Sensing Occupant Comfort using Wearable Technologies

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ABSTRACT

Thermal comfort of building occupants is a major criterion in evaluating the performance of building systems. It is also a dominant factor in designing and optimizing building's operation. However, existing thermal comfort models, such as Finger's model currently adopted by ASHRAE Standard 55, rely on factors that require bulky and expensive equipment to measure. This paper attempts to take a radically different approach towards measuring the thermal comfort of building occupants by leveraging the ever-increasing capacity and capability of mobile and wearable devices. Today's commercially-off-the-shelf (COST) wearable devices can unobtrusively capture a number of important parameters that may be used to measure thermal comfort of building occupants, including ambient air temperature, relative humidity, skin temperature, perspiration rate, and heart rate. This research evaluates such opportunities by fusing traditional environmental sensing data streams with newly available wearable sensing information. Furthermore, it identifies challenges for using existing wearable devices and to developing new models to predict human thermal comfort. Findings from this exploratory study identify the inaccuracy of sensors in cellphones and wearable as a challenge, yet one which can be improved using customized wearables. The study also suggests there exists a high potential for developing new models to predict human thermal sensation using artificial neural networks and additional factors that can be individually, unobtrusively and dynamically measured using wearables.

INTRODUCTION

Thermal comfort of building occupants is a major criterion in evaluating the performance of building systems and a dominant factor in designing and optimizing buildings operation. In the United States, buildings are reported to consume 40% of the total energy consumption while commercial buildings are reported to consume 50% of all buildings' energy demand. Out of the 20% energy consumed by commercial buildings, the Heat Ventilation and Air Conditioning (HVAC) systems consume 43% of buildings' energy demand (U.S. Department of Energy 2012). Studies have shown that improving thermal comfort of building occupants can lead to

improvements in important areas, including occupant productivity and well-being (Frontczak et al. 2012). Furthermore, Americans spend more than 90% of their time inside buildings (U.S. Environmental Protection Agency 2012). That highlights the importance of developing tools and devices that can collect data regarding occupants to maximize their comfort while minimizing building energy demands. Wearable devices present a unique opportunity for collecting individualized human sensation data such as skin temperature and heart rate in addition to sensor data documenting indoor environmental conditions such as air temperature and relative humidity.

Several models have been developed over past decades to understand and measure the thermal comfort of building occupants. A seminal model was developed by Fanger in the 1970s (Fanger 1970). It is based on the physiological processes that influence heat balance between the heat produced by metabolism and the heat lost from the body through skin. Fanger's model was developed using laboratory and climate chamber studies which asked large number of subjects to report their thermal comfort based on 7-point scale (cold, cool, slightly cool, neutral, slightly warm, warm, and hot) according to various indoor environmental conditions. The 7-point scale is represented with an index called Predicted Mean Vote (PMV) using values that range from -3 (cold) to 3 (hot). The model combines two personal variables- activity level and clothing insulation- in addition to four indoor environment variables- air temperature, air velocity, mean radiant temperature, and relative humidity- to form an index that can be used to predict thermal comfort. The index provides a score based on the aforementioned 7-point scale to represent the average thermal sensation of a large group of people in a space. This value equates to a percentage of people dissatisfied among the group, the Predicted Percentage Dissatisfied (PPD). The PMV model is currently adopted by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE). The existing ASHRAE standard requires at least 80% of occupants feel thermally satisfied in the design of buildings (ASHRAE Standard 55 2013; Charles 2009; Fanger 1970). Another model, developed by the Institute for Environmental Research at Kansas State University, showed statistical correlation between level of comfort, temperature, humidity, gender, and exposure duration and yielded an equation to measure PMV values based on air temperature, partial vapor pressure, and three coefficients of spent time and gender of the subject (Rohles 1971). Another thermal sensation model was developed to predict local and overall sensations and comfort based on local skin temperatures and their change over time, and core temperature and its change over time (Zhang et al. 2004). Furthermore, a simulation environment model was developed to simulate air infiltration, ventilation and heat transfer processes in non-commercial building to estimating human thermal sensation and comfort (Tuomaala 2002; Tuomaala et al. 2002). Recently, a Human Thermal Model (HTM) was developed to estimate human thermal sensation and comfort based on simulation of human body which allowed more detailed thermal sensation and estimation of comfort levels better than the traditional model (Holopainen 2012; Zhang et al. 2004).

Furthermore, a number of studies have been conducted to investigate the use of wearable devices, wireless sensors, and mobile applications for identifying thermal comfort of building occupants and their location over time. A recent study developed a battery-powered indoor environment sensor to recognize activity type and location

based on environmental measurements. The environment sensor collects a set of environmental variables including temperature, humidity, ambient light, sensor orientation, and motion detection and can detect eight typical activities, including sitting in lab / cubicle, indoor walking / running, resting after physical activity, climbing stairs, taking elevators, and outdoor walking. The developed device is designed to provide easily deployable sensing infrastructure that can operate for years in a smart buildings or be wearable and portable. The developed device showed that fusion of environmental sensing along with acceleration can achieve classification accuracy up to 99.13% (Jin et al. 2014). Another study investigated the use of wireless system to compute thermal comfort in indoor environments. This system consists of a central control unit and end devices which interface with humidity sensors, inbuilt temperature sensors, light sensors, and accelerometers. The end-device periodically reports data to a coordinator and based on the collected data, this system calculates the PMV that intermittently represents thermal comfort index. It should be noted that the wireless sensors in this study did not measure mean radiant temperature and air velocity. However, the study assumed that air temperature is equivalent (equal) to mean radiant temperature and air velocity in indoor environments varies from 0.1 m/s to 0.3 m/s when calculating PMV (Aswathanarayanajois 2013). Another system was developed to improve thermal comfort for Ambient Assisted Living (AAL) by continuously monitoring indoor environmental parameters that lead to an accuracy of ±0.1 of PMV for multiple positions or occupants in a room. The developed system can be integrated with building management systems to adjust the indoor environment to required comfort level. Input parameters of the system include room geometry and personal parameters of clothing levels and metabolic rate. The system uses infrared sensors to automatically scan the surfaces inside a room and identify their temperature. The air temperature and relative humidity are measured in a single point with a separate sensor. After the room interior surface temperatures measurement, the mean radiant temperature is determined at time t for different subjects in the room. Accordingly, PMV can be calculated and the indoor environment can be adjusted to satisfy comfort levels of the room subjects (Gian Marco Revel et al. 2014). Additionally, a mobile application called "Comfy" is commercially available and allows building occupants to manually adjust temperatures in their surrounding by connecting cell phones to building systems (Comfy 2015).

Despite the significant contribution of the aforementioned models and research, there is limited research on using wearable devices to measure and monitor thermal comfort of building occupants while tracking building occupants to minimize building energy demands. Furthermore, traditional thermal comfort models such as the Fanger's model currently adopted by ASHRAE standard 55, is applicable only to steady-state and uniform thermal environments. Additionally, traditional models do not account for individualized factors that have been shown in a number of studies to correlate to personnel thermal comfort, including gender, age, Body Mass Index (BMI), and fitness (Djamila 2012; Karjalainen 2007; Tuomaala et al. 2013). Accordingly, none of the existing systems and models are capable of passively and accurately using individual sensation to predict thermal comfort in real-time using an unobtrusive sensing device, which can be used to create smart building systems that

dynamically adjust the indoor conditions according to the comfort of individual building occupants.

RESEARCH OBJECTIVE

The objective of this exploratory research is to investigate the feasibility of using wearable devices to measure and monitor thermal comfort of building occupants. Recent technologies of wearable devices such as wristband devices can capture a number of important parameters that can be used to measure thermal comfort of building occupants, including ambient air temperature, relative humidity, skin temperature, perspiration rate, and heart rate. Fusing traditional environmental sensing data with newly available wearable sensing information can be used to (1) create new models for measuring human thermal sensation including physiological signals and factors not considered in existing models such as age, gender, and BMI; (2) develop new metrics to provide accurate and meaningful feedback to building owners and operators regarding aggregate comfort levels in order to identify the optimal trade-off between building comfort and building operation efficiency, and (3) develop thermal comfort report card that can generate scores for buildings based on the thermal satisfaction of building occupants (Abdallah et al. 2015). This research focuses on investigating the use of wearable device and identifying challenges for fusing wearable devices into existing models to measure, monitor, and evaluate thermal comfort of building occupants to lead to the aforementioned outcomes.

METHODOLOGY

The authors conducted a pilot study to investigate the feasibility of using wearable devices to measure thermal comfort. In particular, this pilot study focused on (1) testing a custom mobile application in collecting data of indoor environmental conditions and physiological signals, (2) identifying the accuracy of the collected data using wearable devices, and (3) studying the feasibility of estimating or calculating PMV index based on the collected data of indoor environmental conditions and physiological signals. The pilot study was conducted on August 20th, 2015 in a conditioned laboratory at University of Colorado Denver for two hours within varying indoor environmental conditions. Two Construction Engineering and Management faculty, one Computer Science faculty and graduate student collaborated to participate in the experiment using four cellphones with the developed application installed, four Basis wristband devices (BASIS), thermal comfort equipment and an iBeacon. An iBeacon leverages communication protocol lead by Apple Inc.'s (Apple Inc. 2015) and based on Bluetooth Low Energy (BLE) technology started by Nokia Research Center (Persson 2005) to position a subject using proximity information between them (Namiot 2015). The experiment took place in a laboratory space, as shown in Figure 1. Three additional iBeacons were placed in locations around the floor of the building. Study participants were periodically scheduled to move around the building (outside of the laboratory) for 5 minutes during the experiment to identify if the cellphones are able to identify their locations. A small heater was placed in the laboratory to change the temperature during the experiment, also shown in Figure 1.

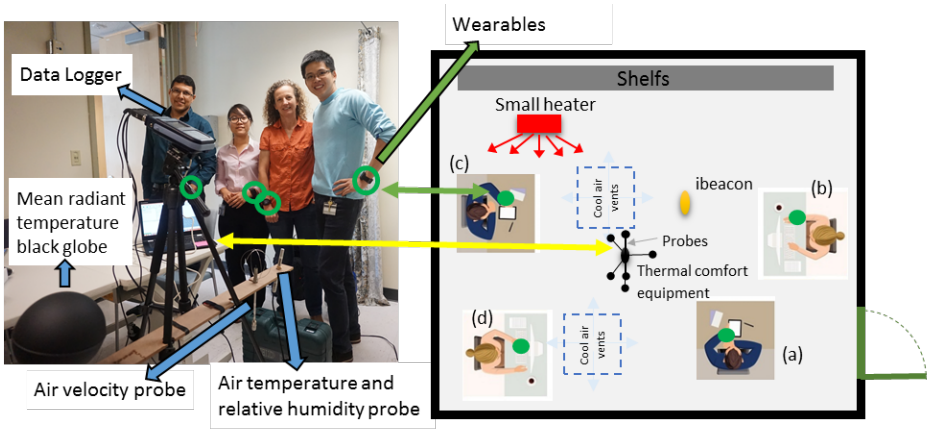
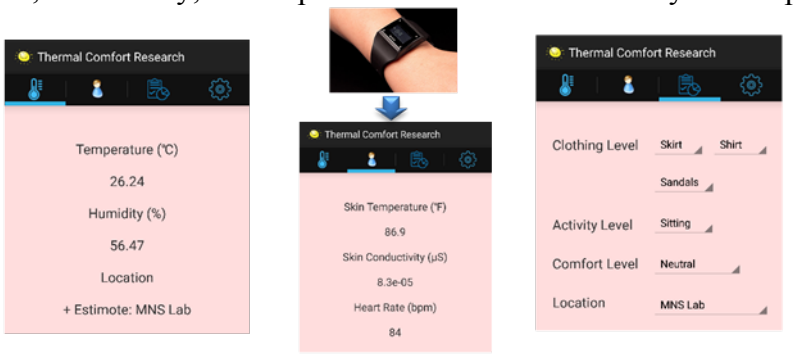


Figure 1. Participants and equipment layout for pilot study

A mobile application was developed, as depicted in Figure 2, to automatically collect and aggregate data from cell phone and wearable sensors on thirty second intervals. In addition, users were prompted by the application to manually select an activity and assign a comfort level using 7-point scale of the PMV index every fifteen minutes via their cell phones, as shown in Figure 2.c. Cell phone sensors were used to collect air temperature and relative humidity data. Wearable sensors were used to collect skin temperature, heart rate, and skin conductivity along with air temperature and relative humidity data. The recordings of the indoor environmental conditions and physiological signals were recoded with time stamps to later facilitate analysis. Finally, and in parallel, thermal comfort equipment consisting of the data logger and probes shown in Figure 1, were used, in some cases redundantly, to log mean radiant temperature, air velocity, air temperature and relative humidity in the space.



a) Environmental tab b) Bio-Information tab c) Self-report tab

Figure 2. Mobile application documenting real-time indoor environmental conditions and physiological signals from cell phones and wearables

Next, the PMV index for each individual was calculated for the duration of the case study using data recorded using traditional thermal comfort equipment in addition to the clothing and activities levels recorded by the mobile application. Finally, the authors investigated how data collected using wearable devices could be used to predict thermal comfort. However, this requires two additional methods:

1) Data smoothing and alignment: Since the sensors built in wearables and mobile devices can capture with high sampling rates, the data had fluctuations due to

noise. Moreover, the difference in the sampling rate of devices makes the collected data asynchronous . By applying these techniques, the shape of the data is represented more clearly and all the data are matched correctly in time. Specifically, the data collected by the mobile application and written to .csv files were smoothed based on five-minute intervals and aligned with the thermal comfort equipment based on a one-minute basis.

2) Machine learning technique: Artificial Neural Networks ANNs is a branch of statistical learning models in machine learning and cognitive science which can be used to estimate or calculate an output relative to a number of inputs. ANNs are generally presented as systems of interconnected neurons which exchange information among each other. The connection have numeric weights that can be tuned based on training process which allow neural networks to adapt to inputs and capable of learning to solve problems (Krose and Smagt 1996; Stergiou and Sigano 1989). Other machine learning techniques such as regression models will be further explored to identify leading models and techniques for predicting human thermal sensation.

In this research, as shown in Figure 3, an ANN was created to evaluate the correlation of an estimated PMV index to inputs that can be measured using a wearable device, including indoor environmental conditions and physiological signals.

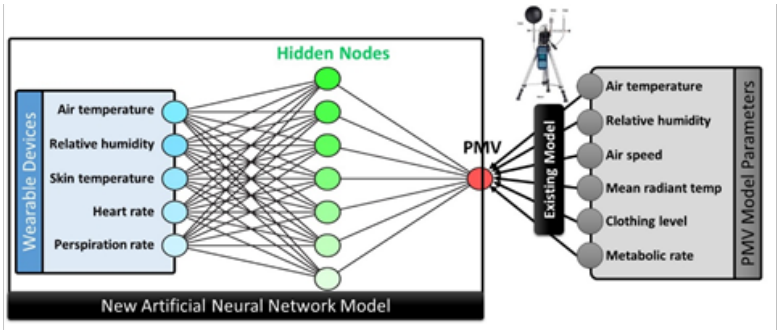


Figure 3. Layout of Artificial Neural Networks

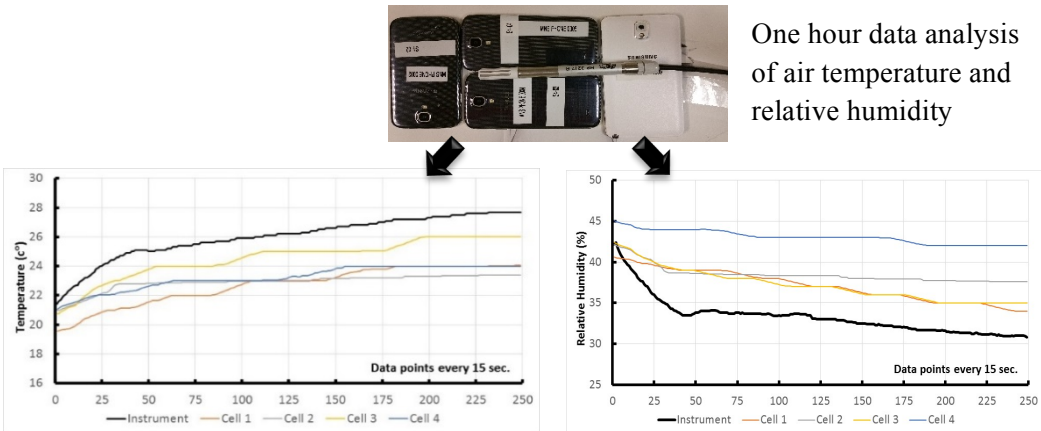
A NeuroSolutions Infinity tool was used to process the collected data. NeuroSolutions Infinity uses 44 functions to analyze the correlation of a number of input parameters with a desired output and to identify the best prediction model (NeuroSolutions 2015).

ANALYSIS

The data collected for each participant was organized and summarized for analysis. Air temperature and relative humidity were measured for each participant using three devices- cell phones, wearable devices, and thermal comfort equipment. The collected data showed variations across devices when measuring air temperature and relative humidity. The thermal comfort equipment had been recently calibrated by the manufacture, and, its data, therefore, was considered to be “ground truth” for the research.

The authors performed a separate analysis comparing cell phone sensors and thermal comfort equipment. For this test, as shown in Figure 4, the four test cell

phones were placed side by side on the table along with the air temperature and relative humidity instrument probe for an hour, while the indoor environmental conditions varied. Results of this analysis revealed discrepancies in measured air temperature and relative humidity across all devices, as shown in **Figure 4**. Accordingly, the authors concluded that sensors both cell phone and wearable devices lacked a degree of accuracy and will require additional testing and calibration in the future.



(a) Temperature Measurements (b) Relative Humidity Measurements

Figure 4. Cell phone sensor accuracy across air temp. and relative humidity

Next the authors organized and summarized the pilot study data collected for each of the participants. As shown in **Figure 5** for two participants, seven data streams captured using both wearable sensors and stationary thermal comfort equipment were graphed, along with an overlay of the aligned PMV index. As previously discussed, the PMV index was calculated using thermal comfort equipment sensors and user inputs regarding clothing and activity level.

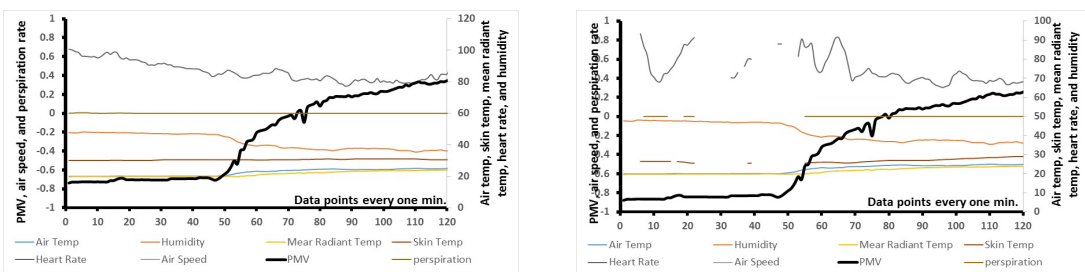
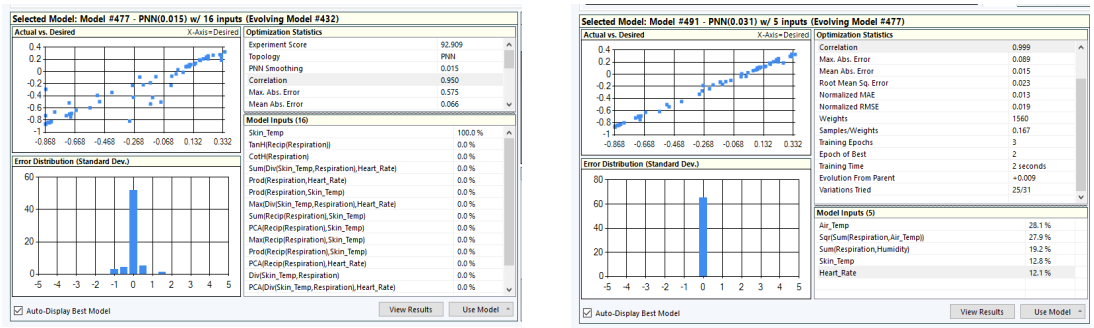


Figure 5. Sample summary of data collected for two participants

Analysis of the data at this scale, did not immediately reveal significant patterns. It is possible to observe, however, that several discontinuities occurred in the data collected using the wearables. As noted by the participants during the pilot test, the wearable devices did not always maintain good contact with the skin's surface due primarily to sizing issues.

To further study the feasibility of using wearable devices to measure thermal comfort of building occupants, the collected data was analyzed as inputs and using ANN to calculate PMV index. Analyses of two data sets were performed using NeuroSolutions Infinity to predict PMV values based on a number of input parameters. In the first analysis, ANN used a dataset consisting of skin temperature, heart rate, and respiration rate to predict the values of PMV. The results of the best model in the first analysis showed 0.95 correlation between 16 inputs and PMV, as shown in Figure 6 (a). In the second analysis, air temperature and relative humidity data were added to the dataset. Therefore, in the second analysis ANN used a dataset consisting of skin temperature, heart rate, respiration rate, air temperature and relative humidity to predict the values of PMV. The results of the best model in the second analysis showed 0.999 correlation between 5 inputs and PMV, as shown in Figure 6 (b). In this case, the correlation provides a maximum absolute error of 0.09 PMV and root mean square error of 0.023 PMV. The five input parameters of the best model were identified as air temperature, square root of the summation of perspiration and air temperature, summation of perspiration and relative humidity, skin temperature, and heart rate with a contribution to PMV index of 28.1%, 27.9%, 19.2%, 12.8%, and 12.1%, respectively. It should be noted that for both analyses, the tool used 75% of the data (244 rows) for training the models, 20% of the data (64 rows) for validating the modes, and 5% of the data (17 rows) for evaluating the models performance.



(a) ANN Model 1 (b) ANN Model 2

Figure 6. Analysis of data collection of wearable devices to calculate PMV index

DISCUSSION

Initial findings of this study are promising and merit further research. Specifically, need exists to increase the suitability of wearables to support thermal comfort assessment. Today's off-the-shelf wearables contain sensors that run at high sampling rates (e.g. 100Hz), designed mainly for activity tracking, health monitoring, and purposes other than thermal comfort evaluation. This design decision is one of the reasons wearable devices exhaust their battery quickly. In most cases, these sampling rates are one to two orders of magnitude higher than needed for comfort evaluation purposes. On the other hand, the sensors' reliability is low and the accuracy fluctuates. In response, we propose to explore a set of sensing algorithms, techniques, designs, and optimizations to increase the suitability of wearable for thermal comfort assessment. We will customize existing sensors to adjust sampling

frequency and sensitivity level, thereby increasing accuracy and saving energy at the same time.

Initial findings identified a model that has a 0.999 correlation to the current PMV model using inputs that can be unobtrusively and dynamically measured with wearables. In contrast, the current model requires cumbersome (expensive, nonspecific) equipment to assess. Using wearables to estimate PMV will not only address problematic data collection, but may also extend the existing PMV model by providing opportunities for generating location-specific, adaptive and individual thermal comfort predictions.

Finally, initial findings also highlight opportunities to eventually develop new metrics (and, eventually,standards) for assessing thermal comfort across buildings. The authors have plans to develop a thermal comfort report card that can generate scores for buildings based on the thermal satisfaction of building occupants as aggregated across spaces (Abdallah et al. 2015). Eventual outcomes could include helping building owners and operators evaluate and compare thermal comfort performance, to identify areas that may require improvements, and to create the opportunity to simultaneously optimize for energy and thermal comfort performance.

CONCLUSION

Thermal comfort of building occupants is a major criterion in designing buildings, evaluating their operation performance, and optimizing their energy usage. This paper studied the feasibility of using wearable devices to measure and monitor thermal comfort of building occupants. A mobile application was developed to collect data of building occupants using sensors in cell phones and wearable devices, including location, air temperature, relative humidity, skin temperature, heart rate, and perspiration rate. A pilot case study of four participants was performed to (1) test the developed mobile application in collecting data of indoor environmental conditions and physiological signals, (2) identify the accuracy of the collected data using wearable devices, and (3) study the feasibility of predicting PMV index based on the collected data of indoor environmental conditions and physiological signals using wearable devices. Calibrated thermal comfort equipment was used to establish "ground truth" PMV estimates for the study. Testing showed variation in the accuracy of cell phone and wearable device sensors. Artificial Neural Networks (ANNs) were used to study the feasibility of predicting PMV index using data that can be collected using wearable devices. Results of ANNs analysis showed 0.999 correlation with maximum root mean square error of 0.023 PMV. The input parameters of the best model were identified as air temperature, square root of the summation of perspiration and air temperature, summation of perspiration and relative humidity, skin temperature, and heart rate with contribution to PMV index of 28.1%, 27.9%, 19.2%, 12.8%, and 12.1%, respectively. These are promising results and suggest significant potential for creating new models that can predict PMV index using parameters that can be measured using wearable devices. However, existing sensors in wearable devices need to be improved and further customized to increase their accuracy and reliability in order to facilitate such predictions.

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