skin temperature of 1.59 ± 1.4 °C. Findings from both studies are in line with the RMSE values of individuals calculated in our study.

4.3. Re-construction of individual models and input refinement

Based on the simulation results of both models, we can conclude that the models still need further physiological refinement to improve individual prediction. Both models consider individual information, such as sex, body fat percentage, height, and weight, and try to scale the model of an average male to a new subject; however, improving individual prediction needs further refinement of local basal distribution values. Scaling the matrices of basal blood flow and basal metabolic rate based on height and weight might not fit the thermal characteristics of every person, because body composition, muscle, and fat distribution may vary between individuals, resulting in local increase or decrease in body insulation. ThermoSEM showed better core temperature prediction in males compared to females, which can be due to the difference in the way the local thermal characteristics were redistributed between sexes. However, mean skin temperature was closer in female experiments, which is due to the decrease in local skin temperatures. The temperature difference in the majority of local body parts was positive in males and negative in females, which led to the conclusion that ThermoSEM was overpredicting local temperatures in males and underpredicting in some local body parts in females. JOS3, on the other hand, showed a smaller distribution error over body parts, which led to a smaller error in mean skin temperature. In addition, based on the simulation results from both models, it is seen that the

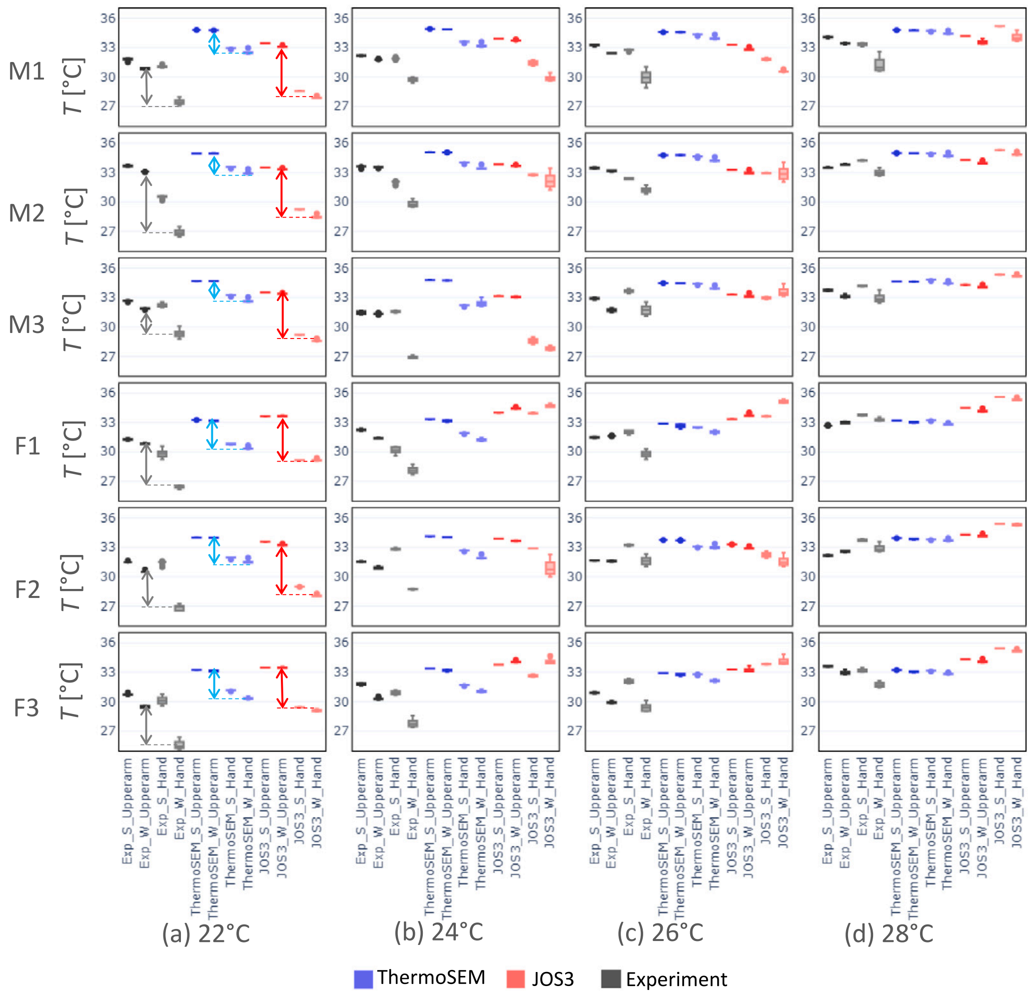

Fig. 10. Comparison of local skin temperature of a forearm and a hand during the first activity (sitting - S) and the final activity (walking - W).

outputs are sensitive to the inputs. In the current work, the inputs were carefully considered by using environmental data from the closest sensor to the person, and by adjusting the air speed to consider the walking speed of the person during walking. Despite the refinements, both models showed instances of errors with a large magnitude of 6 °C. The coefficients and local basal values used in HTPMs influence the prediction of local skin temperatures. Those coefficients are taken from old literature, mainly derived from the work of Stolwijk [35]. The models then calibrated based on those values to represent an average young person. Scaling the model for different people based on little information such as height, weight, and fat percentage might not be sufficient to have an accurate individual prediction. The solution could be to conduct calibration on every scaled model due to the difficulty of measuring local thermal characteristics such as local basal metabolic rate and local blood flow.

ThermoSEM and JOS3 require accurate input for the distribution of clothing insulation, metabolic rate, and environmental factors as close as possible to the subject. Both HTPMs has simplified clothing model where clothing layers are only considered as thermal resistances. When subjects were changing activity type, the air gap between the clothing and skin could have an effect on the heat transfer from the body. Thus, the clothing model considered in both models could have contributed to the errors shown in this study. In addition to the models refinement, the prediction of models is directly affected by the input parameters. Firstly, the way skin temperatures were measured could contribute to the error in prediction. The iButtons for skin temperature measurements were sensors in a metal casing attached to the skin using medical tape. However, the movements of a person could cause the taping of sensors to loosen and, consequently, provide slightly altered results. In addition, a relatively slow response time of the iButtons might contribute to the uncertainty of measurements.

Overall, to have a better prediction for individual skin temperature, certain parts of the models should be further improved such as detailing the environmental inputs at the local level, accurate input of local clothing insulation, improved metabolic rate distribution based on the type of activity, improved blood flow modeling, etc. However, these efforts might complicate the models and their usability as identifying proper inputs might be a challenge. Instead, a possible solution could be developing multiple versions of models according to distinct personal characteristics (e.g., fitness level, acclimatization level, etc.) that could be determined from simple surveying.

5. Conclusion

A comparative study on usability of the dynamic human thermophysiology models ThermoSEM and JOS3 for the prediction of thermal responses was presented in this research paper, focusing on the individual and the local level. ThermoSEM and JOS3 were selected as both models use as input individual parameters that could be scaled to fit a specific person. For the purpose of validation, four experimental protocols at four different environmental temperatures with six subjects evenly distributed between females and males were conducted in a climatic chamber. The different protocols helped to show the performance of the models at different temperatures and at different standardized activities.

Both models can dynamically follow the trend of the experimental results. Positive and negative errors in local skin temperature sometimes resulted in an improved *mean* skin temperature prediction. It was shown that it is important to evaluate the models based on the local values prediction and not to limit to only mean values. The change in activity showed that different people have different energy expenditures even at the same environmental conditions and same activity level. Thus, when considering individuals, it is important to account for the local thermal characteristics and the dynamic energy expenditure, whenever possible. Moreover, information on the human physiology (e.g., metabolic rate, blood flow) and the thermal environment is needed for the period *before* actual validation measurements to improve the simulation accuracy. Generally, continuous measurements of environmental and personalized parameters *before* and *during* the experiments could improve the quality of the input for the simulations.

Models ThermoSEM and JOS3 use data and coefficients from old literature, and the models scale the stored data to fit into a new subject. This approach needs further consideration since measuring local values such as local basal metabolic rate and local blood flow is difficult. A possible solution could be adjusting the model according to distinct personal characteristics (e.g., fitness level, heat-accustomed/cold-accustomed, etc.) that could be determined from surveying. Currently, the models do not consider personalized adaptations. Therefore, further efforts are needed to modify HTPMs in order to represent individuals in a more accurate way and improve the models performance particularly in extremities (hands and feet). Despite some drawbacks, the models still performed well for core body parts (chest, head, abdomen) and adequately predicted the mean skin temperature, which is still useful for overall thermal response prediction.

Overall, this research with somewhat limited number of participants demonstrated than the prediction accuracy of the selected human thermo-physiology models (HTPMs) varies not only between the groups of people (males vs. females) but also as a factor of activity type and thermal exposure. To strengthen the findings and generalize the results, validation experiments with larger number of people representing different demographics should be considered in the future with a special attention to include different activity levels and environmental temperatures.

CRediT authorship contribution statement

Mohamad Rida: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Arjan Frijns:** Writing – review & editing, Supervision, Software. **Dolaana Khovalyg:** Writing – original draft, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

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

Data will be made available on request.

Table A.5
Local clothing insulation measured using a thermal manikin both for summer and winter clothing ensemble.

Body part	Summer I_{cl} [clo]	Winter I_{cl} [clo]
Foot	0.284	1.049
Foreleg	0.220	0.552
Front thigh	0.618	0.546
Back thigh	0.607	0.613
Pelvis	1.073	1.762
Back side	0.493	0.746
Head	0	0
Skull	0	0
Hand	0	0
Fore arm	0	0.554
Upper arm	0.260	0.836
Chest	0.270	0.890
Low back	0.789	1.532
Upper back	0.483	1.223
Stomach	0.400	1.142

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Appendix. Details of selected parameters

A.1. Clothing insulation measurements

The local clothing insulation values were measured using a 22-zone thermal manikin by PT-Teknik (Denmark). The manikin can be operated in a "comfort mode" that simulate the thermoregulation of the human body or at a fixed skin temperature or at a fixed power mode. The measurements of the clothing insulation were carried out in the same climatic chamber as the main experiments with human subjects having the manikin working on comfort mode. The clothing insulation measurements were repeated at two uniform temperatures of 22 and 24 °C. Both nude and clothed local resistances were measured at steady-state when skin temperature variation was less than 0.08 °C. Table A.5 shows the local clothing insulation values of the two ensembles used in the experiment. The body parts shown in the table refer to the manikin body parts.

A.2. Skin temperature sensors calibration

Skin temperature sensors iButton were calibrated in our lab for the experiment using Julabo CORIO CD refrigerated/heating circulator water bath with precision thermometer Klasmeier type "milliK + 2x eXacal Pt100L" which was calibrated by the manufacturer in January 2022. The reference thermometer had an uncertainty of 0.015 °C. For calibration, the iButtons were put in a tight copper enclosure immersed in the middle of the water bath close to the precision thermometer. The temperature of the water was varied between 15 and 48 °C, with two-degree increments. A 30-min time is considered for each temperature setpoint to ensure that a steady state is reached. After the calibration, the accuracy of iButtons was ± 0.2 °C.

A.3. Temperature prediction by ThermoSEM and JOS3

Figs. A.11–A.14 demonstrate the temperature differences between experimental data and simulation results at the local body level and the mean value. Figures show individuals comparison for four different type of activities.

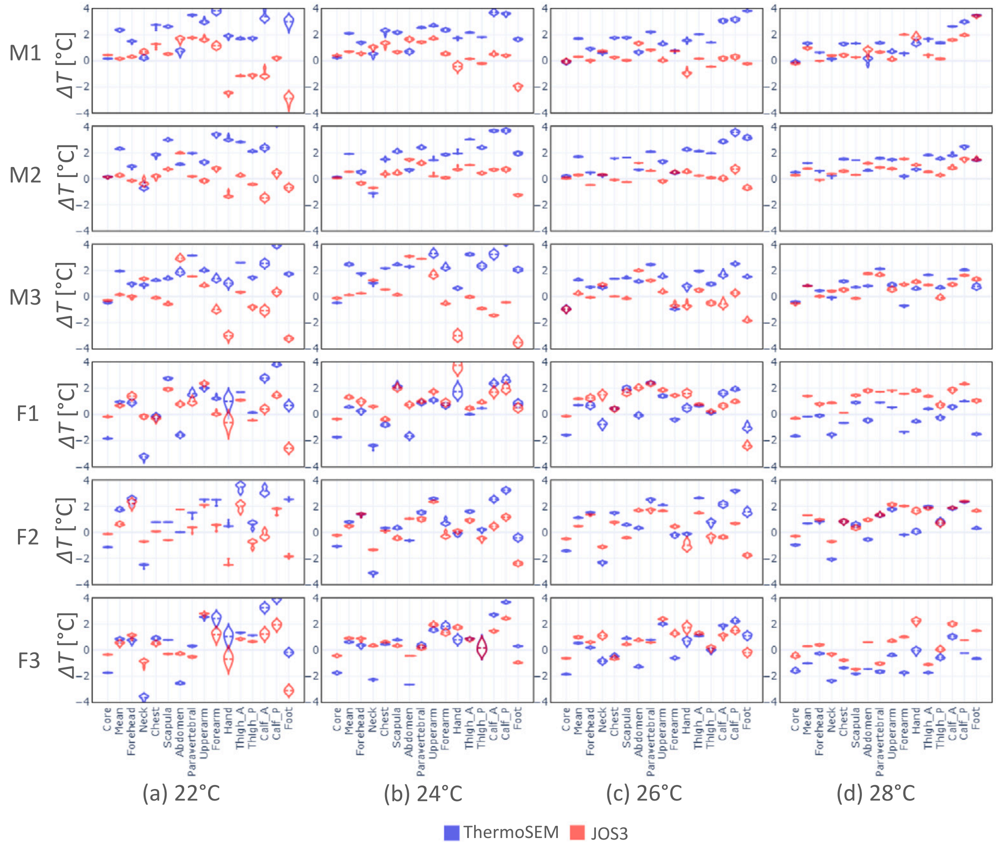

Fig. A.11. Selected temperature difference between the experimental data and ThermoSEM and JOS3 models prediction for sitting activity.

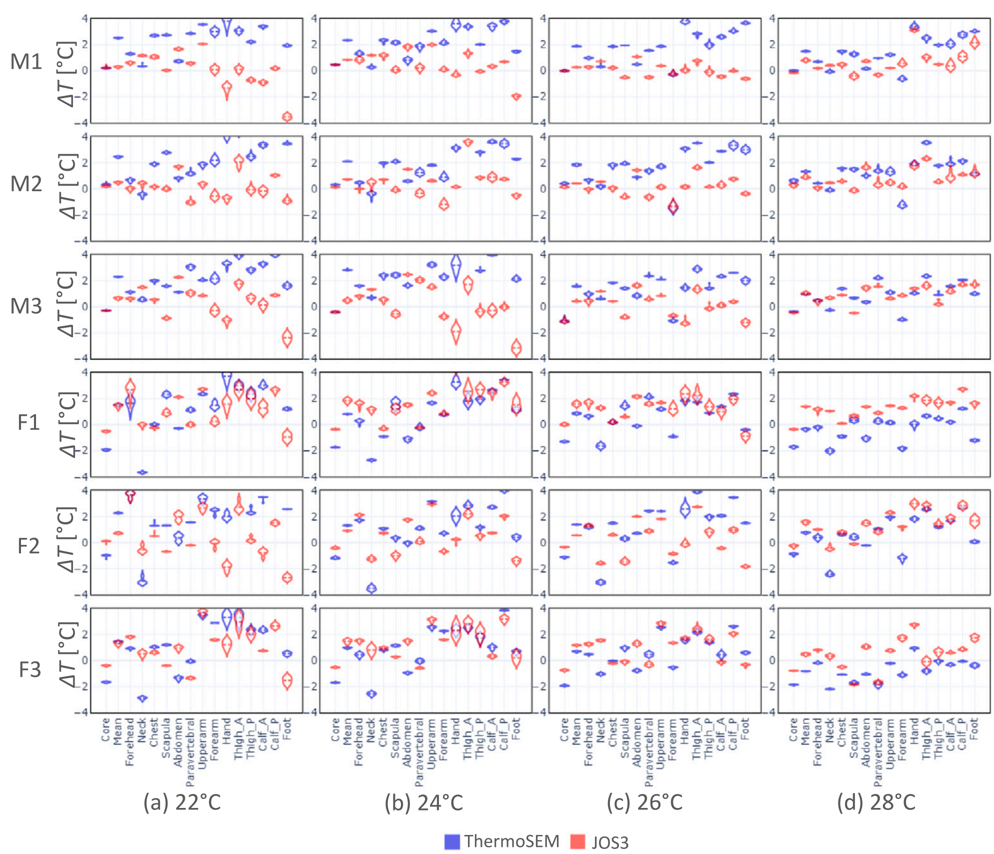

Fig. A.12. Selected temperature difference between the experimental data and ThermoSEM and JOS3 models prediction for standing activity.

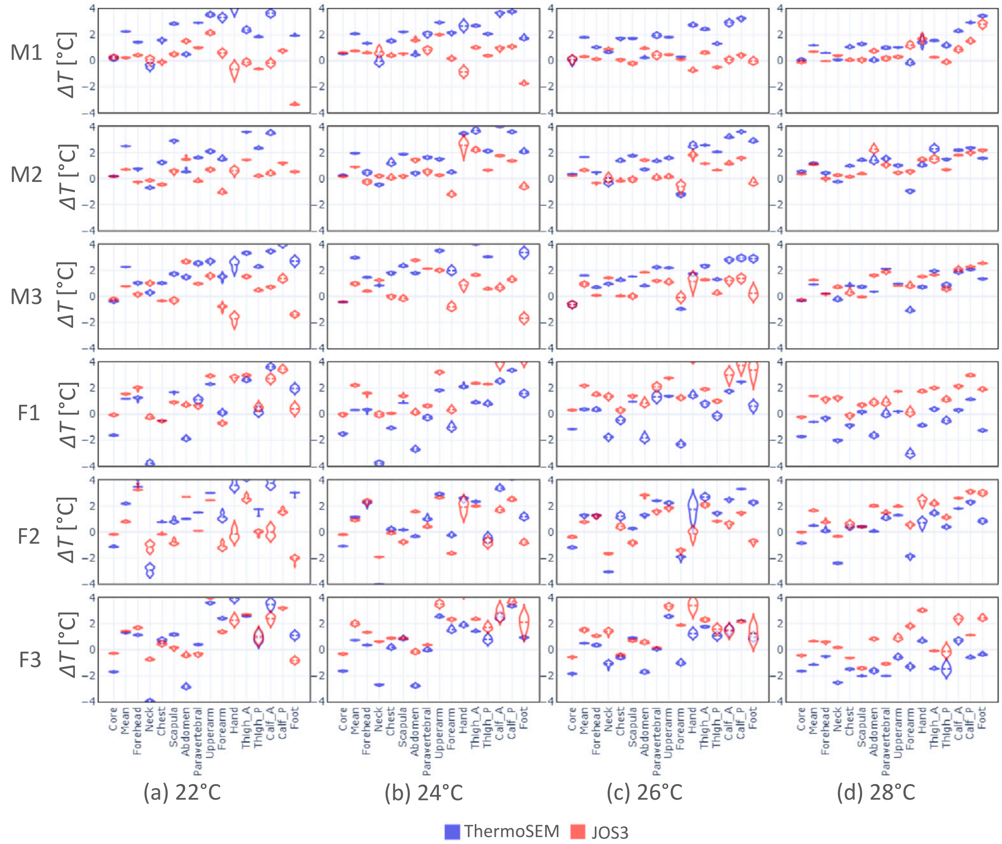

Fig. A.13. Selected temperature difference between the experimental data and ThermoSEM and JOS3 models prediction for typing activity.

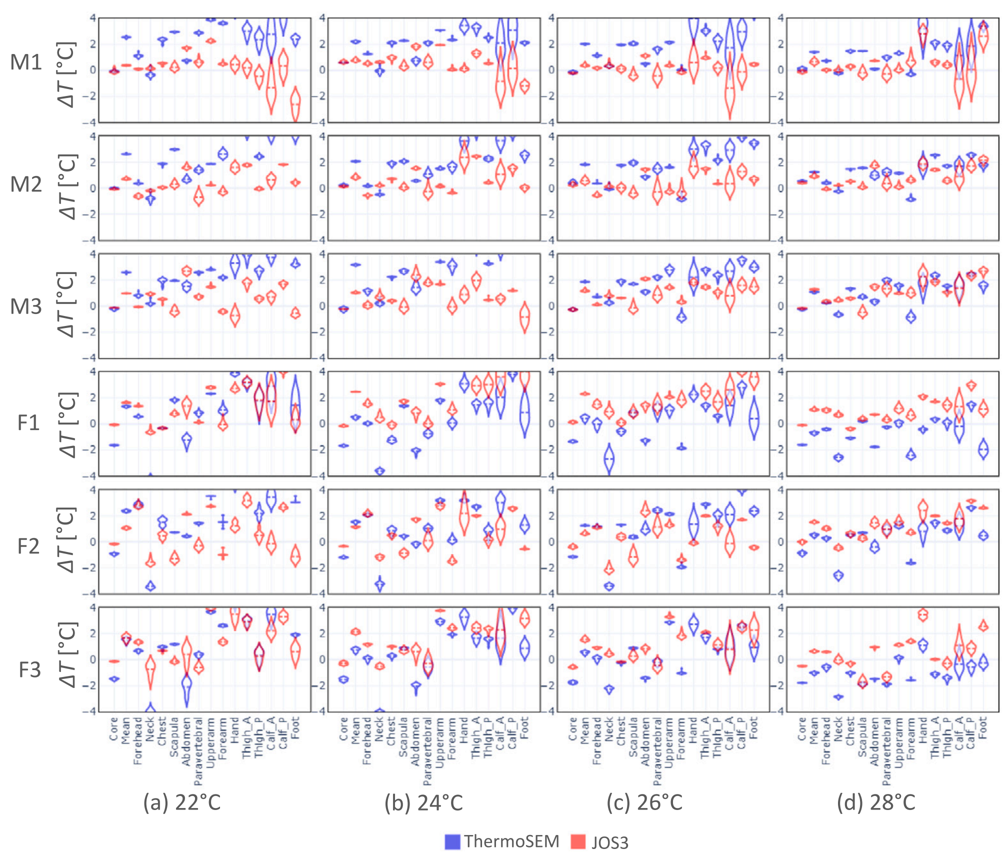

Fig. A.14. Selected temperature difference between the experimental data and ThermoSEM and JOS3 models prediction for walking activity.

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