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Toward the Prediction of Environmental Thermal Comfort Sensation Using Wearables

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Abstract. Thermal comfort is a state of mind in which one is satisfied with the thermal environment that is crucial to human well-being, safety, and productivity in everyday life. Indoor environmental thermal comfort levels usually change due to performing different activities in different situations. Computer systems that can understand these comfort indicators can help to support and increase human well-being. This paper considers a simple wristwatch-like device equipped with various sensors to collect autonomic nervous system activity data. This study offers a preliminary assessment of a physiologically regulated thermal comfort provision based on Pulse Rate Variability (PRV) to see if we could predict the comfort of a hot environment (risk of heatstroke, higher dissatisfaction/more difficult to cope than cold). Therefore, we focus on collecting data in varying temperatures and humidity levels for different work conditions i.e., reading, typewriting, and gymnastics focusing on hot thermal conditions to predict human-environmental thermal comfort using multiple machine learning models. Our results show an average accuracy above 95% with five different machine learning models.

Keywords. Thermal Comfort, Intelligent environment, Wearables, Heart Rate Variability, Machine learning

1. Introduction

In general, comfort is a significantly important concept in daily life that has a directly or indirectly links to individuals' pain, relaxation, anxiety, self-confidence, and sadness as a whole. Thus, thermal comfort is also linked to one's health [1, 2], productivity [3], learning ability [4], and overall well-being [5]. Thermal comfort is an essential factor to consider while designing, operating, and commissioning commercial and residential buildings because thermal comfort is a key factor in creating a comfortable indoor environment. Furthermore, indoor temperature discomfort has an impact on human health and can be especially dangerous in the case of vulnerable patients [6, 7]. Personal variables (age, health state, etc.), duration of exposure [8] and adaptation capability deter-

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mine individuals' vulnerability to exposure to low or high temperatures. People are vulnerable to various adaptation processes depending on their age: for example, a too hot or too warm living environment might jeopardize older people's health.

Therefore, with the advancement of technology, indoor temperature regulators (e.g., air conditioners, electric heaters, etc.) have become indispensable household appliances, allowing for year-round temperature adjustments within a comfortable range. Today, the construction of most buildings and system components follows standards that specify the range of thermal environmental conditions acceptable to most users. However, because of changes in environmental conditions or activities performed in the indoor space, the thermal sensation and comfort of the human body frequently change dramatically. Recent research shows that thermal comfort criteria such as ASHRAE 55 (American Society of Heating Refrigerating and Air-conditioning Engineers) [9] and ISO 7730 [10] understate the number of unsatisfied users in indoor environments [11].

It is also known that the comfortable temperature varies from person to person. However, most thermal comfort delivery technologies (e.g., air conditioning units) provide a neutral thermal condition for all residents of the building. These thermal comfort-providing methods are energy-intensive [12], and they largely fail to cool or heat the regions of the body that have the most significant impact on a person's thermal comfort satisfaction (e.g., the wrist, the feet, and the head). Moreover, it may be feasible to significantly reduce the necessary thermal comfort providing energy by allowing the indoor temperature to wander away from thermal neutrality and adjusting it only when individuals become thermally uncomfortable. In this regard, it is essential to assess thermal comfort mechanisms to produce a comfortable and healthy interior atmosphere in buildings.

In this context, we can present an energy-efficient thermal comfort providing approach using heart rate variability (HRV). As thermal comfort is a subjective psychological sense, providing thermal comfort based on changes in a person's physiological signals would be more effective. Recent studies show that HRV assesses the autonomic nervous system's balance and capability, and a change in the temperature caused measurable changes in people's HRV [13]. Therefore, this research focus on predicting environmental thermal comfort sensation from the pulse rate variability (PRV) data from photoplethysmography (PPG) sensors incorporated in a smartwatch. PRV is significantly associated with HRV and can be used as a substitute for it [14]. During the experiment, we have collected 33 participants' data in various work conditions: i.e., reading, typewriting, and gymnastics, focusing on hot thermal conditions in accordance with the ASHRAE scale: normal, slightly warm, warm, and hot. Mechanically controlled indoor environments use the Predicted Mean Vote (PMV) index to evaluate thermal comfort conditions. The PMV model incorporates human-related factors, namely user clothing insulation, metabolic rate, and environmental values such as temperature, air velocity, mean radiant temperature, and relative humidity. Several HRV features were used as input to Machine Learning (ML) classification algorithms to anticipate users' environmental thermal sensation, providing an average accuracy of 95.17%.

The remaining part of the paper proceeds as follows. First, section 2, begins by reviewing the related literature on estimating thermal sensation, comfort, and preference. Section 3 explains the collected data overview having data collection procedures. Section 4 describes the methodology of data prepossessing, feature extraction, model building machine learning algorithms and evaluation metrics. Section 5 presents the results of prediction different thermal sensations and classification methods with discussions. Conclusions drawn are presented with some future work points in Section 6.

2. Background: Thermal sensation, comfort and preference

The indoor environment is commonly regarded to be a health-related concern in terms of healthy human life [15, 16]. Temperature change is a type of environmental stressor linked to health directly. In this regard, human thermal comfort has been investigated in terms of environmental conditions for decades [17]. However, the thermal sense and comfort of the human body frequently change as a result of changes in ambient circumstances or different activities in the indoor [18]. Previous research has shown that some other factors (e.g., prior thermal history, physiological and psychological processes) have a significant impact on people's thermal comfort [19]. Researchers discovered that physiological reactions of people to skin temperature, heart rate, and heart rate variability are sensitive to temperature step changes in the indoor environment [20].

Several recent research works have used machine learning techniques to construct individualized thermal comfort models [21]. The three primary variables for machine learning models are environmental information, occupant behavior, and physiological signals. Following that field research, other works used physiological testing to determine how different temperature stages affect the human body [22]. For this objective, physiological measures such as rectal temperature, skin temperature [23], sweat rate, and heart rate variability [24] were assessed to measure human thermal comfort. These physiological signals have a significant association with human thermal experience and comfort, in addition to behavior-tracking. The categorization of occupants' personal thermal comfort in terms of temperature and humidity also used a data-driven strategy [25] in conjunction with the interior environment.

As a previous study, Nkurikiyeyezu et al. [13], utilized heart rate variability to predict thermal comfort in three stages: cold, normal, and hot and obtained accuracy of up to 93%. This research implies that changes in temperature and humidity impact heart rate variability, but estimating thermal comfort with a smaller particle size is required to forecast the danger of heatstroke at the appropriate time. 93Although most of the research claimed improved prediction accuracy over traditional PMV and adaptive models, they didn't consider different activity states in indoor environments which is also a vital cause for worsening the health conditions. Therefore, it is necessary to investigate not only the effect of the thermal environment on biological information but also the effect of the mental burden caused by work or the physical burden caused by exercise to prevent the risk of heatstroke. In this research, we verified a model that can estimate the environmental thermal comfort using the PMV model with high accuracy considering various work conditions focusing on hot thermal conditions in accordance with the ASHRAE scale: normal, slightly warm, warm, and hot to predict human thermal comfort in a variety of activities and environments.

3. Data Collection

This section describes the data collection protocol, data collection procedure, and tools used to collect our dataset. The data were obtained with the permission of the local ethics committee, and each participant gave their informed consent to the data being processed.

3.1. Data Collection Protocol

Each participant went through 8 conditions during a single data collection session. The experiment conditions are based on various work conditions: i.e. reading, typewriting, and gymnastics focusing on hot conditions with settings in accordance with the ASHRAE scale: normal, slightly warm, warm, and hot. We set these activities in relation with real-life situations. For example, elderly reading/watching TV at home activity will be aligned with reading activities, office work classroom study will be aligned with reading and typewriting activities, and factory/outdoor work that requires a little more effort will be aligned with heavy work activity radio gymnastics.

For a single session, there were a total of eight experiments. We organized each experiment session with different temperature and humidity conditions for a particular activity. For example, gymnastics activities were recorded in temperature hot (temperature 32°C / humidity 80%) and warm state (temperature was 25°C / humidity 60%). Table 1, presents each experiment condition elaborately.

Table 1. Data Collection States

Experiment order	Task	Temperature	Humidity	Duration (min)
1	Radio Gymnastics	32°C	80%	10
2	Radio Gymnastics	25°C	60%	10
3	Reading	25°C	60%	15
4	Reading	32°C	80%	15
5	Reading	27°C	60%	15
6	Reading	32°C	80%	15
7	Typewriting	32°C	80%	15
8	Typewriting	27°C	60%	15

3.2. Wearable sensors

We asked participants to wear Empatica E4 wristbands; The E4 wristband[2] resembles a watch and has many sensors, including an Electrodermal activity (EDA) sensor (measures the continually changing changes in specific electrical characteristics of the skin), a photoplethysmography (PPG) sensor (measures the Blood Volume Pulse (BVP) which is a metric that may be used to determine heart rate variability to assess sympathetic nervous system activity and heart rate at the same time), a three-axis accelerometer (ACC), and an optical thermometer. At a frequency of 4Hz, EDA illustrates continually chang-

[2]https://www.empatica.com/research/e4/

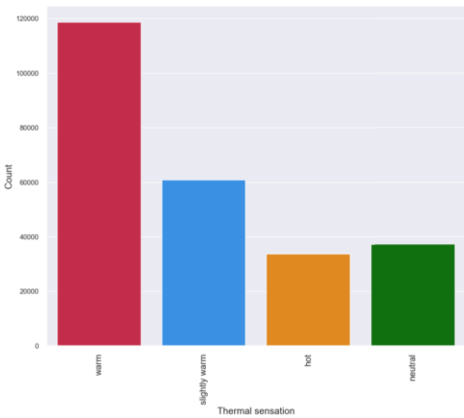

Figure 1. Data set size for each thermal Sensation

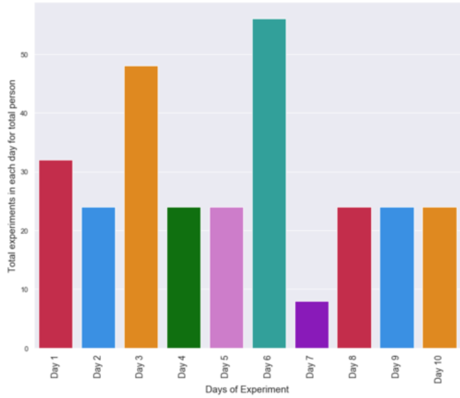

Figure 2. Number of people participating in each day's experiment.

ing changes in skin electrical characteristics. When the level of sweat increases, the conductivity of the skin increases. The inter-beat interval (IBI) and HRV may be calculated using the PPG sensor, which monitors the BVP at 64 Hz. Recent research shows that the Empatica E4 wrist band [26] records HRV accurately under seated rest, paced breathing, and recovery situations. Thus, the E4 is outfitted with sensors that are designed to collect high-quality data. Data were immediately transferred to the E4 connect cloud platform after each experiment session.

3.3. Participants and Procedure

We collected data from 33 participants, ranging from 22 to 50 years old (10 women, 23 men). The participants were instructed to do a specified task in an indoor temperature-controlled environment. Data were gathered for a total of 10 days. For each activity data collection time, we adjusted the temperature and humidity. For 33 adult men and women, continuous pulse intervals were measured in four temperature and humidity environments of normal, slightly warm, warm, and hot, and in three work situations of reading, typewriting, and radio gymnastics. Figure 1 depicts the four thermal states in the dataset, with warm conditions having a disproportionately high number of records compared to other thermal states.

We didn't fix the number of participants in each day's experiment during the data collection period. The number of participants was higher on day six when seven people showed up for the trial. Figure 2 shows the overall number of days in the experiment as well as the number of participants on each day (one day we conducted in total eight experiments in the order stated in Table 1). The first two experiments were radio gymnastics performed in hot and warm temperatures. The HRV standard deviation for these two experiments was higher (because of the high level of activity) than for the other experiments, reading and typing (figure 3 and figure 4).

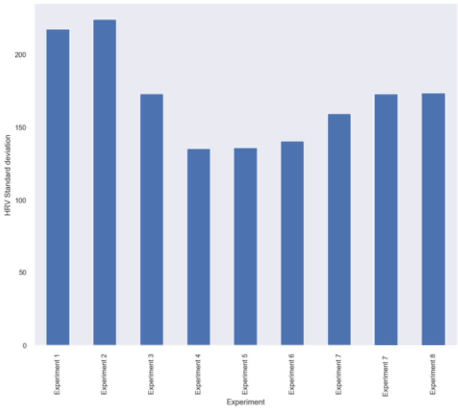

Figure 3. Experiment basis HRV Standard deviation

Figure 4. Activity basis HRV Standard deviation

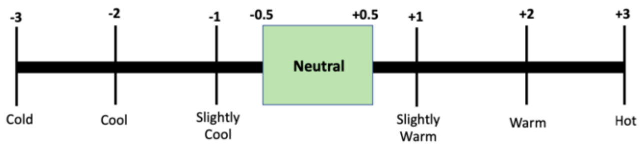

Figure 5. Thermal sensation scale of ASHRAE Standard 55

4. Methodology

The PMV thermal comfort model is based on large-scale laboratory testing on people conducted over a lengthy period of time in various temperature states [27]. To anticipate the mean thermal experience of a large group of individuals, it considers the ambient air temperature, the mean radiant temperature, the air speed, the relative humidity, people's metabolic rate, and their garment insulation level [27]. The PMV model has been used to forecast the mean thermal perception of building occupants since its conception. It has been adopted into worldwide thermal comfort standards for its fair performance [28] (e.g., ISO 7730, ASHRAE 55).

A person's thermal feeling may change depending on the temperature of the air. Here, the subjects' thermal sensations were evaluated using the ASHRAE 7-point scale (Fig. 5). The ASHARE scale is based on how warm or cool the person feels in a certain indoor environment. The predicted PMV is divided into seven stages: cold, cool, little cool, normal, slightly warm, warm and hot. In this study, we set up an experimental environment for the four stages of normal and hot conditions, because we aim to predict the comfort of a hot environment.

4.1. Experimental protocol

Considering that environment temperature influences human thermal sense and comfort [27], the PPG signal was collected using an Empatica E4 wristband at various temperatures and activity levels during the experiments. We synchronized data from the E4 to the smartphone using a mobile app (E4 RealTime) that sent data from the E4 to the smartphone through Bluetooth signals. The button on the E4 allowed us to upload the collected data to (E4 connect) a secure cloud platform after each session ends. We evaluated subjects' IBI (inter-beat interval, is the time interval between individual beats of the heart) signal was extracted via a PPG signal recorded using an Empatica E4 wristband. Using a sliding window technique, we estimated heart rate, inter beat intervals in milliseconds, and heart rate variability from physiological data gathered such as blood volume pulse. The extracted IBI signal is used to forecast the user's thermal comfort using several machine learning models.

4.2. Feature Extraction and Data Prepossessing for Thermal Comfort Prediction

In this study, we selected time-domain and frequency domain analysis of HRV indices. HRV Indices in the time domain are straightforward to calculate and understand. The beat-to-beat variability is described by time domain HRV features. Statistical approaches can be used to characterize beat-to-beat variability for this group. Among various time-domain features, the RMSSD (root mean square of successive differences between normal heartbeats) and pNNx indices (the proportion of absolute deviations between successive normal sinus intervals that exceed a certain threshold value. The most commonly used threshold is 50 msec, and the statistic obtained is termed pNN50) are considered as important features to the HRV research community [29]. The square root of the mean of the sum of differences of successive R-R intervals (beat to beat intervals) is represented by the RMSSD. The proportion of R-R consecutive pairings that vary by x milliseconds is denoted by the pNNx. A 2-min epoch is also required for the percentage of adjacent NN intervals that deviate by more than 50 ms (pNN50).

For frequency-domain feature analysis, spectral HRV analysis methods break pulse variability into its underlying frequency components, allowing for a better understanding of heartbeat variation. There are a variety of methods for calculating HRV spectrum components. The Fast Fourier Transform (FFT) and autoregressive (AR) modeling approaches, in particular, are widely employed [30]. We can divide HRV into its component ULF, VLF, LF, and HF rhythms that function at distinct frequency ranges using FFT or AR modeling [21, 30].

All HRV indices were calculated on a window segment using a window size of 300 samples (something close to 3 minutes and with a step size of 30 seconds). The features are computed using the flirt library [31]. Table 2, describes the selected HRV indices used in this study.

4.3. Machine learning algorithms

To predict thermal comfort, we conducted experiments on 33 participants doing light work (metabolic rate 1.1) and heavy work (metabolic rate 3.0) in four thermal chambers whose settings conform to those of a normal, slightly warm, warm, and hot thermal sensation on a PMV index scale (Table 3). Each experiment was roughly 15 minutes long except radio gymnastics which was 10 minutes long. After extracted HRV indices, the HRV indices of all participants in all temperature settings were combined after they were retrieved. The model was evaluated by 10-fold cross-validation. The dataset was randomly divided into 10 parts, nine of which were used as training data and one as validation data. We repeated the process ten times and evaluated the average of the ten times. We used five

Table 2. Description of the selected HRV indices

HRV index	**Short description**
NUM_IBIS	Number of NNI intervals
HRV_MEAN_NNI	Mean of all NNI intervals
HRV_MEDIAN_NNI	Meadian of all NNI intervals
SDSD	Standard deviation of all interval of differences between adjacent RR intervals
RMSSD	Square root of the mean of the sum of the squares of the difference between adjacent RR intervals
HRV_NNI_50	Percentage of adjacent NN intervals differing by more than 50 ms
HRV_NNI_20	Percentage of adjacent NN intervals differing by more than 20 ms
HRV_pNNI_50	Percentage of R-R consecutive pairs that differ by 50 milliseconds
SDNN	Standard deviation of all NN intervals
HRV_VLF	Spectral power in very low range frequencies (0.0000.04 Hz)
HRV_LF	Spectral power in low range frequencies (0.040.15 Hz)
HRV_HF	Spectral power in high range frequencies (0.15 Hz)
HRV_LF_HF_RATIO	Ratio between LF and HF band powers
TP	Total spectral power (00.4 Hz)
HRV_SD1	SD1 measures Short-term heart rate variability in ms
HRV_SD2	SD2 measures Long-term heart rate variability in ms
HR_MEAN	Mean of Heart Rate measured by the number of heart beats per minute
HR_MIN	Lowest Heart Rate measured by the number of heart beats per minute
HR_MAX	Maximum Heart Rate measured by the number of heart beats per minute
HR_STD	Standard deviation of Heart Rate
HRV_MEAN	Mean of Heart rate variability
HRV_STD	Standard deviation of Heart rate variability
HRV_MIN	Lowest of Heart rate variability
HRV_MAX	Maximum value of Heart rate variability
HRV_SKEWNESS	Skewness of all Heart rate variability
HRV_KURTOSIS	Kurtosis of all Heart rate variability
HRV_PEAKS	Peak value of Heart rate variability
HRV_RMS	Square root of the mean of the sum of the squares of differences between adjacent NN intervals

machine learning [32] classifiers to assess prediction performance: K-Neighbors Classifier(KNN), Decision Tree Classifier(DT), Random Forest Classifier(RF), Extra Trees Classifier(ET), and LGBM Classifier(LightGBM).

5. Results and Discussion

To evaluate the prediction performance among different models, we used accuracy as evaluation metric. The accuracy of the models in Fig. 6 is obtained using Equation 1,

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

Table 3. Thermal Environment Settings

	Hot	Warm	Slightly Warm	Neutral
Activity Level	3.0	1.1	1.0	1.0
clothing level	1	1	1	1
Air Temperature	32.0	32.0	27	25
Humidity	80	80	60	60
PMV	2.85	1.87	0.66	0.06

In the equation, the meanings of TP,TN,FP and FN are stated as: TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative. During different models' performance evaluation time, KNN outperforms the other five classifiers in predicting environmental thermal sensation having a prediction accuracy of 96.41%. All others models' prediction accuracy are also above 90% and the average prediction accuracy is 95.17% (Fig. 6). The confusion matrix (Fig. 7) reveals that the majority of misclassifications occur between the warm and neutral states. We calculated the precision, recall, and F1-score of the model, as well as the support for each class, to assess its performance for the best model. The recall represents the proportion of samples that were misclassified as true, i.e. that are false negative (FN) in the dataset (Equation 3), whereas the precision expresses the proportion of classified true positives (TP) vs false negatives (FP) in the entire dataset ((Equation 2). The F1 score is a harmonic mean of the precision and the recall metrics (Equation 4). From the best model classification report in table 4, it states that the lowest precision score is 90.0% for neutral state and the highest F1-score are for hot and slightly warm states.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} = \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

Thermal comfort is a subjective concept that is influenced by a variety of factors, including a person's psychometrics and biological composition. In this preliminary study, we explore to predict a person's environmental thermal comfort in accordance with ASHRAE scale from the newly collected dataset. The trained classifier has a very high classification accuracy and only a few misclassifications (figure 7). Warm and neutral states are the most commonly misclassified. The data are a bit biased towards the "warm" label, which counts as much as many elements as the other 3 labels combined. The oversampling/undersampling methods are not implemented here to present the actual situation considering a realistic data collection scenario where data imbalance is obvious. Our results show that a small portion of a person's IBI signal can be used to estimate

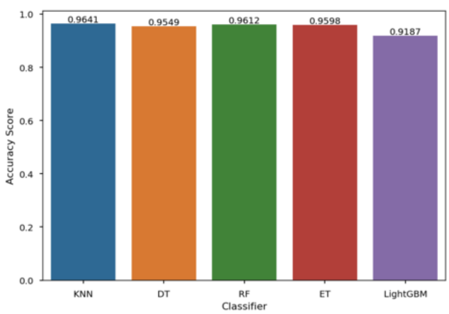

Figure 6. Accuracy comparison for different models

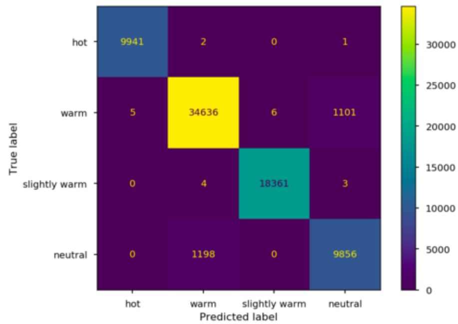

Figure 7. Confusion Matrix (KNeighborsClassifier)

the thermal comfort of the environment. The scope of this research is limited to pulse fluctuation data from where we extracted heart rate variability.

Furthermore, because thermal comfort is a personal experience, in our study, we also collected individuals' thermal assessment report through one mobile application. In the future, we will focus on the individual level and examine the model that can estimate subjective thermal comfort collected during the experiment, and also examine the effect of biological signals other than pulse fluctuation. This experiment, on the other hand, is not limited in scope (33 users and four thermal comfort environmental settings) and conducted in a variety of work environments aligning with natural different work states in home and outdoor. Based on this early evaluation, we will further investigate this dataset in the future in order to forecast subjective thermal comfort and sensation in a variety of work environments which can be applied to the prediction of the risk of individual heatstroke because of variations in the thermal comfort felt by individuals.

Table 4. Best Model's Classification Report

	Precision	Recall	F1-score	Support
Hot	1.00	1.00	1.00	9944
Warm	0.97	0.97	0.97	35748
Slightly warm	1.00	1.00	1.00	18368
Neutral	0.90	0.89	0.90	11054

6. Conclusions and Future Works

To predict human thermal comfort it is necessary to know the environmental thermal sensation. In this research, we widely collected 33 participants data in a variety of work environments in various work conditions i.e., reading, typewriting, and gymnastics focus on hot conditions with settings in accordance with ASHRAE scale normal, slightly warm, warm, and hot. We set these activities in relation with real-life situations and focus on hot thermal conditions (risk of heatstroke, higher dissatisfaction/more difficult to cope than cold). In order to estimate four different environmental thermal sensations, various heart rate variability features are calculated and used to develop a machine learning model. We compared five machine learning models' performance to predict environmental thermal sensation. Our preliminary results show that K-Neighbors Classifier outperforms the other five classifiers in predicting environmental thermal sensation having prediction accuracy of 96.41%. The average accuracy for other models are 95.17%. In future, we will focus on the individual level and examine the model that can estimate subjective thermal comfort collected during the experiment that can be applied to the prediction of the risk of individual heatstroke under various work conditions. In the future, we want to incorporate a variety of age groups, with an emphasis on the elderly, as well as gender balance.

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References

[1] Ormandy D, Ezratty V. Health and thermal comfort: From WHO guidance to housing strategies. Energy Policy - ENERG POLICY. 2011 01;49.

[2] Pantavou K, Theoharatos G, Mavrakis A, Santamouris M. Evaluating thermal comfort conditions and health responses during an extremely hot summer in Athens. Building and Environment. 2013 05:339-44.

[3] Lan L, Wargocki P, Lian Z. Quantitative measurement of productivity loss due to thermal discomfort. Lancet. 2011 05;43:1057-62.

[4] Seppanen O. Some Quantitative Relations Between Indoor Environmental Quality and Work Performance or Health. vol. 12; 2006. .

[5] Chappells H. Comfort, well-being and the socio-technical dynamics of everyday life. Intelligent Buildings International. 2010 01;2:286-98.

[6] Ormandy D, Ezratty V. Thermal discomfort and health: protecting the susceptible from excess cold and excess heat in housing. Advances in Building Energy Research. 2015 02;10:1-15.

[7] Lima F, Ferreira P, Leal V. A Review of the Relation between Household Indoor Temperature and Health Outcomes. Energies. 2020;13(11).

[8] Rocklöv J, Forsberg B, Ebi KL, Bellander T. Susceptibility to mortality related to temperature and heat and cold wave duration in the population of Stockholm County, Sweden. Global Health Action. 2014;7.

[9] ASHRAE 55-2020: Thermal Environmental Conditions for Human Occupancy. ANSI Approved; 2021.

[10] ISO 7730:2005(E): Ergonomics of the Thermal Environment-Assessment of the Influence of the Thermal Environment Using Subjective Judgment Scales; 2005.

[11] Corgnati S, Filippi M, Viazzo S. Perception of the thermal environment in high school and university classrooms: Subjective preferences and thermal comfort. Building and Environment - BLDG ENVIRON. 2007 02;42:951-9.

[12] Arens E, Humphreys M, de Dear R, Zhang H. Are 'class A' temperature requirements realistic or desirable? Building and Environment - BLDG ENVIRON. 2010 01;45:4-10.

[13] Nkurikiyeyezu K, Suzuki Y, Lopez G. Heart rate variability as a predictive biomarker of thermal comfort. Journal of Ambient Intelligence and Humanized Computing. 2018 10;9.

[14] Gil E, Orini M, Bailón R, Vergara J, Mainardi L, Laguna P. Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions. Physiological measurement. 2010 09;31:1271-90.

[15] Sookchaiya T, Monyakul V, Thepa S. Assessment of the thermal environment effect a human comfort and health for the development of novel air conditioning system in tropical regions. Energy and Buildings. 2010 10;42:1692-702.

[16] Toftum J, Langkilde G, Fanger PO. New indoor environment chambers and field experiment offices for research on human comfort, health and productivity at moderate energy expenditure. Energy and Buildings. 2004 09;36:899-903.

[17] Deng Q, Wang R, Li Y, Miao Y, Zhao J. Human thermal sensation and comfort in a non-uniform environment with personalized heating. Science of The Total Environment. 2016 06;578.

[18] Liu S, Das HP, Jin M, Spanos C. Personal thermal comfort models with wearable sensors. Building and Environment. 2019 07;162:106281.

[19] Nicol JF, Humphreys MA. Adaptive thermal comfort and sustainable thermal standards for buildings. Energy and Buildings. 2002;34(6):563-72.

[20] Xiong J, Zhou X, Lian Z, You J, Lin Y. Thermal perception and skin temperature in different transient thermal environments in summer. Energy and Buildings. 2016 06;128.

[21] Nkurikiyeyezu K, Yokokubo A, Lopez G. Affect-aware thermal comfort provision in intelligent buildings. International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW). 2019 Sep.

[22] Cao B, Shang Q, Dai Z, Zhu Y. The Impact of Air-conditioning Usage on Sick Building Syndrome during Summer in China. Indoor and Built Environment. 2013 06;22:490-7.

[23] Choi JH, Loftness V. Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations. Building and Environment. 2012;58:258-69.

[24] Nkurikiyeyezu K, Suzuki Y, Tobe Y, Lopez G, Itao K. Heart rate variability as an indicator of thermal comfort state; 2017. p. 1510-2.

[25] Ghahramani A, Tang C, Becerik-Gerber B. An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling. Building and Environment. 2015;92:86-96.

[26] Menghini L, Gianfranchi E, Cellini N, Patron E, Tagliabue M, Sarlo M. Stressing the accuracy: Wrist-worn wearable sensor validation over different conditions. Psychophysiology. 2019 07;56.

[27] Fanger PO. Assessment of man's thermal comfort in practice. British Journal of Industrial Medicine. 1973;30:313 324.

[28] Halawa E, van Hoof J. The adaptive approach to thermal comfort: A critical overview. Energy and Buildings. 2012;51:101-10.

[29] Sassi R, Cerutti S, Lombardi F, Malik M, Huikuri H, Peng CK, et al. Advances in heart rate variability signal analysis: Joint position statement by the e-Cardiology ESC Working Group and the European Heart Rhythm Association co-endorsed by the Asia Pacific Heart Rhythm Society. Europace. 2015 07;17.

[30] Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health. 2017;5.

[31] Föll S, Maritsch M, Spinola F, Mishra V, Barata F, Kowatsch T, et al. FLIRT: A feature generation toolkit for wearable data. Computer Methods and Programs in Biomedicine. 2021 10;212.

[32] Mitchell TM. Machine learning, International Edition. McGraw-Hill Series in Computer Science. McGraw-Hill; 1997.