Received: 15 March 2021 | Revised: 26 April 2021 | Accepted: 6 May 2021

DOI: 10.1111/ina.12859

ORIGINAL ARTICLE

WILEY

Predicting thermal pleasure experienced in dynamic environments from simulated cutaneous thermoreceptor activity

Thomas Parkinson[1] | Hui Zhang[1] | Ed Arens[1] | Yingdong He[1] | Richard de Dear[2] | John Elson[3] | Alex Parkinson[4] | Clay Maranville[3] | Andrew Wang[1]

[1]Center for the Built Environment (CBE), University of California Berkeley, Berkeley, California, USA

[2]Indoor Environmental Quality Lab, School of Architecture, Design and Planning, The University of Sydney, Sydney, NSW, Australia

[3]Ford Motor Company, Dearborn, Michigan, USA

[4]Department of Mathematics, Macquarie University, Sydney, NSW, Australia

***Correspondence**
Richard de Dear, The University of Sydney, Indoor Environmental Quality Lab, School of Architecture, Design and Planning, Sydney, NSW, Australia.
Email: richard.dedear@sydney.edu.au

Funding information
This work was principally funded by the Ford Motor Company through the University Research Program (URP). Thomas Parkinson was partially supported by the Republic of Singapore's National Research Foundation Singapore through a grant to the Berkeley Education Alliance for Research in Singapore (BEARS) for the Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) Program.

Abstract

Research into human thermal perception indoors has focused on “neutrality” under steady-state conditions. Recent interest in thermal alliesthesia has highlighted the hedonic dimension of our thermal world that has been largely overlooked by science. Here, we show the activity of sensory neurons can predict thermal pleasure under dynamic exposures. A numerical model of cutaneous thermoreceptors was applied to skin temperature measurements from 12 human subjects. A random forest model trained on simulated thermoreceptor impulses could classify pleasure responses (F1 score of 67%) with low false positives/negatives (4%). Accuracy increased (83%) when excluding the few extreme (dis)pleasure responses. Validation on an independent dataset confirmed model reliability. This is the first empirical demonstration of the relationship between thermoreceptors and pleasure arising from thermal stimuli. Insights into the neurophysiology of thermal perception can enhance the experience of built environments through designs that promote sensory excitation instead of neutrality.

KEYWORDS
alliesthesia, dynamic environments, machine learning, pleasure, predictive model, thermal physiology, thermoreceptor

1 | INTRODUCTION

Attempts to understand thermal perception in dynamic environments[1-7] indicate that popular steady-state heat-balance models such as the predicted mean vote[8] are inappropriate for predictions of sensation or comfort. Zhang et al.[6,7,9] and de Dear[10] proposed alliesthesia as a theoretical framework capable of describing perceptual processes in non-steady-state exposures. Based on the ground-breaking work by Cabanac,[11] alliesthesia describes the psychophysiological phenomenon of pleasure arising from stimuli that play a corrective role within a regulated system. In the context of thermal comfort, examples include suddenly elevated air movement for a warm occupant or providing radiant heating for a currently cool occupant. A more detailed description of alliesthesia in built environments can be found in Parkinson & de Dear.[12] Subsequent work[13] demonstrated that pleasure responses can occur within the thermoneutral zone and appear to be driven largely by changing skin temperatures. This was reinforced by later works[14,15] showing that pleasure responses follow a particular psychophysiological pattern that included skin temperature change. This empirical evidence, along with suggestions by Cabanac[16] and de Dear,[10] indicates that efforts to understand thermal alliesthesia should closely examine the role of cutaneous thermoreceptors in eliciting pleasure.

Afferent neurons in the skin, commonly referred to as thermoreceptors, provide the functional system for the perception of temperature in humans.[17-19] The somatosensory system relies on thermoreceptors to detect changes in ambient temperature over a wide range of conditions.[20] Pioneering electrophysiological studies of various mammals[21-29] identified structurally and functionally distinct warm-sensitive and cold-sensitive neurons. The molecular basis of this temperature transduction remains largely unclear, but more recent investigations have uncovered subpopulations of temperature-sensitive neurons that encode and transmit skin temperature over specific temperature ranges[30-32] as shown in Figure 1.

A comprehensive review of cutaneous thermoreceptors by Hensel[18] is a foundational contribution to our understanding of temperature perception. Much of the content has been reviewed in earlier papers on alliesthesia (see [10] and [12]) but it is worth revisiting some relevant details:

1. There is a difference in discharge frequency at static temperatures compared to the heightened response during skin temperature change.[19,22,26,28] For example, Figure 2 shows the discharges from a cold thermoreceptor dramatically increase following sudden cooling of the skin, but gradually decrease and stabilize once the temperature is static. The volley of thermoafferents generated during rapid temperature changes allows for better discrimination of both magnitude and time course than slower drifts.[21,34,35,36]
2. Cold receptors are located at shallower depths in the skin (0.1–0.2 mm) compared to warm receptors (0.5 mm),[18] although Ivanov et al.[37] reported finding subcutaneous cold receptors at depths of 2.0–2.5 mm from the surface.
3. Thermoreceptors are ubiquitous in mammalian cutaneous tissue—of the estimated one million sensory neurons comprising the somatosensory system, 280 000 are thought to be responsible for temperature transduction.[38] However, they are unevenly distributed across body sites, and cold receptor density is greater than that of warm receptors.[18] Investigations of local sensation responses have associated receptor densities as the neurophysiological basis of weighting coefficients for predicting the contribution of skin temperature to sudomotor actions and perceptual responses.[5,6,7,39,40,41,42]
4. The shallower depth, higher density of receptors, and larger dynamic response lead to increased activity of cold receptors [21,22] during rapid temperature decreases (up to 30 times greater) compared to warm receptors during rapid temperature increases (up to 5 times greater).[43]

Practical implications

- Pleasure experienced during changes in temperature can be predicted using machine learning and simulated activity of receptors in the skin
- This knowledge could inform tools for architects or engineers to design buildings and spaces that elicit thermal pleasure responses
- Represents a paradigm shift in understanding and modeling of human thermal perception in dynamic environments

Some studies investigated body-region sensitivity to peripheral thermal stimuli by applying a small thermode to various body parts.[45-47] Luo et al.[48] used this method to obtain warm and cool sensitivity maps for the entire body. Aside from those local thermal sensitivity analyses, researchers also investigated the effect of warming or cooling one body segment on the whole-body thermal sensation. Nakamura et al.[49] asked subjects to evaluate both thermal sensation and thermal comfort while selectively forcing local skin temperatures of four body sites. Although the face generally exhibited the largest change in local thermal sensation during local cooling or warming, thermal comfort can differ in its response pattern with respect to magnitude and direction. These results align with the findings of similar investigations of local thermal comfort[5,6,7,50] and led the authors to conclude that thermoreceptor density alone cannot explain observed regional sensitivity. Other efforts to understand the neuronal pathways responsible for thermosensation have suggested that higher-order processing by the central nervous system largely influences perceptual processes.[20,21,31,34,51,52,53] As the neural pathways for

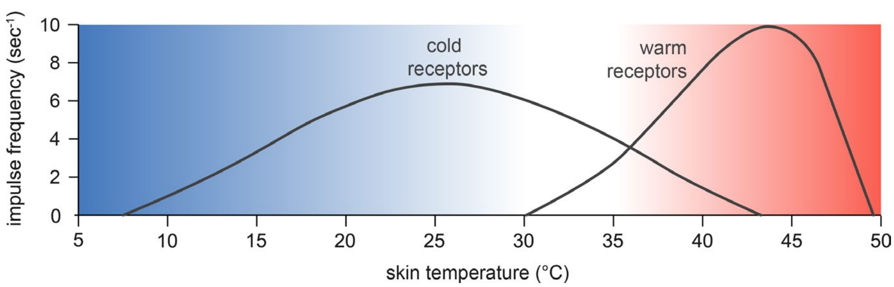


FIGURE 1 The static discharge rate of cold and warm thermoreceptors over a range of skin temperatures. Modified after Guyton and Hall[33]

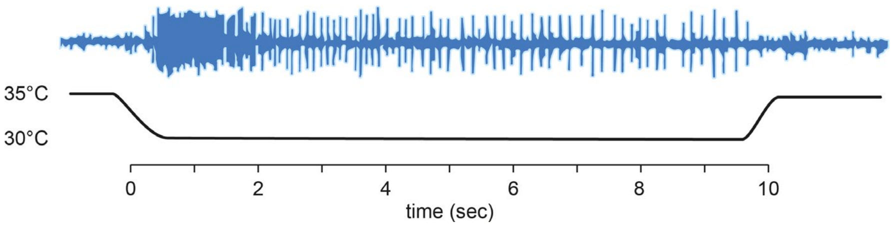


FIGURE 2 The dynamic and static response profile of a cold thermoreceptor recorded in a human subject during sudden cooling. Modified after Campero et al[44]

temperature perception are unclear, efforts by thermal comfort researchers to investigate the neurophysiological basis should focus attention toward using simplified models of known functional aspects of thermoreceptors.

There are two distinct dimensions of stimulus perception—the objective evaluation (magnitude and intensity), and the affective evaluation (quality or valence). Existing work has explored the psychophysical connection between the objective dimension of environmental stimuli (thermal sensation) and the somatosensory system (thermoreceptor activity) by simulating thermoreceptor discharge frequencies in non-steady-state exposures. The first, by de Dear et al.,[54] involved transitioning human subjects through temperature step-changes (both up- and down-steps) of differing magnitudes while recording immediate impressions of thermal sensation. Thermoreceptor impulses were simulated using the numerical model developed by Ring & de Dear[55] based on first principles of heat transfer through human skin. The resulting Dynamic Thermal Stimulus (DTS) model of receptor activity showed a clear relationship with the observed change in sensation votes immediately following temperature step changes. More recently, Kingma et al. [56] used observed skin and core temperatures from human subjects exposed to ramping ambient conditions as input variables to their mathematical model of thermoreceptor discharge rates based on the coefficients in Mekjavic & Morrison.[57] The simulated outputs from the thermosensation model performed well, with an average root mean square error of only 0.38 in the prediction of dynamic thermal sensation votes.

In addition to investigations of thermal sensation and neurophysiology, significant attention has been given to exploring how thermoafferent pathways could potentially contribute toward the control of body temperature.[53,57,58,59,60,61,62] All this research interest in the neurophysiological mechanisms of thermosensation highlights the potential of this exciting field of knowledge to contribute toward our understanding of thermal comfort and perception in dynamic environments. Yet our review of extant literature found no published work attempting to connect functional aspects of neurophysiology to the affective dimension of thermal perception. Despite phenomenological differences between thermal sensation and thermal pleasure, the sensory inputs that form these experiences originate from cutaneous thermoreceptors.

To examine the relationship between sensory neurons and thermal pleasure, we used a numerical model to simulate thermoreceptor activity in dynamic environments. Simulations were based on human skin temperatures measured during climate chamber experiments. A random forest model trained on the thermoreceptor activity was developed to predict thermal pleasure experienced during temperature changes. We validated the model using an independent dataset of psychophysiological measurements.

2 | METHODS

Physiological and psychometric data from an earlier human-subject chamber experiment on thermal alliesthesia[13] were used to train the machine learning predictive model. Thirteen volunteers (six women and seven men) participated in the study; key anthropometric data are reported in the original paper. Our focus for this study was on warm exposures (warm displeasure with a cool corrective change). We used data from a subsequent experiment to test the predictive skill of the model on an independent dataset with different environmental conditions and subjects.

2.1 | Thermoreceptor model

The model of heat diffusion in cutaneous tissue introduced by Ring & de Dear [55] and refined again by de Dear et al.[54] and Ring et al.[63] was used to simulate thermoreceptor activity. This numerical model presents human skin as a slab consisting of 36 layers with one-dimensional heat transfer (see Figure 3). Each layer is considered with its own thermal properties (capacity, conductivity); further details are given in Ring & de Dear.[55] The boundary layers in direct contact with the skin slab are defined as the subcutaneous tissue (layer 0) and the skin surface (layer 36). Thermoreceptors are "implanted" into the layers relative to their approximate depth in the skin; a cold receptor sits two layers below the skin surface in layer 34, and the warm receptor in layer 32. Both the dynamic and static thermoreceptor discharge rates are calculated based on empirically derived thermal sensitivity coefficients from Hensel.[18]

Changes to the way the thermoreceptor model defines the boundary layer conditions were made during the rewrite of the model from Fortran to C++ to adapt it to the current investigation. Rather than assuming a constant temperature for layer 0, the ability to read-in values for each time step was added to allow for a closer temperature approximation of the subcutaneous layer. This is particularly relevant when calculating heat transfer through the skin of distal sites in which the subcutaneous tissue has been cooled by heat losses through arterial and skin blood flows. Similarly, the option to read-in observed skin temperature for layer 36 was included, eliminating the need to consider clothing layers and the microclimatic boundary in the heat transfer

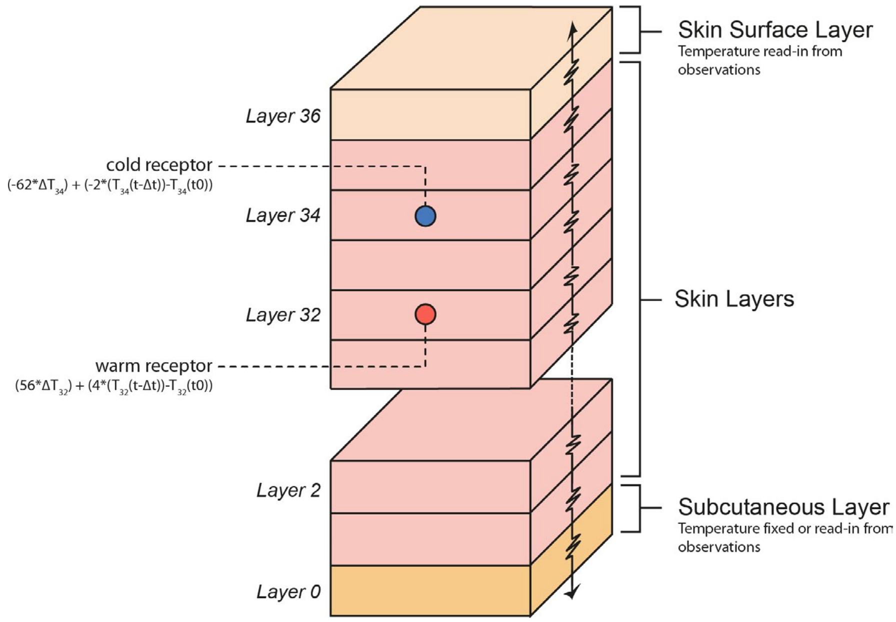


FIGURE 3 Graphical representation of the thermoreceptor model modified after de Dear et al.[54] Heat flows through each of the skin layers. The location of the cold and warm receptors in the skin slab is shown in layer 34 and 32, respectively. Formulae give the coefficients for the static and dynamic receptor responses

calculations. Using observed skin temperature directly is advantageous as it implicitly considers convective, conductive, radiative, and evaporative heat loss. Furthermore, this process should be straightforward to implement in detailed thermophysiological models with some modification.

2.2 | Dataset for model development

The laboratory experiments in Parkinson et al.[13] included sequenced environmental temperature step changes and ramps designed to elicit particular alliesthesia responses. A fan was placed behind the 12 subjects (wearing light clothing ensembles of 0.31 clo) to provide elevated air movement (0.5 m/s) during ramping temperatures in the warm exposure (from minute 10, t10). Ten subjects chose to initiate the fan. Data from two temperature down-steps—one more mild (t40) and the other following exercising in a warm room (t125)—were used to train the model for stronger (dis)pleasure responses.

Skin temperatures from 12 sites across the body[64] were the physiological inputs to the thermoreceptor model. An additional skin temperature measurement on the back of the neck was included as an unclothed site being directly forced by the targeted air movement. Linear interpolation of skin temperature records increased the temporal resolution from 0.2 Hz to 1 Hz to limit the square wave response of the model caused by changes in temperature over each time step. For the purposes of this analysis, the temperature of the subcutaneous layer was fixed at 36°C for proximal body segments (forehead, shoulder blade, lower back, chest, abdomen, upper arm, and thigh) and 35°C for distal sites (forearm, hand, calf, and foot) as a rudimentary consideration of the insulative effect of muscle and fat tissue, and additional heat loss from skin blood flow and countercurrent heat exchange.

Thermoreceptor impulses at each local body site were simulated at 20 Hz to get both the steady-state and dynamic responses of cold and warm receptors. Simulated receptor activity was summed to get the cumulative impulse count over one-minute periods to match the frequency of thermal pleasure responses. When combining receptor activity across body sites (eg, calculating total impulse rates across all sites), we used an unweighted average of the summed impulses based on three considerations: (a) the nonlinear response of thermoreceptors would lead to significant errors if a single mean (whole-body) skin temperature was used as input for the simulation of thermoreceptor activity[56] (b) there is currently no 12-point perceptual weighting scheme for local body sites, and (c) that sensitivity alone does not explain regional contributions to overall thermal perception.[49] All receptor impulse counts were scaled and centered per subject. This resulted in 52 input parameters to train the alliesthesia model—four simulated thermoreceptor impulse rates for 13 body sites—for model development.

Time series data in Figure 4 show skin temperature responding to changes in ambient temperature, and these changes are mirrored in the associated thermoreceptor response. The dynamic response to sudden temperature changes is evident in the cold receptor activity at t40 and t125 following the temperature down-steps. Mean thermal pleasure also reflects thermoreceptor impulses, with increasing displeasure as warm receptor impulses increase and pleasure occurring during spikes of cold receptor activity following temperature step changes.

2.3 | Dataset for model validation

We used an independent dataset from different subjects (n = 22) and distinct protocol of dynamic exposures to validate the alliesthesia model. This independent dataset is from a laboratory study investigating thermal pleasure responses to elevated air speeds (both cooled and ambient temperature) targeting the face and back of the neck in a warm environment (26°C) after exercises; see supplementary material for a data summary. Skin temperature was measured on the forehead, cheek, front of the neck, back of the neck, and the hand using thermocouples. We used the same method of simulating and processing thermoreceptor impulse rates to build the validation dataset as was used for the model development dataset.

2.4 | Machine learning alliesthesia model

There were a total of 1260 records of simulated thermoreceptor impulses and associated thermal pleasure votes. We tested several different model development techniques, ranging from simple linear regression through to supervised machine learning including support vector machine and gradient boosting algorithms. We decided to use the "RandomForest" implementation of the random forest classifier[65] to explore different models, and a random forest

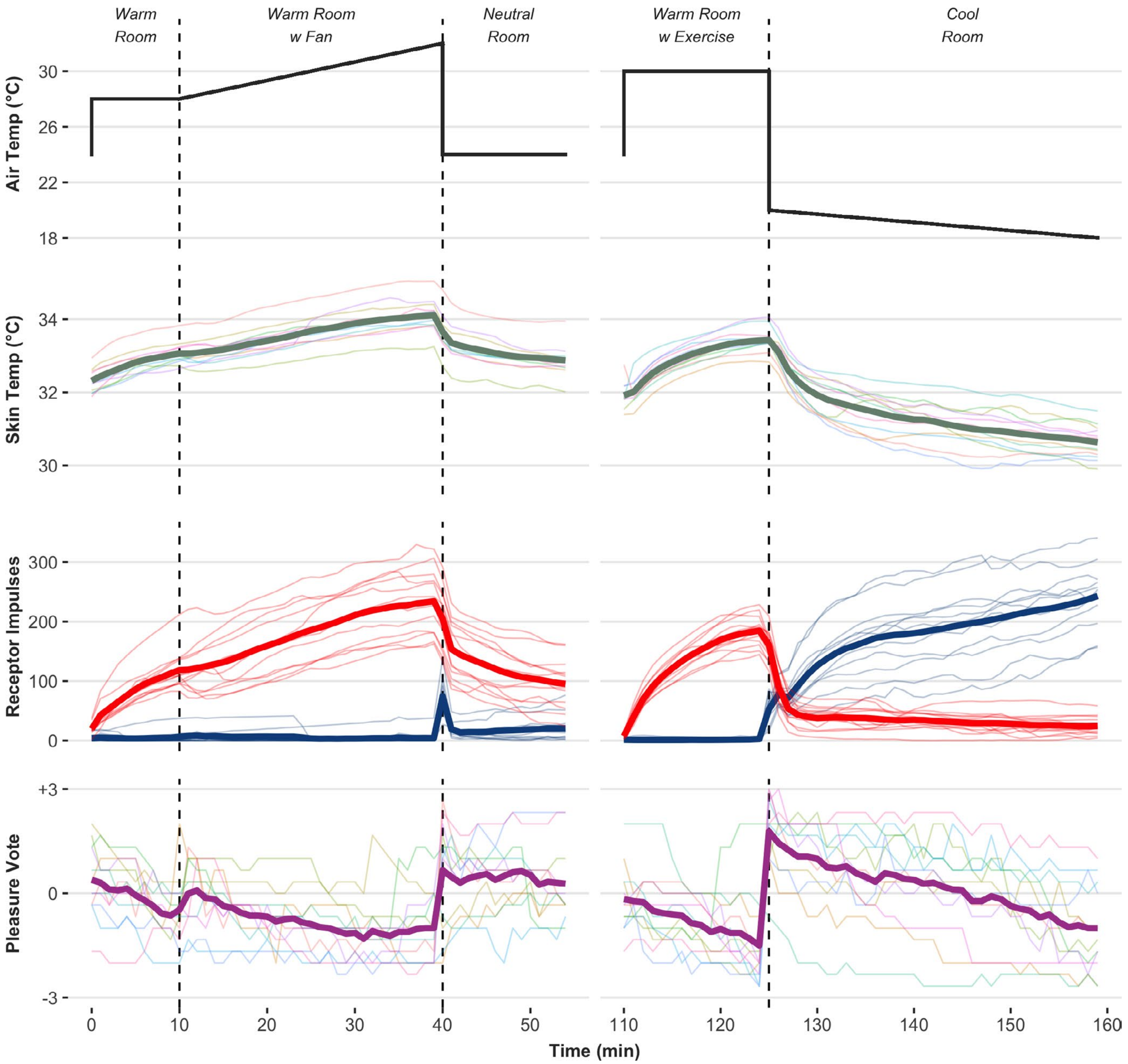


FIGURE 4 Time series data from Parkinson et al.[13] for room air temperature (top; first) mean skin temperature (second), cumulative receptor impulses per minute for all body sites (third), and thermal pleasure votes (fourth; bottom). Pleasure votes were cast every minute on a 7-point Likert scale, ranging from +3 (very pleasant) to 0 (indifferent) to −3 (very unpleasant). Data from individual subjects (faint) and the group (solid) are shown. Red lines show the total cumulative warm receptor impulses, and the blue lines show the cold receptors. Slight changes in skin temperature before transitions are due to changes in posture and movements when preparing to enter and exit the test chamber

regression model for final testing and validation. The random forest algorithm was chosen for performance and the availability of methods to develop interpretable machine learning models for explaining black box systems. We tested different hyperparameters to decide to limit models to 100 trees to balance accuracy and model complexity. Data were partitioned into training (80%) and testing (20%) datasets, and 10-fold 3-repeat cross-validation was used to ensure robust and reliable results.

2.5 | Data Analysis Software

We used R (version 3.5.0) and RStudio IDE (version 1.2.5033) for all analyses, along with the following packages: tidyverse,[66] caret[67] (version 6.0-86), yardstick[68] (version 0.0.6), ggpubr[69] (version 0.2.5), pdp[70] and ggridges[71] (version 0.5.2).

3 | RESULTS

3.1 | Simulated thermoreceptor impulses

A summary of thermal pleasures votes and simulated thermoreceptor impulses is shown in Figure 5. The model development dataset had more negative than positive pleasure votes, with the majority of responses ranging between slightly unpleasant (−1) and slightly pleasant (+1). The distribution of thermoreceptor impulses shows the predominant activity is the static response from the warm receptors. There was more warm receptor activity when subjects were experiencing displeasure and more cold receptor activity when experiencing pleasure. This is expected given the exposures were designed to create warm displeasure followed by a pleasant, cool corrective change.

We used k-means clustering to group thermal pleasure votes to test for differences in the responses between the 12 subjects. Figure 6 shows two distinct trends in thermal pleasure votes. Age, gender, and BMI were considered as the basis of cluster membership, but the most important factor was subjects' response to a general thermal preference question ("do you prefer warmer or cooler temperatures on average"). The "Cool Preference Cluster" was comprised of 4 subjects and the "Warm Preference Cluster" had 6 subjects. Two subjects who responded with "neither" were in the warm preference cluster based on the k-means analysis. Clustered subjects with a cool preference had a lower mean pleasure vote when in the warmer rooms than the warm preference subjects but responded positively to the cold step-changes (t40 and t125) and maintained pleasure throughout the cold room exposure (t125–t160).

A psychological parameter (general thermal preference) seemed to delineate cluster membership, and we wanted to explore physiological differences between these groups. Figure 7 shows statistically significant differences in thermoreceptor response between the two clusters for some of the room exposures in the experimental sequence. Warm receptor impulses were significantly higher for the cool preference cluster in the second (warm room with fan) and third (neutral) exposures in the sequence, and significantly lower in the final cool room exposure. Given the thermoreceptor model's reliance on skin temperature input, this result suggests potential neurophysiological differences between subjects that shape their thermal perception.

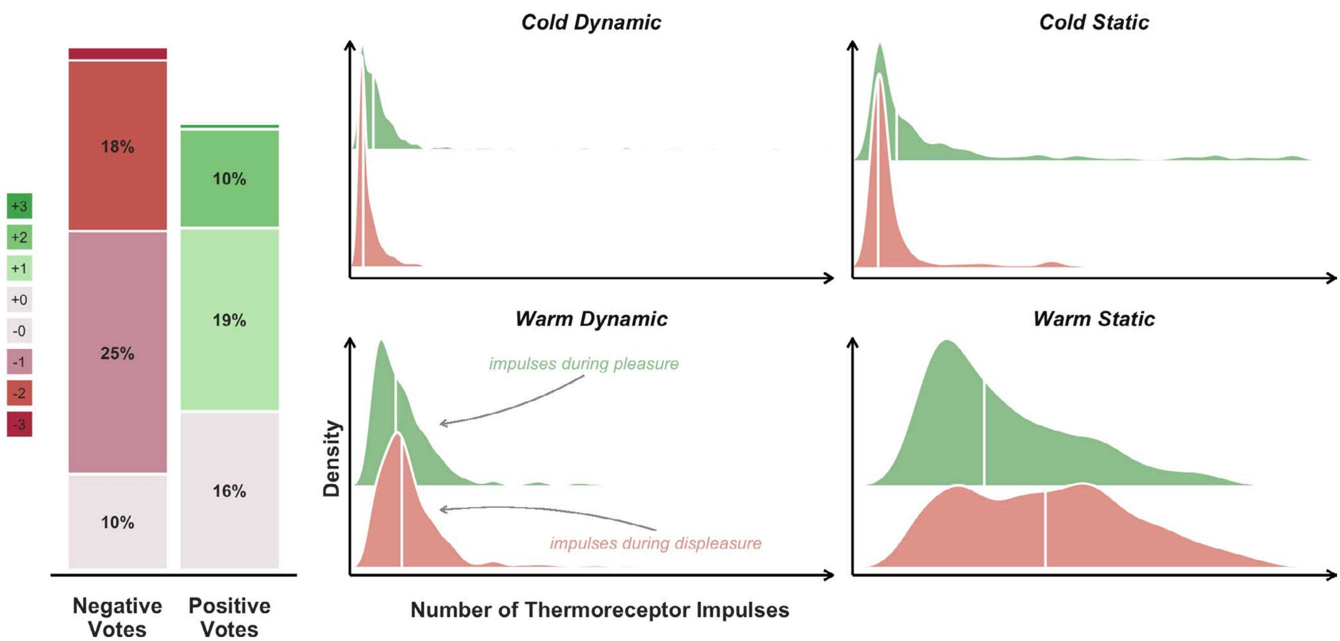


FIGURE 5 Summary data for thermal pleasure votes (left) and receptor impulses (right) for the model development dataset. Pleasure votes are separated by valence (red is negative; green is positive). The distribution of receptor impulses is shown by type (warm/cold; dynamic/static) and separated based on the valence of the contemporaneous pleasure response. The white line indicates the median

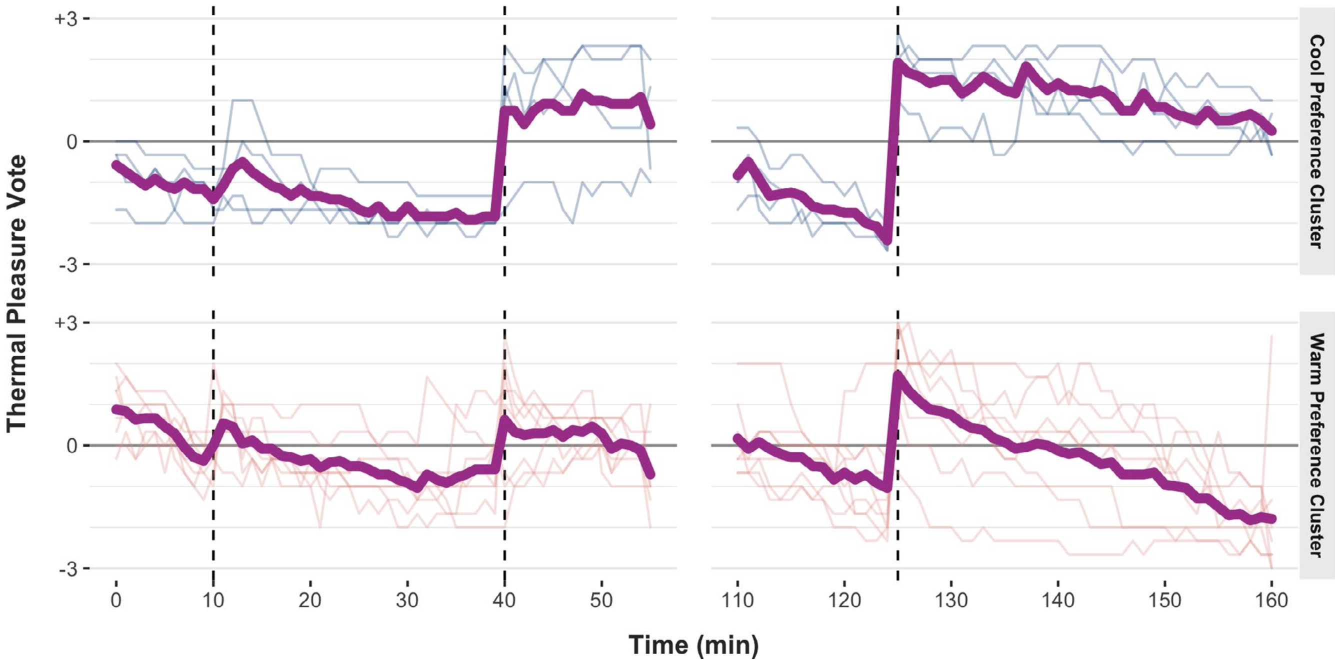


FIGURE 6 Time series of thermal pleasure votes separated by cluster membership. The cluster in the top panel is subjects with a preference for cooler temperatures and the bottom a preference for warmer temperatures

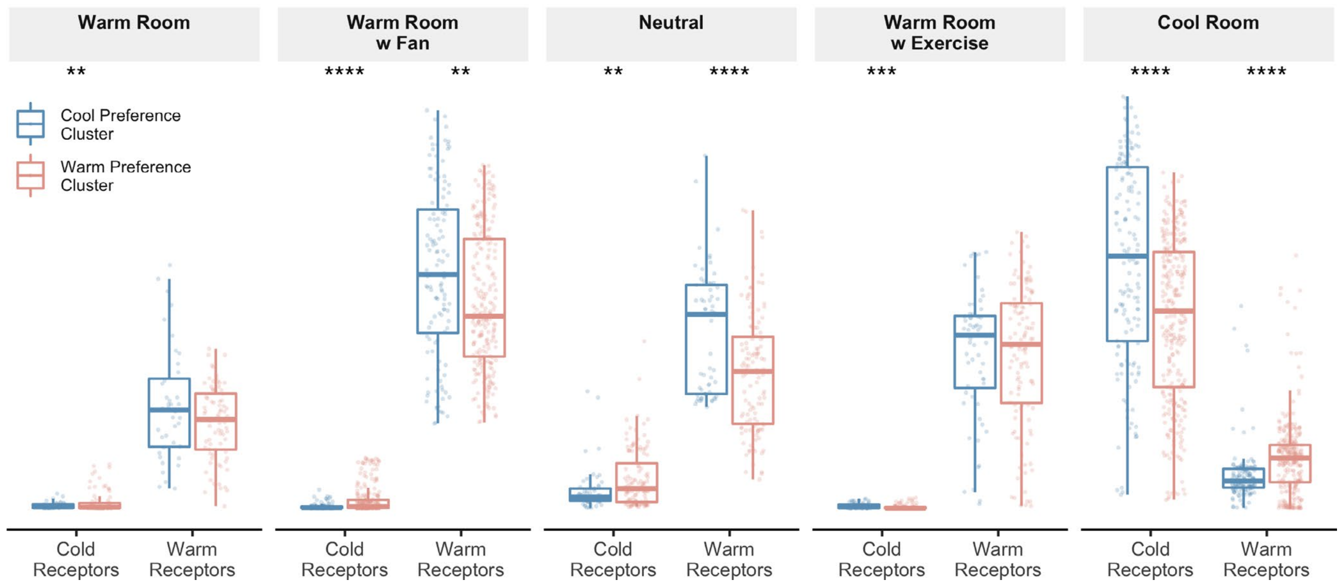


FIGURE 7 Box plot of warm thermoreceptor and cold thermoreceptor impulses for the different room exposures. Subjects were grouped by cool (blue) and warm (red) preference as determined by k-means clustering. t test significance is shown inset where differences were found (**≤0.01, ***≤0.001, ****≤0.0001)

3.2 | Model development

We tested and compared the performance of four random forest classification models in predicting alliesthesia. All models used simulated thermoreceptor impulses to perform multi-class classification into the 7-point thermal pleasure scale. We simplified the features (inputs) across the four models while attempting to balance overall accuracy. A summary of model performance is shown in Figure 8.

The "Full Model" was the most complex, using all 52 features (the dynamic/static response of warm/cold receptors for 13 body sites) to predict thermal pleasure. It had the highest accuracy and was able to correctly classify 87% of mid-range pleasure responses. In almost all cases, the predicted pleasure was ±1 vote from the observed, and only ~4% of responses were false negatives/positives. However, the feature importance of the model did not provide much logical inference for understanding alliesthesia. While the F1 score was acceptably high (72%), there was significant multicollinearity between the thermoreceptor response type (static/dynamic) and body sites (see Figure S2). Principal component analysis (PCA) found that eight components could explain 74% of the variance in the 52 features.

The PCA coordinates of the eight components have limited practical use but did demonstrate the need for dimension reduction. We focused on the theoretical framework of alliesthesia that posits pleasure is driven by the whole-body (load error) and local (corrective change) states. Correlation analysis (see Figure S2 for full correlation matrix) found that receptor activity at the *chest* was highly correlated with total *warm* impulses (dynamic = 0.70, static = 0.88) and the *shoulder* with total *cold* impulses (dynamic = 0.91, static = 0.94). The importance of cold thermoreceptors at the shoulder is explained by the positioning of the fan behind subjects. Using the simulated thermoreceptor activity from these two sites, a parsimonious "Rational Model" was set up and was able to achieve accuracy of 67% from only eight features. Despite the reduced accuracy, the confusion matrix in Figure 8 shows a mid-range accuracy (83%) comparable to the "Full Model" and a negligible increase in false positives/negatives. The static response of the warm receptors was the most important feature for classifications of both displeasure and pleasure. The experiment protocol offers insight into these results; this will be discussed in a later section.

We tested two other models based on the summed receptor impulses for all body sites ("Total Model") and selecting the site with the maximum impulses from the warm and cold receptors ("Max Model"). There was a drop in the F1 score and mid-range accuracy compared to the "Full Model" and "Rational Model," but both were able to reasonably predict thermal pleasure responses. Despite fewer correct classification of pleasure votes, the valence and general magnitude of the predicted pleasure votes was acceptable. The feature importance of the "Total Model" showed that the static responses of receptors contributed most to both displeasure and pleasure.

3.3 | Model validation

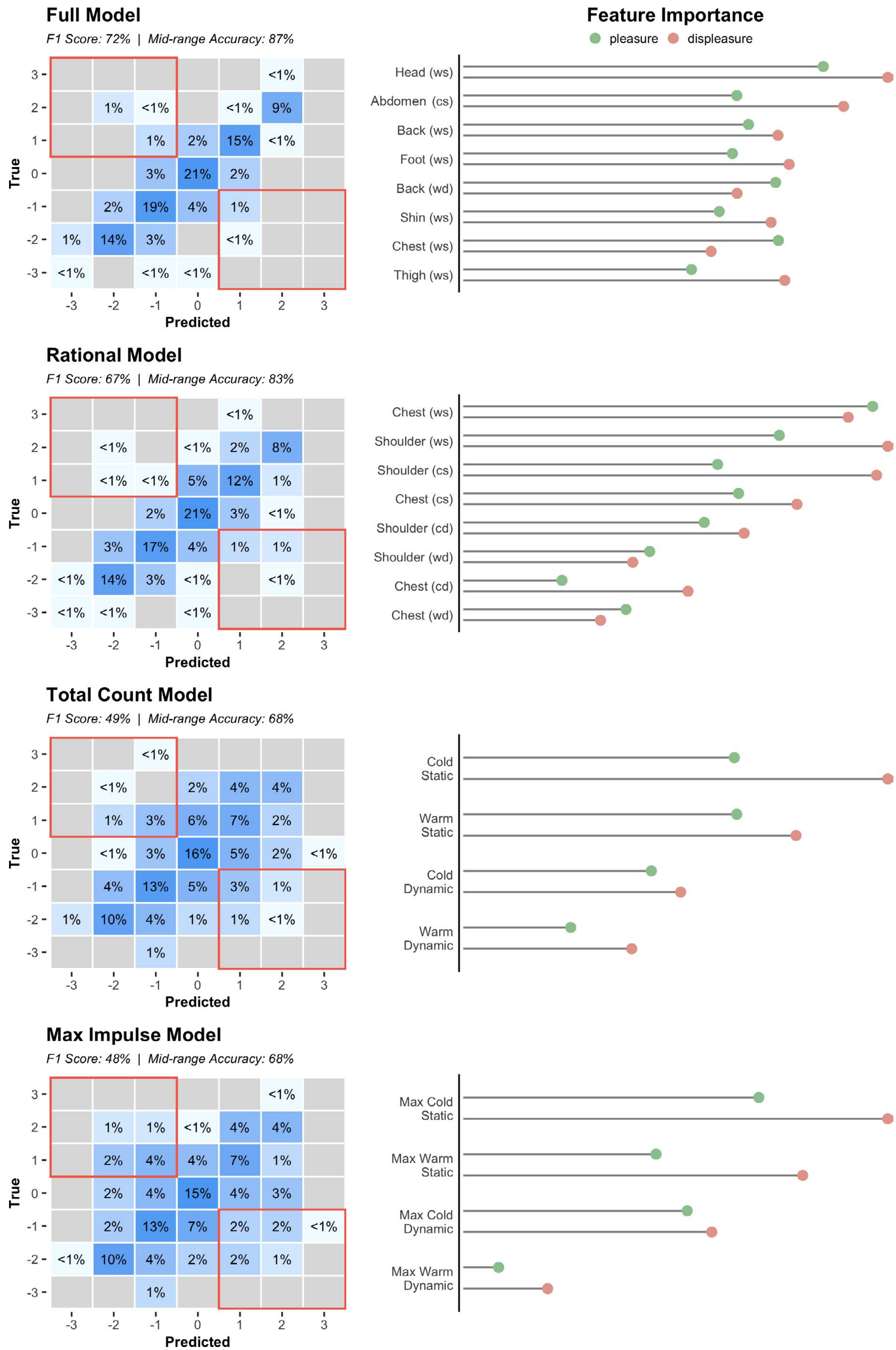
With the exception of the "Rational Model," these approaches have the practical limitation of depending on an increasing number of measurements of skin temperatures across the body to achieve acceptable performance. This constraint, along with the accuracy and feature selection of the tested models, led us to focus on the rational approach based on receptor impulses from the shoulder (local) and chest (whole-body). The "Rational Cluster Model" uses the receptor activity from the shoulder and chest as inputs to a random forest regression. It also considers the cluster membership based on a two-class thermal preference (cooler, warmer).

The dataset from Parkinson et al. [13] was partitioned so that 80% was used for training the model and 20% for testing. Figure 9 shows the predicted thermal pleasure votes for the testing dataset using the "Rational Cluster Model". There is good agreement between the model predictions and the observed thermal pleasure votes, with a mean absolute error (MAE) of 0.35 for the cool preference group and 0.51 for the warm preference group. Despite the volatility of individual votes, the model is able to predict the general trend in mean thermal pleasure as well as the differences between subject clusters. It also captures the immediate pleasure responses following the temperature step-changes at t40 and t125. The residuals show no clear systematic bias in the predictions, with errors likely reflecting inter-individual differences in pleasure. This is also evident in that the thermal preference cluster membership ranks fifth in feature importance.

While the "Rational Cluster Model" performance on the training dataset is encouraging, it is important to test on an independent dataset to determine whether the modeling technique is generalizable. We used data from a completely independent human-subject laboratory test (see Figure S1 for data summary) and extracted the necessary features (inputs) for the "Rational Cluster Model." Skin temperatures at the shoulder and chest were not monitored, so we used correlation analysis to determine that the hand was most similar to the total warm static response (r = 0.78) and the forehead most similar to the total cold dynamic response (r = 0.73) (see Figure S5 for full correlation matrix). These two sites were used as inputs in place of the chest and shoulder, respectively. Finally, k-means clustering found two distinct groups in the independent dataset based on thermal pleasure votes. The same labels from the model training exercise were used to assign cool (n = 13) and warm (n = 9) preference clusters.

The results of the "Rational Cluster Model" validation on the independent dataset are shown in Figure 10. Despite using different body sites, the model was able to capture the different pleasure responses between groups. There is reasonable agreement between the observed and predicted mean thermal pleasure for the front facing fan exposures, with a MAE of 0.55 for the cool preference group and 0.33 for the warm preference group. However, the model fails to capture the pleasure response during the back-facing fan exposures. The mean absolute error for the cool preference group is much higher for the back-facing fan cases (1.47). Such a large error is expected because the model used simulated receptor activity on the forehead to predict pleasure responses, a site which did not experience cooling from the fan placed behind the subject. The error is lower in the warm preference group because the pleasure response

FIGURE 8 Performance of different random forest models in predicting thermal pleasure. Confusion matrices (left side) show the classification of predicted (*x*-axis) and observed pleasure (*y*-axis). Cell percentages represent the share of the total sample. Red squares are used to mark areas of false negatives and false positives. F1 Score shows the overall model performance, and we dropped the 4% of very (un)pleasant responses to recalculate the "Mid-range Accuracy" for responses ranging from unpleasant (−2) through to pleasant (+2). Feature importance (right side) ranks input parameters based on their overall contribution to model predictions. Importance is split according to the contribution to pleasure (green) and displeasure (red) responses. Coding is used to distinguish warm (w) and cold (c) receptors and their static (s) and dynamic (d) responses


Full Model
F1 Score: 72% | Mid-range Accuracy: 87%
Feature Importance
pleasure
displeasure
Head (ws)
Abdomen (cs)
Back (ws)
Foot (ws)
Back (wd)
Shin (ws)
Chest (ws)
Thigh (ws)
Rational Model
F1 Score: 67% | Mid-range Accuracy: 83%
Chest (ws)
Shoulder (ws)
Shoulder (cs)
Chest (cs)
Shoulder (cd)
Shoulder (wd)
Chest (cd)
Chest (wd)
Total Count Model
F1 Score: 49% | Mid-range Accuracy: 68%
Cold Static
Warm Static
Cold Dynamic
Warm Dynamic
Max Impulse Model
F1 Score: 48% | Mid-range Accuracy: 68%
Max Cold Static
Max Warm Static
Max Cold Dynamic
Max Warm Dynamic
True
Predicted

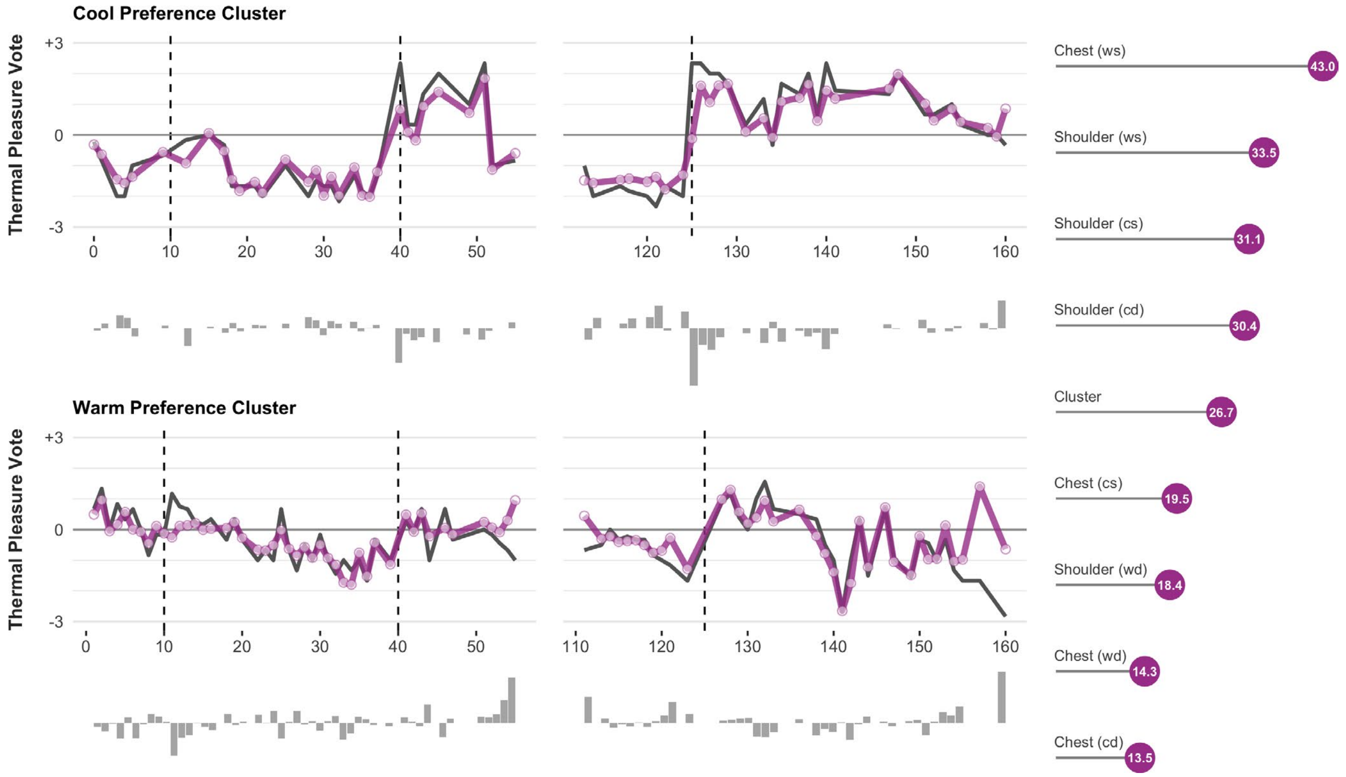


FIGURE 9 Predicted thermal pleasure of the "Rational Cluster Model" based on chest and shoulder thermoreceptor activity and thermal preference clusters. The top panel shows the predicted (purple) and observed (gray) thermal pleasure for the cool (top) and warm (bottom) preference clusters. Bar charts below the panels show the residuals. The side panel shows the ranked feature importance of the final model

was more muted. Despite this, the results indicate that a modeling approach based on neurophysiology can predict thermal pleasure in dynamic conditions.

4 | DISCUSSION

Previous work on alliesthesia[13,72] has indicated that pleasure responses appear to be cutaneous in origin, where changes in skin temperature with a restorative or corrective effect on body temperature are pleasant. While most attempts at modeling thermal perception have traditionally used skin temperature,[5,6,7,73] this study used the simulated activity of cutaneous thermoreceptors.[55] The advantage of using the activity of sensory neurons responsible for temperature transduction is that this is the basis of human thermal perception. The model worked well in estimating thermoafferent traffic of subjects exposed to dynamic thermal environments, with both cold- and warm-receptor responses following logical patterns. The response of receptors to sudden temperature changes better represented the rapid perceptual processes that were muted in skin temperature trends.

The model training dataset had more displeasure responses and greater warm receptor activity due to the experimental design. The sequence of exposures in Parkinson et al[13] was designed to induce warm displeasure followed by a cool corrective change either through a temperature step-change or elevated air movement. The distribution of receptor activity in Figure 5 shows that displeasure was generally associated with higher warm receptor activity, while the cold receptor activity is heightened during thermal pleasure. This demonstrates the usefulness of the thermoreceptor model in summarizing the thermal experience of subjects. Previous attempts have shown a relationship between receptor activity and thermal sensation,[54,56] and our findings support the validity of the approach for predicting pleasure responses in dynamic environments.

It is beyond the expertise of the thermal comfort research community to validate thermoreceptor models, but we believe the absolute measurement of receptor impulses is not required to successfully model thermal perception using neurophysiology. Indeed, we scaled simulated receptor activity for each subject before training the models. Correctly estimating the coefficients in the receptor model is unlikely to yield significant improvements in the accuracy of predictions of thermal pleasure given the abstraction of our approach, for example, free-floating skin model, simplification of cutaneous layers across all body sites, totaling receptor impulses per minute. However, it may be useful to apply sensitivity weightings to simulated receptor impulses at different body sites to reflect the downstream integration and processing of thermoafferents by the central nervous system. Investigations of regional thermosensitivity by Zhang et al,[6] Cotter and Taylor,[39] Filingeri et al.,[74] and Luo et al.[48] all offer weighting coefficients that could be adopted in future modeling efforts.

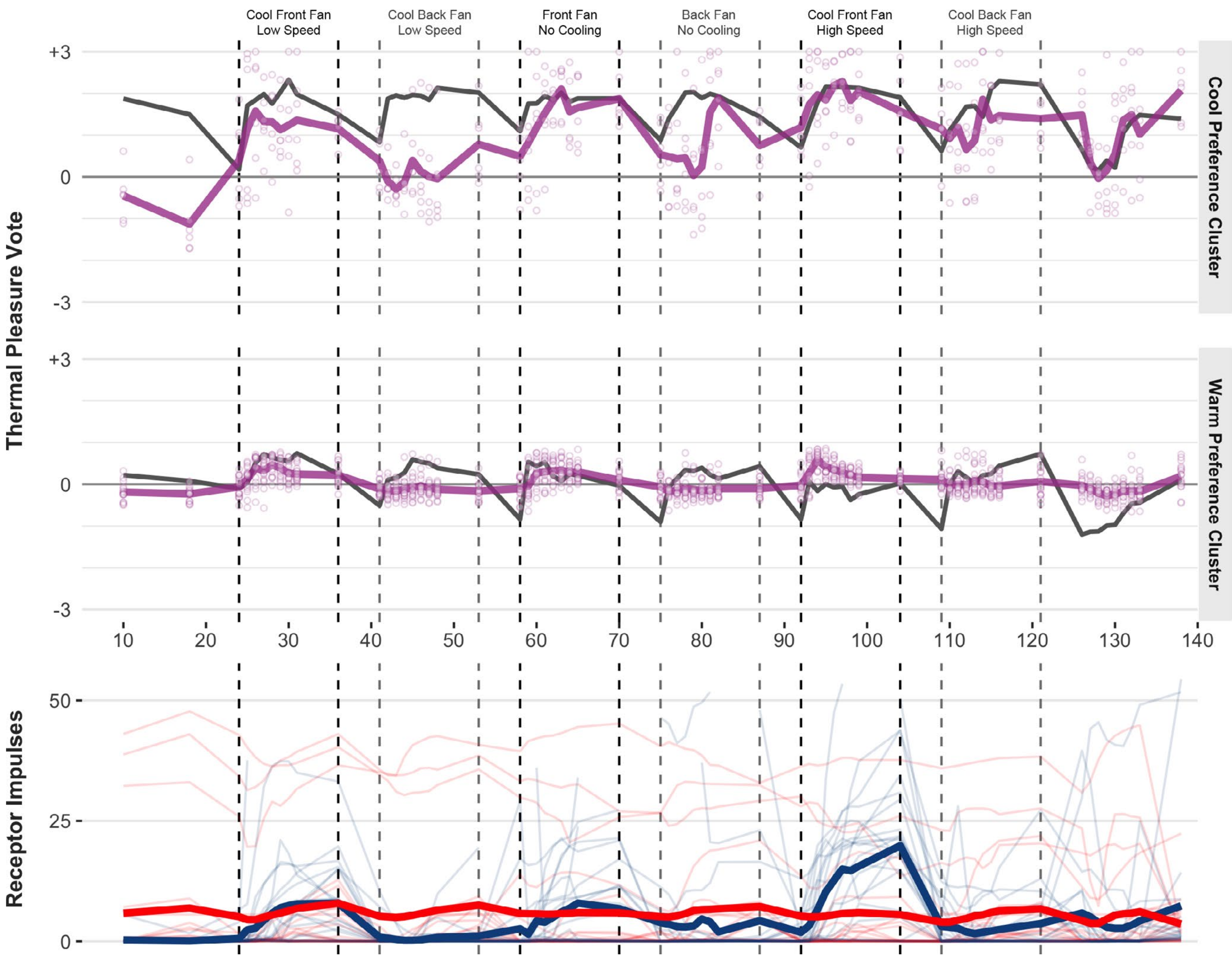


FIGURE 10 Predicted thermal pleasure for the independent dataset using the final alliesthesia model. The top panel shows the time series of predicted (purple) and observed (gray) thermal pleasure for the cool (top) and warm (bottom) preference clusters. Points show individual votes and solid lines are group means. The bottom panel shows the simulated warm thermoreceptor activity of the hand (red) and cold thermoreceptor activity of the forehead (blue) during the exposure. Light lines show individual data and heavy lines are group means

4.1 | Model feature selection

A principal aim of this paper is to use machine learning techniques to understand the relationship between neurophysiology and thermal pleasure. Comparing different modeling approaches and the subsequent feature selections allowed us to shed light on the operating mechanics of thermal alliesthesia. It is unsurprising that the most accurate model reported in Figure 8 ("Full Model") was based on 52 inputs of thermoreceptor activity. However, ranked feature importance for that model appeared to be a statistical artifact rather than useful inference. We also tested other features (eg, lagged thermal pleasure vote) that improved model accuracy but were inconsistent with the alliesthesial framework. Understanding how these models operate highlights a challenge of using machine learning - interpretability. Simpler techniques like linear and logistic regression are popular in part because insights are easily extracted from statistical outputs. Black-box machine learning methods are powerful predictive tools but often lack clear insights.

The multicollinearity of features reported by correlation and principal component analyses (see Figure S2) requires dimension reduction to improve model interpretability and avoid overfitting. Overlapping feature importance for warm and cold receptor activity in Figure 8 suggests it may be possible to further simplify models by using the activity of one receptor type (warm or cold) per body site. The increasing activity of one temperature-specialized receptor intrinsically results in decreased activity in the other type for the same body site. While the consequences of this relationship for numerical modeling appear logical, there is an important difference in pleasure response taking place during the rapid increase in one receptor's activity and the simultaneous decrease in activity in the other. Parkinson & de Dear[75] reported two distinct phases in pleasure response over time: marked change in thermal pleasure for the first few minutes of the change (onset), and a more gradual shift over time depending on the nature of the change and physiological state (tail). It was suggested that the rapid perceptual shift during the onset phase is indicative of the dynamic receptor response, while the gradual change during the tail period is characteristic of the steady-state response. We anticipated the dynamic response of receptors ranking highly in feature importance for pleasure predictions, but the static response made a greater contribution in all cases. The numerical relationship reflected in the simultaneous change in activity between warm and cold receptors may explain this result. It is also possible that if the target variable was the change in thermal pleasure vote at each time step, then the importance of dynamic responses of thermoreceptors to model predictions would rank higher.

4.2 | Model performance

The "Rational Cluster Model" provided an accurate solution to predicting thermal (dis)pleasure on a 7-point scale while supporting the general alliesthesia hypothesis. It is noteworthy that it reliably predicts trends in pleasure responses for a subject pool exposed to a sequence of environments different from the model training dataset (Figure 10). Furthermore, there are no inputs about the exposure type, duration, and sequence or subject anthropometrics. And simplifying the classification problem to three (positive, neutral, or negative pleasure) or even two (positive or negative pleasure) classes would likely improve all model performance metrics.

Using correlation analysis to determine body sites that characterize whole-body state and local change (see Figure S2 and S5) was a reliable dimension reduction technique. The "Rational Cluster Model" was trained using receptor activity at the shoulder and chest but accurately predicted pleasure responses in the validation exercise using the impulses at the forehead and hand, respectively. While the hand and forehead have been identified as important body sites for thermosensitivity,[1,50] agnosticism to body site suggests that the principal requirement is capturing the *physiological load error* along with the *local corrective stimuli*. Indeed, the model failed during back-cooling exposures because the stimuli were not reflected in the forehead receptor activity. It is likely that any practical implementation of the model needs to capture those two components of spatial alliesthesia as a minimum. These findings indicate that the pleasure from corrective thermal stimuli at a single body site largely shapes the whole-body experience.

Performance metrics show that simulated receptor activity is a sufficient basis for a predictive model of thermal pleasure. Comparison of the trends in pleasure votes and receptor activity reveals a relationship between neurophysiology and affective responses. In Figure 10, the constant warm receptor activity maintained throughout the experiment represents the physiological load error incurred from prolonged exposure to elevated air temperatures (~26°C). The model predicts thermal pleasure votes increased at the onset of cooling and is maintained as long as the cooling persists. The timing and magnitude of the positive pleasure appear commensurate with the cold receptor activity. We anticipate similar relationships between neurophysiology and pleasure when modeling analogous exposures of cold displeasure and warm corrective pleasure; future work will test the same modeling approach in different dynamic thermal environments.

4.3 | Model personalization

Earlier works on alliesthesia[1,13] have emphasized the importance of inter-individual difference in understanding thermal pleasure. This reflects a broader trend within the thermal comfort research community to perform analyses of individual comfort as well as group averages.[76,77] This is particularly relevant for alliesthesia research because, unlike thermal sensation, thermal pleasure is nonmonotonic within a subject sample. The model we presented can accurately predict the mean thermal pleasure of the subject group but is less accurate when modeling individuals. The importance of thermal preference clusters in Figure 9 demonstrates the need to include inter-individual differences through variables we have yet to identify that capture and encode measures of personalization.

The cluster membership determined by k-means cluster was assumed to relate to thermal preference. It is possible that other psychological or anthropometric parameters better explain the differences in thermal pleasure votes between the two clusters. However, in our results, including both gender and thermal preference did not improve model accuracy beyond that achieved using thermal preference alone. It is difficult to determine the precise reason for cluster membership, but our preliminary analysis in Figure 7 indicates there may be a neurophysiological basis for reported differences. This may be a promising avenue for research into the psychophysiological basis of thermal preference.

4.4 | Model applications

This work was a fundamental investigation of thermal perception in dynamic environments. However, we see several real-world applications for the findings. They may provide a research framework to explore the cellular, neurological, psychological, and physiological mechanisms of alliesthesia. The determination of the fundamental underlying mechanism would allow it to be accurately measured or proxy effects to be identified that would enable more accurate and customizable models. Our model predictions are based on skin temperature measurements from only two body sites. This is significantly fewer inputs than traditional heat-balance models of comfort require, but acquiring the requisite physiological data presents unique challenges. In many cases, it would be difficult to determine *a priori* the two body sites that reflect the local and whole-body experience. Some environments such as vehicular cabins make these assumptions more valid because the position of the occupant relative to possible thermal stimuli can be reliably estimated. In such cases, contactless measurement of skin temperature by infrared cameras[78] could generate the necessary data. For many indoor environments, skin temperatures could be estimated using multi-node thermophysiological models.[79,80] It is possible to directly integrate machine learning algorithms with these advanced comfort models for real-time predictions of occupant pleasure experienced under any architectural solution. Such a tool would mark a paradigm shift by empowering architects to purposefully design thermal textures within indoor environments, thereby deprioritizing the heavily conditioned spaces promoted by traditional heat-balance comfort models.

5 | LIMITATIONS

Our aim was to encourage the uptake of the alliesthesia hypothesis by developing a "proof-of-concept" model to highlight a potential avenue for further research efforts. The lack of intensive and potentially invasive thermophysiological factors limits the application to relying on assumptions for subcutaneous temperature values and receptor coefficients. Although the feature importance and model performance metrics are useful, they are only applicable to these datasets. In addition, the sample size and the subject pool used for model training are small for machine learning applications and limit the generalizability. It is also unbalanced, with a majority of pleasure votes within the range between slightly unpleasant (−1) and slightly pleasant (+1) with few strong (dis)pleasure votes. Future efforts will focus on using a more balanced, diverse, and comprehensive set of psychophysiological data to train a robust model.

6 | CONCLUSIONS

This is the first study to demonstrate the use of neurophysiological parameters to predict thermal pleasure. We used simulated thermoreceptor activity across several body sites to build a random forest model to predict thermal pleasure during temperature step-changes, ramps, and asymmetrical exposures. Comparison of different approaches to feature selection and model development provided insight into the operating characteristics of alliesthesia. The first finding is that simulated thermoreceptor activity captures the fast response of the somatosensory system to changes in the thermal environment. This suggests that neurophysiological variables are more suitable than skin temperature for modeling thermal pleasure in dynamic conditions. Second, decision trees (random forest) are a promising approach for the development of a predictive model of alliesthesia. Interpretation of such models is a key challenge, but our analysis suggests that estimates of pleasure votes are derived in a way consistent with alliesthesia theory. Third, our approach relied on only two body sites that reflected the whole-body state and the local corrective change. This further supports the spatial alliesthesia concept and simplifies the necessary inputs for predicting thermal pleasure. Lastly, parameters that capture inter-individual differences are necessary to improve the accuracy of estimates of thermal pleasure. Further work is needed to identify those personalization variables that actively shape individual thermal perception.

The findings we presented here demonstrate that thermal pleasure can be modeled in a manner consistent with alliesthesia theory. This marks an exciting paradigm shift in understanding thermal perception in dynamic environments. It is hoped that this will serve as a useful reference for future efforts to explore and model alliesthesia in the built environment.

ACKNOWLEDGEMENTS

Special thanks to experiment participants at both The University of Sydney and Center for the Built Environment (CBE) at UC Berkeley. Thanks to Maohui Luo for assistance with the CBE chamber tests.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

AUTHOR CONTRIBUTIONS

Edward Arens involved in conceptualization (support); writing—review and editing (support); resources (equal); funding acquisition (support). **Richard de Dear involved in** conceptualization (support); writing—review and editing (lead); software (support); resources (equal). **John Elson involved in** conceptualization (support); funding acquisition (support); resources (equal); writing—review and editing (support). **Yingdong He involved in** data curation (support); resources (equal); writing—review and editing (support). **Clay Maranville involved in** funding acquisition (support); resources (equal); writing—review and editing (support). **Alex Parkinson involved in** software (support); writing—review and editing (support). **Thomas Parkinson involved in** conceptualization (lead); data curation (lead); resources (equal); writing—original draft; writing—review and editing (support); formal analysis; software (lead); funding acquisition (support). **Andrew Wang involved in** data curation (support). **Hui Zhang involved in** funding acquisition (lead); conceptualization (support); writing—review and editing (support); resources (equal).

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/ina.12859.

DATA AVAILABILITY STATEMENT

Data were not deposited to any database repositories. Data related to this paper may be requested from the authors.

ORCID

Thomas Parkinson https://orcid.org/0000-0002-0088-8754

REFERENCES

1. Arens EA, Zhang H, Huizenga C. Partial- and whole-body thermal sensation and comfort–Part II: Non-uniform environmental conditions. *J Therm Biol*. 2006b;31(1–2):60-66.
2. Chun C, Kwok A, Tamura A. Thermal comfort in transitional spaces–basic concepts: literature review and trial measurement. *Build Environ*. 2004;39(10):1187-1192.
3. Jones BW. Capabilities and limitations of thermal models for use in thermal comfort standards. *Energy Build*. 2002;34(6):653-659.

4. Van Hoof J. Forty years of Fanger's model of thermal comfort: comfort for all? *Indoor Air*. 2008;18(3):182-201.
5. Zhang H, Arens EA, Huizenga C, Han T. Thermal sensation and comfort models for non-uniform and transient environments: part I: Local sensation of individual body parts. *Build Environ*. 2010a;45(2):380-388.
6. Zhang H, Arens EA, Huizenga C, Han T. Thermal sensation and comfort models for non-uniform and transient environments: part II: local comfort of individual body parts. *Build Environ*. 2010b;45(2):389-398.
7. Zhang H, Arens EA, Huizenga C, Han T. Thermal sensation and comfort models for non-uniform and transient environments: part III: Whole-body sensation and comfort. *Build Environ*. 2010c;45(2):399-410.
8. Fanger PO. *Thermal Comfort*. Copenhagen: Danish Technical Press; 1970.
9. Zhang H. Human thermal sensation and comfort in transient and non-uniform thermal environments, PhD Thesis, Center for Environmental Design Research (CEDR), University of California at Berkeley; 2003. http://www.escholarship.org/uc/item/11m0n1wt
10. de Dear RJ. Revisiting an old hypothesis of human thermal perception: alliesthesia. *Build Res Inf*. 2011;39(2):108-117.
11. Cabanac M. Physiological role of pleasure. *Science*. 1971;173(4002):1103-1107.
12. Parkinson T, de Dear RJ. Thermal pleasure in built environments: physiology of alliesthesia. *Build Res Inf*. 2015;43(3):288-301.
13. Parkinson T, de Dear RJ, Candido C. Thermal pleasure in built environments: Alliesthesia in different thermoregulatory zones. *Build Res Inf*. 2016;44(1):20-33.
14. Parkinson T, de Dear R. Thermal pleasure in built environments: spatial alliesthesia from contact heating. *Building Research & Information*. 2016;44(3):248–262. https://doi.org/10.1080/09613218.2015.1082334
15. Parkinson T, de Dear RJ. Thermal pleasure in built environments: spatial alliesthesia from air movement. *Build Res Inf*. 2017;45(3):320-335.
16. Cabanac M. Sensory Pleasure. *The Quarterly Review of Biology*. 1979;54(1):1–29. https://doi.org/10.1086/410981
17. Dhaka A, Viswanath V, Patapoutian A. TRP ion channels and temperature sensation. *Annu Rev Neurosci*. 2006;29(1):135-161.
18. Hensel H. Thermoreception and temperature regulation. *Monogr Physiol Soc*. 1981;38:1-321.
19. Spray DC. Cutaneous temperature receptors. *Annu Rev Physiol*. 1986;48:625-638.
20. Schepers RJ, Ringkamp M. Thermoreceptors and thermosensitive afferents. *Neurosci Biobehav Rev*. 2010;34(2):177-184.
21. Darian-Smith I, Johnson KO. Thermal sensibility and thermoreceptors. *J Invest Dermatol*. 1977;69(1):146-153.
22. Dodt E, Zotterman Y. Mode of action of warm receptors. *Acta Physiol Scand*. 1952;26(4):345-357.
23. Hensel H, Kenshalo DR. Warm receptors in the nasal region of cats. *J Physiol*. 1969;204(1):99-112.
24. Hensel H, Zotterman Y. The response of the cold receptors to constant cooling. *Acta Physiol Scand*. 1951;22(2–3):96-105.
25. Hensel H, Andres KH, v. Düring M. Structure and function of cold receptors. *Pflügers Archiv*. 1974;352(1):1-10.
26. Iggo A. Cutaneous thermoreceptors in primates and sub-primates. *J Physiol*. 1969;200(2):403-430.
27. Kenshalo D, Holmes C, Wood P. Warm and cool thresholds as a function of rate of stimulus temperature change. *Percept Psychophys*. 1968;3(2):81-84.
28. Konietzny F, Hensel H. The dynamic response of warm units in human skin nerves. *Pflügers Archiv*. 1977;370(1):111-114.
29. Zotterman Y. Special senses: thermal receptors. *Annu Rev Physiol* 1953;15:357-372.
30. Lumpkin EA, Caterina MJ. Mechanisms of sensory transduction in the skin. *Nature*. 2007;445(7130):858-865.
31. Patapoutian A, Peier AM, Story GM, Viswanath V. ThermoTRP channels and beyond: mechanisms of temperature sensation. *Nat Rev Neurosci*. 2003;4(7):529-539.
32. Vriens J, Nilius B, Voets T. Peripheral thermosensation in mammals. *Nat Rev Neurosci*. 2014;15(9):573-589.
33. Vriens AC, Nilius JE. *Textbook of Medical Physiology*. Philadephia, London: W. B. Saunders; 2002.
34. Dykes RW. Coding of steady and transient temperatures by cutaneous 'cold" fibers serving the hand of monkeys. *Brain Res*. 1975;98(3):485-500.
35. Darian-Smith I, Johnson KO, LaMotte C, Shigenaga Y, Kenins P, Champness P. Warm fibers innervating palmar and digital skin of the monkey: responses to thermal stimuli. *J. Neurophysiol*. 1979;42:1297-1315. https://doi.org/10.1152/jn.1979.42.5.1297.
36. Darian-Smith I, Johnson KO, Dykes R. "Cold" fiber population innervating palmar and digital skin of the monkey: responses to cooling pulses. *J. Neurophysiol*. 1973;36:325-346. https://doi.org/10.1152/jn.1973.36.2.325.
37. Ivanov K, Konstantinov V, Danilova N. Thermoreceptor localization in the deep and surface skin layers. *Journal of Thermal Biology*. 1982;7(2):75–78. https://doi.org/10.1016/0306-4565(82)90033-x
38. Breipohl W. Thermoreceptors. In: Bereiter-Hahn J, Matoltsy AG, Richards KS, eds. *Biology of the Integument*, vol. 2., Vertebrates. Berlin: Springer-Verlag; 1986:561-585.
39. Cotter JD, Taylor N. The distribution of cutaneous sudomotor and alliesthesial thermosensitivity in mildly heat-stressed humans: an open-loop approach. *The Journal of Physiology*. 2005;565(1):335-345.
40. Crawshaw LI, Nadel ER, Stolwijk JAJ, Stamford BA. Effect of local cooling on sweating rate and cold sensation. *Pflügers Arch Eur J Physiol*. 1975;354(1):19-27.
41. Filingeri D. Neurophysiology of skin thermal sensations. *Compr Physiol*. 2016;6(3):1429-1491.
42. Nadel ER, Mitchell JW, Stolwijk JAJ. Differential thermal sensitivity in the human skin. *Pflügers Arch Eur J Physiol*. 1973;340(1):71-76.
43. Hensel H. Thermoreceptors. *Annu Rev Physiol*. 1974;36(1):233-249.
44. Campero M, Serra J, Bostock H, Ochoa JL. Slowly conducting afferents activated by innocuous low temperature in human skin. *J Physiol*. 2001;535(3):855-865.
45. Stevens JC, Choo KK. Temperature sensitivity of the body surface over the life span. *Somatosens Mot Res*. 1998;15(1):13-28.
46. Stevens JC. Variation of cold sensitivity over the body surface. *Sens Process*. 1979;3:317-326.
47. Stevens JC, Marks LE, Simonson DC. Regional sensitivity and special summation in the warmth sense. *Physiol Behav*. 1974;13:825-836.
48. Luo M, Wang Z, Zhang H, et al. High-density thermal sensitivity maps of the human body. *Build Environ*. 2020;167:106435.
49. Nakamura M, Yoda T, Crawshaw LI, et al. Regional differences in temperature sensation and thermal comfort in humans. *J Appl Physiol*. 2008;105:1897-1906.
50. Arens E, Zhang H, Huizenga C. Partial- and whole body thermal sensation and comfort, Part I: uniform environmental conditions. *J Therm Biol*. 2006a;31(1–2):53-59.
51. Gybels J, Handwerker HO, Van Hees J. A comparison between the discharges of human nociceptive nerve fibres and the subject's ratings of his sensations. *J Physiol*. 1979;292(1):193-206.
52. Johnson KO, Darian-Smith I, LaMotte C, Johnson B, Oldfield S. Coding of incremental changes in skin temperature by a population of warm fibers in the monkey: correlation with intensity discrimination in man. *J Neurophysiol*. 1979;42(5):1332-1353.
53. Nakamura K, Morrison SF. A thermosensory pathway that controls body temperature. *Nat Neurosci*. 2008;11(1):62-71.

54. de Dear RJ, Ring JW, Fanger PO. Thermal sensations resulting from sudden ambient temperature changes. *Indoor Air.* 1993;3(3):181-192.
55. Ring JW, de Dear RJ. Temperature transients: a model for heat diffusion through the skin, thermoreceptor response and thermal sensation. *Indoor Air.* 1991;1(4):448-456.
56. Kingma BR, Schellen L, Frijns AJH, van Marken Lichtenbelt WD. Thermal sensation: a mathematical model based on neurophysiology. *Indoor Air.* 2012;22(3):253-262.
57. Mekjavic IB, Morrison JB. A Model of shivering thermogenesis based on the neurophysiology of thermoreception. *IEEE Trans Biomed Eng.* 1985;32(6):407-417.
58. Boulant JA. Neuronal basis of Hammel's model for set-point thermoregulation. *J Appl Physiol.* 2006;100(4):1347-1354.
59. Hammel H. Phylogeny of regulatory mechanisms in temperature regulation. *J Therm Biol.* 1983;8(1–2):37-42.
60. Ivanov K, Konstantinov V, Danilova N, Sleptchuck N, Rumiantsev G. Thermoreceptor distribution in different skin layers and its significance for thermoregulation. *J Therm Biol.* 1986;11(1):25-29.
61. Jessen C. Thermal afferents in the control of body temperature. *Pharmacol Ther.* 1985;28(1):107-134.
62. Kingma BR, Vosselman MJ, Frijns AJH, van Steenhoven AA, van Marken Lichtenbelt WD. Incorporating neurophysiological concepts in mathematical thermoregulation models. *Int J Biometeorol.* 2014;58(1):87-99.
63. Ring JW, de Dear RJ, Melikov AK. Human thermal sensation: frequency response to sinusoidal stimuli at the surface of the skin. *Energy Build.* 1993;20(2):159-165.
64. Hardy JD, Du Bois EG. The technic of measuring radiation and convection. *J Nutr.* 1938;15(5):461-475.
65. Liaw A, Wiener M. Classification and regression by randomForest. *R News.* 2002;2(3):18-22.
66. Wickham H, Averick M, Bryan J, et al. Welcome to the tidyverse. *J Open Source Software.* 2019;4(43):1686.
67. Kuhn M. caret: Classification and Regression Training. R package version 6.0-86. https://CRAN.R-project.org/package=caret
68. Kuhn M, Vaughan D. yardstick: Tidy Characterizations of Model Performance. R package version 0.0.6.; 2020. https://CRAN.R-project.org/package=yardstick
69. Kassambara A. ggpubr: 'ggplot2' Based Publication Ready Plots. R package version 0.2.5. 2020. https://CRAN.R-project.org/package=ggpubr
70. Greenwell BM. pdp: An R package for constructing partial dependence plots. *R J.* 2017;9(1):421-436.
71. Wilke CO. ggridges: Ridgeline Plots in 'ggplot2'. R package version 0.5.2. https://CRAN.R-project.org/package=ggridges
72. Mower GD. Perceived intensity of peripheral thermal stimuli is independent of internal body temperature. *Journal of Comparative and Physiological Psychology.* 1976;90(12):1152–1155. https://doi.org/10.1037/h0077284
73. Fiala D, Lomas K, Stohrer M. Computer prediction of human thermoregulatory and temperature responses to a wide range of environmental conditions. *Int J Biometeorol.* 2001;45(3):143-159.
74. Filingeri D, Zhang H, Arens EA. Characteristics of the local cutaneous sensory thermoneutral zone. *J Neurophysiol.* 2017;117(4):1797-1806.
75. Parkinson T, de Dear RJ. Thermal pleasure in built environments: spatial alliesthesia from contact heating. *Build Res Inf.* 2016;44(3):248-262.
76. Kim J, Zhou Y, Schiavon S, Raftery P, Brager G. Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. *Build Environ.* 2018;129:96-106.
77. Wang Z, de Dear R, Luo M, et al. Individual difference in thermal comfort: a literature review. *Build Environ.* 2018;138:181-193.
78. Ghahramani A, Castro G, Karvigh SA, Becerik-Gerber B. Towards unsupervised learning of thermal comfort using infrared thermography. *Appl Energy.* 2018;211:41-49.
79. Huizenga C, Hui Z, Arens E. A model of human physiology and comfort for assessing complex thermal environments. *Building and Environment.* 2001;36(6):691-699. http://dx.doi.org/10.1016/s0360-1323(00)00061-5
80. Kobayashi Y, Tanabe S. Development of JOS-2 human thermoregulation model with detailed vascular system. *Build Environ.* 2013;66:1-10.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Parkinson T, Zhang H, Arens E, et al. Predicting thermal pleasure experienced in dynamic environments from simulated cutaneous thermoreceptor activity. *Indoor Air.* 2021;31:2266–2280. https://doi.org/10.1111/ina.12859