Evaluating the performance of thermal sensation prediction with a biophysical model

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INTRODUCTION

For near-steady-state thermal environments, it is widely established that humans express on average a neutral thermal sensation when they are in thermal conditions allowing their body to maintain heat balance without sweating. Elaborate experiments and analyses have provided a wealth of information on this topic and have led to heat balance equations that are used in international thermal comfort standards.\(^1,2\)

When applying these heat balance equations, the average human is often represented as a single node with a specific metabolic rate (=heat production) associated with an activity level. For typical office conditions, the activity level is assumed between 1.0 and 1.2 METs (heat equivalent by convention 58-70 W/m\(^2\)).\(^1,3\) For near-steady-state thermal indoor environments, which allow the body to maintain heat balance, it is then assumed that the body is able to maintain the internal temperature, ie, the body core temperature, within physiologically healthy boundaries. Thereby, the internal heat balance is a function of metabolic rate and body tissue insulation and is constrained by the range of body core temperature that is required to sustain living (see Figure 1).

The importance of body tissue insulation in maintaining internal heat balance is well described in classical thermophysiological literature,\(^5\) and it is a crucial factor in all thermophysiological models that simulate body temperatures for analyses of thermal environments.\(^6,7\)

Body tissue insulation is determined by body composition (ie, muscle-,

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Abstract

Neutral thermal sensation is expected for a human body in heat balance in near-steady-state thermal environments. The physiological thermoneutral zone (TNZ) is defined as the range of operative temperatures where the body can maintain such heat balance by actively adjusting body tissue insulation, but without regulatory increases in metabolic rate or sweating. These basic principles led to the hypothesis that thermal sensation relates to the operative temperature distance from the thermoneutral centroid (dTNZ\(_{\text{op}}\)). This hypothesis was confirmed by data from respiratory climate chamber experiments. This paper explores the potential of such biophysical model for the prediction of thermal sensation under increased contextual variance. Data (798 votes, 47 participants) from a controlled office environment were used to analyze the predictive performance of the dTNZ\(_{\text{op}}\) model. The results showed a similar relationship between dTNZ\(_{\text{op}}\) and thermal sensation between the dataset used here and the previously used dataset. The predictive performance had the same magnitude as that of the PMV model; however, potential benefits of using a biophysical model are discussed. In conclusion, these findings confirm the potential of the biophysical model with regard to the understanding and prediction of human thermal sensation. Further work remains to make benefit of its full potential.

KEYWORDS
biophysical model, indoor temperature, performance evaluation, prediction, thermal comfort, thermal sensation
fat tissue and morphology) and is adjusted through muscle blood flow and skin blood flow. Nota bene, in resting conditions 90% of body tissue insulation is determined by low-perfused muscle tissue, and higher appendicular muscle mass is associated with lower overall body tissue insulation.

Several attempts have been made to include body tissue insulation in simple steady-state heat balance models. For instance, Humphreys used the approach to rationally describe how metabolic rate and body tissue insulation influence the globe temperature required for thermal balance (see Figure 2). With body tissue insulation ranging between 0.03 m²K/W and 0.12 m²K/W, Humphreys assumed the mid-region of body tissue insulation (0.04-0.09 m²K/W) to be associated with thermal comfort.

Later, Kingma et al. independently considered the whole range of body tissue insulation and concluded that indeed the mid-region of body tissue insulation is associated with thermal comfort by cross-referencing comfort-associated skin temperatures from experimental studies.

For a given metabolic rate, skin wettedness, and body core temperature, the body tissue insulation level dictates the range of skin temperatures that support thermal balance. The center of this skin temperature range corresponds to the center range of body tissue insulation, and consequently, body tissue insulation depends on the environmental conditions that support external thermal balance.

The physiological thermoneutral zone (TNZ) is defined as the range of operative temperatures where the body can maintain thermal balance, without regulatory increases in metabolic rate or sweating (see Figure 3). Within this temperature range, the body actively adjusts body tissue insulation by skin blood flow regulation (body tissue insulation is increased by vasoconstriction and decreased by vasodilation). The center of the physiological thermoneutral zone thus also coincides with the center range of body tissue insulation.

Above-described basic principles related to human thermoregulation have led the authors to test and confirm the hypothesis that thermal sensation relates linearly to the distance of operative temperature from the thermoneutral centroid (dTNZop); see Figure 4 for a schematic view of thermal sensation vs. dTNZop.

This analysis was based on data from 16 young adult female participants who performed light office work during a dynamic temperature protocol in a combined climatic and respiratory chamber (for measurement of metabolic rate) at the Metabolic Research Unit Maastricht. The thermoneutral centroid was calculated for the participants with a steady-state biophysical analysis. The results indicated that 95% of the variation in average thermal sensation was explained by the distance to the thermoneutral zone. However, the space for general interpretation is limited due to the small homogenous sample and low contextual variance (due to lab conditions and specific temperature protocol the participants were exposed to).

The aim of this paper is to evaluate the performance of the biophysical analysis beyond a physiological laboratory setting, with data from a controlled office environment with increased contextual variance.

In relation to this aim, we posed the following research questions:

1. Is it possible to replicate the results of the biophysical analysis on data from less controlled experiments?
2. How good is the performance of using dTNZop for the prediction of thermal sensation?
3. Which are influencing factors on the predictive performance?

2 | METHODS

The analysis in this study is performed by reusing data from studies on occupants’ behavior and thermal perception in the LOBSTER. The facility, participant characteristics, and experimental designs are shortly summarized; for details see aforementioned papers.
2.1 | The LOBSTER

The LOBSTER (Laboratory for Occupant Behaviour, Satisfaction, Thermal comfort, and Environmental Research) combines positive aspects of field studies and laboratory experiments as follows. First, indoor air and radiant conditions can be controlled via the ventilation systems and activated surfaces; on the one hand, these control options allow for comparable conditions within each study, and on the other hand, the variations in experimental designs and associated pre-defined thermal conditions led to a wide range of conditions over all studies considered for this paper. Second, participants are able to view the outdoors through real windows and are allowed to interact with the indoor and outdoor thermal environment by various means of control. The number and degree of controls can be varied according to the experimental design.

The facility houses two identical office rooms (24 m² of floor area, 3 m high). One of their walls is a post and beam façade of 4 m width including two operable windows (0.9 m width by 1.5 m high) and two operable top light windows (0.9 m width and 0.5 m high). The glazing is a triple glazing \((U_g=0.7 \text{ W/m}^2\text{K})\), total solar transmittance\(=0.5\); the opaque balustrade is equipped with vacuum insulation panels \((U_{\text{panel}}=0.2 \text{ W/m}^2\text{K})\). The other exterior surfaces are made of a timber frame construction with wood fibers as insulation material and \(U\)-values of 0.13 W/m²K for the exterior walls, 0.12 W/m²K for the roof, and 0.12 W/m²K for the floor, which is elevated from the ground due to a rotating assembly underneath.

2.2 | Participants and experimental designs

In total 65 healthy adults (31 females, age: 25.5y±4.5, height: 175cm±8.8, weight: 72kg±15.5) participated in three experimental campaigns all conducted at warm outdoor conditions\(^{17–19}\). The participants were clothed according to the season \((0.57\text{clo}±0.2)\) and performing light office work. All participants were asked to work on their own tasks for one, two, or three 8-hour working days starting from 9 am and including a 30-minute lunch break. Depending on the protocol, they were allowed to tilt one or both windows, use the external Venetian blinds, adjust the lighting level, and/or use the ceiling fan (Table 1).

![FIGURE 2](image2.png) Comfort zones (gray areas) for globe temperature vs. metabolic rate and varying clothing level according to Humphreys.\(^{11}\) The gray comfort bandwidths are a function of internal tissue insulation, external insulation (clothing), and metabolic rate. The copyright holder permitted reproduction of the figure provided the following message was included: "© BRE, reproduced with permission from CP 14/71 (1970). Note that the diagram shows historical data and might not represent current best practice"

![FIGURE 3](image3.png) Schematic view of the thermoneutral zone (TNZ), which is situated between the lower critical temperature (LCT) and upper critical temperature (UCT). Below the LCT the body can maintain heat balance by metabolic regulation; above the UCT the body maintains heat balance via sweating. Within the TNZ heat balance is regulated via regulation of skin blood flow

![FIGURE 3](image4.png) Thermal sensation vs. operative temperature. The scheme shows the concept that the distance to the thermoneutral center \((d\text{TNZ}_{\text{op}})\) scales linearly with thermal sensation. The position of the thermoneutral center point is a function of metabolic rate, range of tissue insulation, clothing, wind speed, and relative humidity
The participants work was interrupted by filling in comfort questionnaires every 90 minutes on average for a total of six times a day. Among other questions, the comfort questionnaire consisted of the seven-point ASHRAE thermal sensation scale. The clothing level was assessed through a questionnaire at the beginning of the day. Changes in the clothing level were reported together with each comfort questionnaire. In addition, physiological measures such as the skin temperature were monitored continuously at an interval of 1 minute.

Physical parameters indoors (air temperature, globe temperature, air velocity, relative humidity) and outdoors were measured in the middle of the room and logged in a 1-minute interval. The operative temperature was calculated according to ISO 7726:2001 using the measurements of air temperature, globe temperature, and air velocity. The states of windows, blinds, ceiling fans, and artificial lighting devices were logged in a 1-minute interval. Participants were allowed to use the restrooms upon necessity and to drink liquids at room temperature whenever they wished.

All studies were approved by the ethical committee and data protection officer. Informed consent was signed by the participants prior to their participation.

2.3 | Biophysical model

The theoretical center of the TNZ is calculated based on the biophysical model developed by Kingma et al., see Figure 3 for a graphic example of TNZ center. To calculate body core temperature, the model assumes a steady-state heat balance within the body and between the body and its environment (see Figure 1). The mathematical procedure is described in the Supplementary Information. Model variables are given in Table 2.

2.4 | Data preparation and description

In this study, the heat equivalent of activity level associated metabolic rate is scaled with individual body characteristics using the revised Harris & Benedict equation (H&B). The revised H&B equation predicts resting metabolic rate (~1 met) based on height, weight, gender, and age. The empirical relation has a reasonable accuracy for average metabolic rate for populations where BMI ranges between 18 kg/m² and 25 kg/m², with an explained variance of 86%. To minimize the influence of this prediction error to the analysis, the data points from participants with a body mass index >25 kg/m² or <18 kg/m² were removed. In addition, five measurements from four participants were excluded based on regression diagnostics using the linear mixed effect model described below (see eq. (5)). Therefore, the Cook’s distance was calculated for each data point, which is a measure of the influence of the data point on the result. According to the literature, data points associated with a Cook’s distance greater than 4/n, with n being the number of observations, can be regarded as highly influential observations. Therefore, the five observations with a Cook’s distance greater than 0.005 (4/800 observations) were removed. The remaining data consisted of 798 votes by 47 participants as summarized in Table 3.

For each measurement sample, i, the independent variable \(dTNZ_{op}\) was calculated according to the procedure described in the Supplementary Information using the R-package comf and the assumptions presented in Table 2. In addition, PMV values were computed using the R-package comf and the same assumptions as for calculation of \(dTNZ_{op}\).

2.5 | Data analysis

After calculating \(dTNZ_{op}\), the data were analyzed in four steps related to the three research questions presented in Introduction. Software package R was used throughout the analysis.

The first research question was approached in two ways:

First, we looked at a subset of the data to replicate the findings in Kingma et al. This subset was chosen to be as identical in its nature as possible compared to the dataset used in their analysis. Therefore, only data from females participating in study A during condition A1, where they were placed in a single office, were used. The mean per voting timepoint±95% confidence interval was derived for actual (observed) thermal sensation votes (ASVs), predicted mean votes (PMVs), as well as aspects related to the perception of the thermal indoor

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Next, the following linear regression model was fitted to the mean values of each voting timepoint:

$$\text{mean (ASV)}_i = \beta_0 + \beta_1 \text{mean (dTNZop)}_i + \epsilon_i \quad (1)$$

The outcome of this regression analysis was used to calculate a predicted thermal sensation vote (PSV) for each measurement based on dTNZop through:

$$\text{mean (PSV)}_i = \beta_0 + \beta_1 \text{mean (dTNZop)}_i \quad (2)$$

For the second way to approach the first research question, the complete dataset with individual measurements, ie, the 798 votes by 47 participants, was analyzed fitting an ordinal mixed effect logistic regression model and a linear mixed effect regression model. Mixed effect models were used to account for the repeated votes (up to 18 times) of each participant.

The ordinal mixed effect logistic regression model was fitted, because the ASVs were given on a categorical scale and do not necessarily comply with the assumptions of equidistance. The ordinal regression analysis, a cumulative link model with the logit function as link function was used. With a cumulative link model, the probability,

$$P(\text{ASV} \leq j)$$

of an observation, $i$, falls in a response category, $j$, can be expressed. The cumulative link mixed model used for this study denotes the probability of ASV falling in category $j$ of the seven categories of the thermal sensation vote and can be expressed by:

$$\text{logit}(P(\text{ASV}_i \leq j)) = \theta_j - \beta_1 \text{dTNZop}_i - \nu_{\text{Subject}}, \quad (3)$$
where $i$ is the index of the measurement, $j$ the category of the thermal sensation vote, and $\theta_j$ the intercept of category $j$. $\nu_{Subject}$ represents the random effects imposed by the participants’ individuality.

$P$-values were obtained by likelihood ratio tests of the model presented in eq. (3) with the effect of $dTNZ_{op}$ against the model without $dTNZ_{op}$. R-package ordinal\textsuperscript{28} with function clmm was used for this analysis.

For an easier interpretation of the result, predicted probabilities will be obtained and presented for each category through:

$$P(ASV_i) = \frac{1}{1 + e^{-\theta_i - \beta_0 dTNZ_{op}}},$$

(4)

The probability that a participant votes cool on the thermal sensation scale given a specific value of $dTNZ_{op}$ can be calculated by:

$$P(\text{cool}) = \frac{1}{1 + e^{-\theta_{\text{cool}} - \beta_0 dTNZ_{op}}},$$

(5)

The linear mixed effect regression analysis was included to compare the results with ordinal regression analysis. Should the distance between the linear mixed effect regression analysis and the ordinal regression analysis be small, the coefficients of the linear mixed effect regression analysis could be compared to coefficients presented by Kingma et al.\textsuperscript{14} The following linear mixed effect regression model was fitted to the dataset with individual measurements:

$$ASV_i = \beta_0 + \beta_1 dTNZ_{op} + \nu_{Subject_i} + \epsilon_i,$$

(6)

$P$-values were obtained by likelihood ratio tests of the model presented in eq. (6) with the effect of $dTNZ_{op}$ against the model without $dTNZ_{op}$. R-package lme\textsuperscript{49} with function lmer was used for this analysis.

For the second research question, the coefficients derived with the linear mixed effect regression analysis were used to predict the thermal sensation based on $dTNZ_{op}$ by:

$$PSV_i = \beta_0 + \beta_1 dTNZ_{op},$$

(7)

The resulting values of $PSV$ were categorized to $PMV_{cat}$ to be comparable with the values of $ASV$, which were given on a categorical scale. For the categorization, all $PSVs$ with values below or equal to $-2.5$ were categorized to be $-2$, $PSVs$ above $-2.5$ and below or equal to $-1.5$ as $-1$, and so on. The same procedure was applied to the values of $PMV$ to create the variable $PMV_{cat}$. The performance of $ASV$, $PSV_{cat}$, and $PMV_{cat}$ was then assessed through the following four performance criteria:

First, the root mean square error is, eg, given by

$$\text{root mean square error} = \sqrt{\frac{\sum_{i=1}^{n} (PSV_{cat} - ASV_i)^2}{n}},$$

(8)

with $n$ being the number of votes.

Second, the average accuracy\textsuperscript{30} was calculated by

$$\text{average accuracy} = \frac{\sum_{i=1}^{n} tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i},$$

(9)

with $j$, the number of categories, ie, in case of the thermal sensation scale=7, and $tp$, $tn$, $fn$, and $fp$, the number of true positives, true negatives, false negatives, and false positives of the corresponding category. To give an example, the number of true positives in the category warm is the number of votes observed and predicted as warm, while the number of false positives is the number of votes observed and predicted as not warm, and the number of false negatives is the number of votes observed as warm, but predicted as not warm. Therefore, the average accuracy shows the average effectiveness per category, whereby the effectiveness of a category is the ratio of truly predicted votes to the total number of votes.

Third, the mean bias,\textsuperscript{31,32} ie, the mean difference between predicted and actual sensation vote, was calculated by

$$\text{mean bias} = \text{mean} (PSV_i - ASV_i)$$

(10)

Fourth, the true positive rate,\textsuperscript{15} which is the proportion of the true positive cases (TP), ie, those cases where $ASV$ is equal to $PSV_{cat}$ or $PMV_{cat}$, respectively, is given by

$$\text{true positive rate} = \frac{\sum_{i=1}^{n} TP_i}{n},$$

(11)

with $n$, the number of votes, and $j$, the number of categories of the thermal sensation scale.

All performance criteria except root mean square error were calculated using R-package caret.\textsuperscript{25}

The third research question was addressed looking at the difference between ASV and PSV (the prediction error). First, this difference was plotted against

- indoor environmental parameters (operative temperature, relative humidity, air velocity, and temperature change rate during the last 10 minutes before the vote),
- the running mean outdoor temperature,\textsuperscript{33}
- individual factors (clothing insulation level (CLO), sex, and body mass index (BMI)), and
- the session type related to differences in the type of controls and number of participants in the office. These were modeled as binary variables, ie, either being the session type in question (1) or not (0).

Second, a linear regression model and a linear mixed effect regression model were fitted for each of these parameters. The fitted models were of the form:

$$\text{(ASV}_i - \text{PSV}_i) = \beta_0 + \beta_1 x_i + \nu_{Subject_i} + \epsilon_i,$$

(12)

$$\text{(ASV}_i - \text{PSV}_i) = \beta_0 + \beta_1 x_i + \nu_{Subject_i} + \epsilon_i,$$

(13)

where $x$ is the parameter analyzed, eg, the operative temperature.

### 3 | RESULTS AND DISCUSSION

#### 3.1 | Analysis of mean values per voting timepoint

This section presents and discusses the results based on the subset of data being as similar as possible with respect to sex and age of the sample as well as indoor environmental conditions to the dataset used by Kingma et al.\textsuperscript{14}
Linear regression analysis on means for all six voting timepoints showed no significant relation at \( P<0.05 \) between actual thermal sensation votes (ASVs) and calculated dTNZ\(_{op}\) but a tendency toward significance \((\beta_0: 0.28 \pm 0.08 \text{ (standard errors)}, \beta_1: 0.18 \pm 0.07, P=0.08, r^2=0.58)\). For comparison, the relation between ASV and calculated PMV value was not significant \((P=0.19, r^2=0.39)\).

The outcome of this regression analysis was then used to calculate a mean predicted thermal sensation vote (PSV) for each voting timepoint based on dTNZ\(_{op}\) (PSV dTNZ\(_{op}\)) according to eq. (2).

In Figure 4, the mean PSV (dTNZ\(_{op}\)) at each voting timepoint is shown together with the mean values of ASV and PMV (Fanger). The following can be observed from Figure 5:

- mean ASV at the second voting timepoint was low compared to mean PSV (dTNZ\(_{op}\)) and mean PMV (Fanger). Indoor environmental conditions and clothing level did not suggest such decrease between the first and third voting timepoint (Figure 5 right),
- from third to last voting timepoint, the course of mean ASV and mean PSV was parallel—with PSV being slightly below ASV,
- mean PMV followed ASV for third and fourth voting timepoint, but did not capture the dynamics of fifth and sixth voting timepoint, and
- confidence intervals overlap in most cases, so that the differences are not statistically significant.

The differences in the second, fifth, and sixth voting timepoint require further discussion. The rather low mean ASV at the 2nd voting timepoint was neither predicted by the biophysical model presented in this study nor to be expected looking at the course of physical conditions. A possible explanation lies within the combination of experimental design and the type of thermal sensation scale used. The first voting timepoint was around 30 minutes after participants entered the controlled office environment of the test facility. At this point, participants’ metabolic rate can be expected to be still slightly elevated for those having arrived with the bicycle. In addition, stress level might have been slightly increased for those participating the first day, because the environment was new to them. At the time of the second voting timepoint (105 minutes after entering the office), both, metabolic rate and stress level, can be expected to be decreased, because the participants were seated and doing non-stressful office work. At the same time, thermal conditions did not change much, so that the participants might have perceived the office space to be slightly cooler than during the first voting timepoint, because of the decrease in internal heat generation. When people feel differences, they prefer to report them by changing their vote on the given scale. In this study, they could change their previous vote only by one category, because of the categorical scale used. Consequently, the second vote could have ended up much lower than expected. Further analyses going beyond the scope of this paper would be required to confirm or reject such assumptions.

The difference between mean ASV and mean PMV observed for the fifth and sixth voting timepoint is in line with previous findings, which showed that the PMV model underestimates the cooling effect of elevated air speeds.

To address the question, whether the regression outcome presented by Kingma et al. can be reproduced within a less controlled environment, their results (preceded in the following by K16) will be compared with the results presented above (S16). The intercept (S16: 0.28±0.22 (CI) vs. K16: 0.18±0.21) is slightly higher in this study. The slope (S16: 0.18±0.07 vs. K16: 0.28±0.02) is slightly lower in this study. For intercept and slope, confidence intervals are overlapping, so that these differences are not significant.

### 3.2 Analysis of individual measurements

In the following the results based on individual votes are presented. Ordinal mixed effect logistic regression analysis of ASV against dTNZ\(_{op}\) showed that dTNZ\(_{op}\) affected ASV \((\chi^2(3)=210.3, P<0.0001)\), with an ordered log-odds estimate of about 0.75±0.08 (standard errors), and the cut-points between two categories, \(\theta\), of \([-2|−1]=−4.58\pm0.36, \{-1|0|=−2.0\pm0.18, \{0|1|=1.46\pm0.17, \{1|2=4.29\pm0.25, \{2|3=7.61\pm0.59]\). The log-odds estimate can be interpreted in such a way that an increase in dTNZ\(_{op}\) by one unit would increase the log-odds of obtaining a thermal sensation vote in a higher category (ie, toward the hot end of the scale) by 0.75, the odds by 2.12 (=e^0.75), and the probability by 0.68 (=2.12/(1+2.12)). For comparison, tossing a two-sided coin would have a probability of 0.50, odds of 1, and log-odds of 0.

The resulting predicted probabilities for each category for values of dTNZ\(_{op}\) between −4 and +4 are presented in Figure 6. The highest probability of obtaining a neutral vote was related to a dTNZ\(_{op}\) around −0.2.
The linear mixed effect regression analysis on individual votes including the individual ASV as fixed effect and the participant code as random effect for intercept and slope revealed that dTNZop affected ASV significantly ($\chi^2(3)=205.0, P<.0001$). Intercept and slope of fixed effects resulted in $\beta_0=0.08\pm0.04$ and $\beta_1=0.23\pm0.02$ ($r^2=.43$). These coefficients were used in the following to estimate PSV (dTNZop) by eq. (7). Testing a second-order polynomial model for the linear mixed effect regression between dTNZop and ASV showed no significant effect of the second-order polynomial.

To compare the results of ordinal and linear mixed effect analysis, the sum of the probabilities based on the ordinal regression model multiplied with the value of each category was used for comparison with the linear mixed effect regression model. There was a very high correlation between the sum of probabilities and PSV based on linear mixed effect regression analysis (Pearson-$r=.9996$). Therefore, the following analyses are based on linear regression analyses despite ASV being ordinal.

### 3.3 Performance evaluation

Table 4 presents the performance criteria for PSVcat—based on the coefficients obtained through linear mixed effect regression analysis described above—and PMVcat against the observed thermal sensation votes (ASVs). Root mean square error and average accuracy are (nearly) the same, while the mean bias of PSVcat is slightly closer to 0 and its true positive rate is slightly higher; ie, PSVcat is performing slightly better for these two criteria. Nevertheless, both models—dTNZ and PMV—perform in the same magnitude.

### 3.4 Influencing factors on prediction error

Prediction errors, ie, the difference between ASV and PSV, range between $-2.5$ and $+2.2$ (mean: 0.03, SD: 0.73). Figure 7 shows the relationship between Top and the prediction error. The mixed effect regression analysis with Top as predictor and the prediction error as outcome variable showed a statistically significant influence of Top on the prediction error (intercept: $-0.98\pm0.6 (P<.05)$, slope: $0.038\pm0.02 (P<.05)$). However, with an $R^2$ value of .02, only 2% of the variance in the prediction error was explained by the variations in Top. The small explained variance together with the small slope showed that the prediction error caused by the dTNZ model is not systematically affected by Top.

In the Supplementary Information, the same analysis is presented for vapor pressure, air velocity, the temperature change rate during the last 10 minutes before the vote, the running mean outdoor temperature, the clothing insulation level, body mass index, sex and experimental condition. Among these variables, only the slopes for clothing insulation level the session type, where participants were not allowed to open the windows (K), were significant at $P<.01$. The explained variance was highest for the clothing insulation level with 6%.

The finding that the setting in which the participants were not allowed to open a window led to the warmest perception of comparable thermal conditions supports the findings of previous studies, that people tolerate warmer conditions when they have the opportunity to open the windows.36,37,39

In general, the prediction error was closest to 0, ie, a perfect fit, around those conditions presented in the data of Kingma et al.14: Top $\sim24-26{^\circ}\text{C}$, AV <0.2, CLO $\sim0.5$. The observation that there is a better fit at conditions within the thermoneutral zone suggests that thermal

<table>
<thead>
<tr>
<th>TABLE 4</th>
<th>Performance criteria for PSVcat and PMVcat</th>
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<tbody>
<tr>
<td></td>
<td>PSVcat</td>
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<tr>
<td>Root mean squared error</td>
<td>0.73</td>
</tr>
<tr>
<td>Average accuracy</td>
<td>0.84</td>
</tr>
<tr>
<td>Mean bias</td>
<td>$-0.03$</td>
</tr>
<tr>
<td>True positive rate</td>
<td>52.6</td>
</tr>
</tbody>
</table>

FIGURE 6 Probabilities for each category of sensation votes in relation to dTNZop

FIGURE 7 Residual analysis of prediction error for operative temperature (red: linear model, green dashed: mixed effect model (fixed effects), blue dotted: loess fit (1st degree, span 0.2))
sensation is affected by more than a linear distance to the TNZ center (eg, non-linear internal scaling of dTNZ_op). This may relate to the non-linear characteristic of temperature-sensitive neurons that are responsible for thermal reception. Nevertheless, regression coefficients are very low for all these variables. These findings can be used to adjust the mapping of dTNZ_op to thermal sensation.

4 | GENERAL DISCUSSION

The results confirm the potential of the biophysical model to predict the thermal sensation of humans. In this study, the prediction performance of the dTNZ_op concept on average thermal sensation votes proved to be comparable to the current PMV standard and on individual level dTNZ_op significantly explains thermal sensation over a wide variety of contextual variances (r² = .43)—again comparable to the PMV model (r² = .41). The main difference between both approaches is the inclusion of body tissue insulation in the biophysical model, which allows for calculation of the thermal condition with least internal thermal strain (ie, midpoint of body tissue insulation range). This study applied a population-averaged value for the range of body tissue insulation that yields comparable prediction to the PMV standard. To make more precise predictions, the body tissue insulation ranges of various subpopulations that differ in body composition (muscle and fat mass) or ability to regulate skin blood flow could be included. For instance, the thickness of the subcutaneous fat layer positively relates to body tissue insulation. Potential comparisons between subpopulations could be, eg, lean vs. obese and males vs. females who differ in body composition, or young vs. old, and diabetic vs. non-diabetics who differ in ability to regulate skin blood flow. This type of analysis was not possible with the current dataset, and remains future work. It is also not certain that the addition of specific knowledge on body tissue insulation actually improves thermal sensation prediction because of the added uncertainty with an extra variable relative to the PMV model. However, exploring the influence of body tissue insulation seems worthwhile to pursue given that both PMV model and the dTNZ_op with averaged body tissue insulation values explain around 50% of the variance in thermal sensation. The question is whether thermal sensation is indeed explainable by heat balance only up to approximately 50% and to which level this can be improved by taking into account body tissue insulation.

Going beyond physiological factors to further increase the predictive performance, the biophysical model presented here could also be combined with the framework for an adaptive thermal heat balance model to account for physiological, behavioral, and psychological adaptive processes. In this context, it should be noted that this paper showed the relationship between dTNZ and thermal sensation, but does not attempt to establish a relationship between dTNZ and thermal comfort. Such note is crucial, because it is possible that a non-neutral sensation or sweating is still perceived as comfortable depending on the thermal experiences of the body. Such aspect is beyond the scope of this paper and to be investigated in the future.

Limitations in the applicability of these results lie in the uncertainty related to the values of clothing level and activity rate. In contrast to the procedure presented by Kingma et al., these values were not measured in the studies which the dataset used for this paper is based on. The clothing level was estimated from the participants’ answers using the classifications given in ISO 7730. However, such assumption related to the activity level might capture neither all variations in activity level throughout the day nor other aspects affecting metabolic rate such as diet-induced thermogenesis (~10%) after the lunch break, or seasonal variations in metabolic rate. These uncertainties might be able to explain part of the observed variance or, if systematic, alter the results. However, there is no more accurate procedure for assessing the exact clothing insulation value available except for detailed measurements of individual clothing garments worn by participants or the provision of standardized clothing items. As the former would be unfeasible to be conducted on a daily level for a number of participants and the latter would affect the general level of satisfaction, these procedures were not applied. As for the activity level, guidance would be necessary to which extent the metabolic rate increases during the day depending on activity and nutrition.

5 | CONCLUSIONS

This study confirms the linear relationship between the distance of operative temperature to the center of the thermoneutral zone (dTNZ_op) calculated based on a biophysical model and thermal sensation votes obtained by measurements within a variety of thermal conditions and contextual factors.

The results indicate that the performance of the biophysical model in predicting thermal sensation on average and on individual levels is of the same magnitude as that of the well-established PMV model. Both models predicted around 50% of the thermal sensation votes correctly, which is—with seven categories of thermal sensation—significantly better than a random guess. These findings point to the potential of the biophysical model with regard to the understanding and prediction of human thermal sensation.

For this study, the biophysical model was fed with population-averaged ranges for body tissue insulation. In the future, the biophysical model and the relationship between dTNZ_op and thermal sensation may be tuned to specific subpopulations that differ in body composition or ability for thermoregulation such as obese vs. non-obese, young vs. elderly. Such adjustment could lead to a higher performance of the biophysical model in predicting thermal sensation of specific subpopulations. At the same time, the question remains what part of thermal sensation is explained purely by physiology and heat balance and what part has to be explained by psychological factors.

REFERENCES

SCHWEIKER ET AL.


SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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