ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Project Coolbit: can your watch predict heat stress and thermal comfort sensation?

To cite this article: Negin Nazarian *et al* 2021 *Environ. Res. Lett.* **16** 034031

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
29 June 2020

REVISED
15 November 2020

ACCEPTED FOR PUBLICATION
7 December 2020

PUBLISHED
23 February 2021

LETTER

Project Coolbit: can your watch predict heat stress and thermal comfort sensation?

Negin Nazarian[1,2,15,*], Sijie Liu[1,2], Manon Kohler[3,4], Jason K W Lee[5,6,7,8,9], Clayton Miller[3], Winston T L Chow[4], Sharifah Badriyah Alhadad[9,14], Alberto Martilli[13], Matias Quintana[3], Lindsey Sunden[10] and Leslie K Norford[11,12]

1 Climate-Resilient Cities Lab, UNSW Built Environment, University of New South Wales, Sydney, Australia
2 ARC Centre of Excellence for Climate Extremes, UNSW, Sydney, Australia
3 National University of Singapore, Singapore, Singapore
4 Singapore Management University, Singapore, Singapore
5 Human Potential Translational Research Programme, Yong Loo Lin School of Medicine, National University of Singapore, Singapore, Singapore
6 Global Asia Institute, National University of Singapore, Singapore, Singapore
7 N.1 Institute for Health, National University of Singapore, Singapore, Singapore
8 The Institute for Digital Medicine, National University of Singapore, Singapore, Singapore
9 Department of Physiology, Yong Loo Lin School of Medicineepartment of Physiology, National University of Singapore, Singapore, Singapore
10 Fitbit, Inc., San Francisco, CA, United States of America
11 Department of Architecture, Massachusetts Institute of Technology, MA, United States of America
12 Singapore-MIT Alliance for Research and Technology, Singapore, Singapore
13 Environment Department, Research Center for Energy, Environment and Technology (CIEMAT), Madrid, Spain
14 Saw Swee Hock School of Public Health, National University of Singapore, Singapore, Singapore
15 #2026 Red Centre West Wing (H13), UNSW, Sydney, NSW 2052, Australia
* Author to whom any correspondence should be addressed.

E-mail: n.nazarian@unsw.edu.au

Keywords: heat stress, thermal comfort, wearable technologies, personalized heat exposure, urban climate

Abstract

Global climate is changing as a result of anthropogenic warming, leading to higher daily excursions of temperature in cities. Such elevated temperatures have great implications on human thermal comfort and heat stress, which should be closely monitored. Current methods for heat exposure assessments (surveys, microclimate measurements, and laboratory experiments), however, present several limitations: measurements are scattered in time and space and data gathered on outdoor thermal stress and comfort often does not include physiological and behavioral parameters. To address these shortcomings, Project Coolbit aims to introduce a human-centric approach to thermal comfort assessments. In this study, we propose and evaluate the use of wrist-mounted wearable devices to monitor environmental and physiological responses that span a wide range of spatial and temporal distributions. We introduce an integrated wearable weather station that records (a) microclimate parameters (such as air temperature and humidity), (b) physiological parameters (heart rate, skin temperature and humidity), and (c) subjective feedback. The feasibility of this methodology to assess thermal comfort and heat stress is then evaluated using two sets of experiments: controlled-environment physiological data collection, and outdoor environmental data collection. We find that using the data obtained through the wrist-mounted wearables, core temperature can be predicted non-invasively with 95 percent of target attainment within $\pm 0.27\,^{\circ}$C. Additionally, a direct connection between the air temperature at the wrist ($T_{a,w}$) and the perceived activity level (PAV) of individuals was drawn. We observe that with increased $T_{a,w}$, the desire for physical activity is significantly reduced, reaching 'Transition only' PAV level at 36 °C. These assessments reveal that the wearable methodology provides a comprehensive and accurate representation of human heat exposure, which can be extended in real-time to cover a large spatial distribution in a given city and quantify the impact of heat exposure on human life.

1. Introduction

Heat exposure directly impacts our wellbeing, productivity, and cognitive performance [1, 2] and presents an increasing concern to human health in the face of global climate change [3, 4]. Urban areas are particularly vulnerable to the impacts of heat, as they concentrate large numbers of vulnerable people (such as young children, elderly, and those with existing physical and mental health conditions [5]) in settings where ambient temperatures are often higher than suburban and rural areas (Urban Heat Island effect [6]). The combined effect is detrimental to the health of urban residents. Heat mortality is referred to as 'private and silent deaths' and even in developed countries such as Australia and the United States, heatwaves are reported to kill more than any other natural disaster [5, 7, 8]. Therefore, it is paramount that we deeply understand and closely monitor not only the climatic factors but also the personalized responses of the population to assess the impact of urban heat exposure on human health and wellbeing.

Currently, measurements for thermal comfort and heat stress are done through two main methods: (1) measurements of microclimate and physiological parameters, commonly in fixed locations or laboratory settings, and (2) surveys of human sensation in response to thermal environments [9–14]. Although the information gathered contributes significantly to our knowledge of thermal comfort, several limitations persist:

1. Measurements are scattered in time and space. The spatial and temporal distributions of thermal environment and comfort in the city are not readily available through the experiments and have been mainly achieved by numerical modeling [15–19].
2. Data gathered on thermal comfort often do not include the 'human factor,' i.e. physiological and behavioral parameters corresponding to the thermal comfort of individuals, despite the fact that the response and vulnerability to thermal environments vary greatly between individuals [20–22].
3. Data gathered on heat stress often do not represent realistic conditions in urban environments and are not obtained in real-time. For instance, the majority of temperature-mortality/-morbidity relations are drawn based on temperatures recorded at fixed monitoring stations [23], which may not resemble what people experience as they go about their lives in the city.

Project Coolbit is motivated by the challenges and limitations of existing methods. Innovative methods of obtaining data are needed to (a) span larger spatial and temporal distributions in cities, (b) obtain real-time, unsupervised, and non-intrusive data on thermal comfort and heat stress in the built environment, and (c) provide human-centric assessments, such that we extend previous approaches to thermal comfort and heat stress.

These objectives can be achieved through crowdsourced monitoring as opposed to centralized experimentations. Crowdsourcing or ubiquitous sensing (i.e. obtaining data by using a distributed number of sensors) has recently become feasible due to the rapidly growing number of affordable internet-enabled sensing devices [24]. Among these, wearable technologies represent a range of opportunities for comfort and health assessments. These devices enable us to generate a significant amount of data about people's immediate environments, add behavioral and physiological components [25, 26], and approach thermal comfort and heat stress as 'human-centric' as opposed to 'one-size-fits-all'. Additionally, wearables travel with the individuals in realistic exposure scenarios and, therefore, data collected by wearables combined with GPS data can provide a spatiotemporal distribution of environmental parameters and individual's exposure. However, to date, there is no wearable sensing (neither commercial nor in academic use) available nor tested that can combine all the parameters relevant to thermal comfort and heat stress. Accordingly, we propose and test a methodology based on wearable devices here, which can ultimately enable a comprehensive yet unsupervised and non-invasive assessment of thermal comfort and heat stress in the built environment.

The current generation of wearables monitors such physiological parameters as heart rate, which helps understand various aspects of human wellbeing and health including sleep quality. However, to assess thermal stress and comfort, the measurements should be extended. Human skin is the mediator between the environment and human body and, therefore, skin temperature and conductance play a major role in thermoregulatory processes involved in thermal comfort and heat stress [27, 28]. Sim *et al* [28] showed that wrist skin temperatures can be used to predict whole-body thermal sensation. Additionally, several studies have used heart rate data to indicate thermal stress in the built environment. A study by Buller *et al* [29] introduced a non-invasive and continuous method of estimating the human core temperature, the main factor in determining heat stress, from sequential heart rate observations. They showed that out of 52 000 observations, 95% of all core temperature estimates fell within ±0.63 °C of measurements. This, in addition to the advancement of ubiquitous sensing in the built environment, has opened new doors to use wearables for thermal exposure assessments. Nonetheless, this is an emerging field and there are only a handful of studies

Figure 1. Schematic of an Integrated Wearable Weather Station for personalized assessment of urban heat exposure. In this format, three components of heat exposure are captured: (1) environmental parameters (such as air temperature, humidity, or radiation) are recorded on the outside of the strap (right image), (2) physiological response to heat exposure (including skin temperature and humidity) is captured based on sensors placed on the inner strap (left image), and (3) the smartwatch app is used to monitor activity level, location, and individuals' momentary assessment of heat exposure (center). All emojis designed by OpenMoji – the open-source emoji and icon project. License: CC BY-SA 4.0

that investigate wearable solutions [16, 25, 26, 30]. Among these, Nakayoshi *et al* [25] represents a comprehensive measurement of thermal comfort, monitoring four relevant environmental parameters in the proximity of the human body as well as physiological responses (heart rate and skin temperature) and subjective feedback, and found a correlation between skin temperature and thermal comfort index in a semi-controlled testing environment. The wearable system involved five sensing units worn by the participants on multiple locations: hat, belt, hand, and forehead skin, and carried in a small sash. Although comprehensive for research purposes, this methodology cannot be employed in unsupervised settings and is considered impractical for implementation in real-life applications. Wrist-mounted wearables can address such concerns regarding scalability in realistic applications, particularly as smartwatches have recently dominated the wearable tech worldwide [31]. However, the challenges of using wearables as sensing methodologies are still numerous and, to date, reliability of wrist-mounted wearable data collection under dynamic use are not fully assessed. There is an urgent need to quantitatively assess the performance of wearables for heat exposure monitoring, which motivates the present study. Here, we propose an Integrated Wearable Weather Station for unsupervised assessment of urban heat impact on individuals (section 2.1), and further discuss experiments that rigorously assess the feasibility of this methodology for various heat exposure evaluations in the built environment (section 2.2). In sections 3.1 and 3.2, we evaluate the prediction of body core temperature (as the main predictor of heat stress) and thermal comfort sensation using collected data and lastly, we discuss the implication of these findings as well as future research that can extend this methodology for real-time and unsupervised evaluation of urban heat impacts on human life in section 4.

2. Methodology

2.1. Integrated wearable weather station: human-centric assessment of thermal comfort and heat stress

Innovative methods of obtaining data are needed to assess dynamic exposure to thermal environments in cities in a human-centric way. However, the assessment of thermal exposure is notoriously complex as it requires consideration of three critical components: (a) environmental factors, (b) physiological thermoregulation mechanisms of the human body, and (c) subjective psychological perceptions and behavioral patterns as well as cultural and climatic backgrounds of individuals. Accordingly, the integration of all these components into one sensing unit hasn't been accomplished so far.

Unprecedented potentials are now emerging through the rise of Internet-of-Things sensing and wearable technologies for fitness, performance, and health tracking. Various wearable sensors have enabled continuous and real-time monitoring of physiological parameters over the last few years, with limited attention given to thermal exposure assessments [32–34]. Smart devices further provide interfaces for continuous interaction with users and data collection regarding behavioral patterns of human activities. Tapping on these emerging potentials, we propose wrist-mounted smart wearable devices as a novel approach to obtaining dynamic (spatially and temporally variable) data on thermal exposure. Integrated Wearable Weather Stations (figure 1) proposed here aim to record (1) microclimate parameters (such as air temperature and humidity) in the immediate environment of individuals, (2) physiological responses to heat (including heart rate, skin temperature and humidity), and (3) human activity and subjective feedback with regards to the thermal environment. Combined, this methodology aims to provide a comprehensive, integrated, and personalized assessment that improves our understanding of personal thermal comfort and heat stress in cities.

As the first example of a wearable weather station for heat exposure assessments, we employed Fitbit smartwatches [35] worn on the wrist that are equipped with the PurePulse (photoplethysmography) technology for heart rate monitoring [36, 37]. The Fitbit smartwatches are then equipped with two coin-sized iButton environmental sensors (i.e. wireless data logger in the form of a 1.3 cm radius stainless steel button [38]), which are placed at the inner and outer face of the watch strap to collect temperature and humidity of air and skin. The iButton Hygrochron temperature/humidity data loggers (DS1923) are attached to the Fitbit devices with a 3D printed harness (figure 2) and measure the air/skin temperature and humidity ranging between -20 to 85 °C and 0% to 100% with $\pm$0.5 °C and $\pm$0.6% accuracy, respectively. The use of the smartwatch app for obtaining subjective feedback was also assessed in a separate study (preliminary work presented by Jayathissa *et al* [39]). The feasibility of such integrated sensing for inferring the personalized heat exposure in the built environment is assessed in section 2.2.

2.2. Experimental campaigns: assessing the robustness of data collection using wrist-mounted devices

Detailed measurements are carried out and compared with conventional sensing methods to investigate the accuracy of physiological and environmental data collected by wearables. We conducted two sets of experiments: (1) controlled-environment experiments in a climate chamber, and (2) semi-controlled experiments in a range of indoor-outdoor built environments. In the first experiment, the environmental conditions were kept unchanged while the metabolic rate was varied based on activity level, while the second experiment focused on the changes in the heat exposure and thermal comfort based on microclimate characteristics. The detailed setup and specification of each experiment are discussed here. Ethics approval for conducting human subject research was received from NUS Institutional Review Boards (Reference code N-18-071).

2.2.1. Controlled-environment test in the climate chamber

We conducted controlled-environment experiments in a climate chamber (figure 3) at the Department of Physiology of the National University of Singapore. These experiments aim to collect physiological responses to heat (such as heart rate and skin temperature and humidity at the wrist) and further evaluate the relationship between wearable data and the body core temperature as the main indicator for heat strain [29].

For the assessment of body core temperature, participants were asked to ingest VitalSense telemetric capsules [40] 8–10 h prior to the trial. For continuous monitoring of skin temperature (T_{sk}), four iButtons were placed at four right-hand sides of each participant's body (chest, upper arm, thigh, and calf) which, in addition to the iButton attached to the Fitbit strap, provide the distribution and mean skin temperature of participants throughout the experiment [41]. Heart rate is continuously monitored by the watch, as well as the chest strap heart rate monitoring device. Fifteen participants (seven female and eight male) were recruited between the age of 18–45. To have a representative group, the participants were evenly distributed among three categories: (1) Singaporean (or those from a similar tropical climate), (2) acclimatized expatriates (>3 years stay), and non-acclimatized expatriates (0–6 months stay). During the experimental trial, participants went through a low to moderate exercise on a treadmill (figure 3) in a moderate environment resembling outdoor conditions in Singapore (T_a = 27 °C–29 °C, RH = 70%–80%). The experiment consisted of three stages and the exercise intensity was specified using rating of perceived exertion (RPE, Borg [42]). Borg's RPE scale ranges from 6 to 20, resembling 'very light' to 'extremely hard' and is subjective. In our experiment, the three stages of activity (each 15 min) corresponded to RPE of 8–9, 10–11 and 12–13 to induce 'fairly light,' 'moderate,' and 'somewhat hard' efforts in individuals, respectively. Accordingly, although generally healthy adults were targeted, there was no required threshold level of fitness. The run/walk exercise on the treadmill in this experiment resulted in a change in the metabolic rate and therefore body core temperature, which is needed for assessment of this methodology in a range of daily human activities.

2.2.2. Semi-controlled environment test in the built environment

We further conducted environmental monitoring campaigns to evaluate and compare the wrist-mounted sensor data with microclimate measurements at fixed locations and calibrate the subjective individual thermal sensation with objective environmental measurements. Semi-controlled environment tests were performed where participants walked through a predefined path (covering different built environment characteristics—figure 4), while passing through a network of sensors and answering thermal comfort surveys (figure 5).

Figure 2. Fitbit Ionic and sensor attachments deployed here for monitoring of (a) temperature and humidity of air in the proximity of human body, (b) heart rate, skin temperature, and humidity at wrist, and (c) activity level and momentary feedback. Two iButton sensors [38] are placed on the watch strap using a 3D printed harness. The Fitbit acitivity trackers used have a 3-axis accelerometer to track the wearer's motion patterns (e.g. those that indicate walking, swimming or cycling) to approximate the number of steps taken, calories burned, floor climbed, and length of time performing exercises. The PurePulse (photoplethysmography) technology for heart rate monitoring [36, 37] uses LED lights installed at the back of the instrument to detect blood volume changes that are due to capillary expansion and contractions, and has been shown to tracks heart rate well when compared to three-lead electrocardiography [37]. The design and use of the smartwatch app will be further discussed in future studies.

Fifteen sessions were organized over six days in October–November (inter-monsoon period), distributed over different hours of the day with approximately 40% conducted at noon and 20% each in the morning, afternoon, and evening. Sixty-two participants (with 48.2% female representation) were recruited for this study with age distribution of 19–48. Before the experiment, participants arrived at an indoor site and answered a questionnaire with regards to their personal profile (such as age, gender, and income level) as well as general preference toward the thermal environment. The project team then noted the participants' height, weight, and clothing level for the calculation of thermal comfort indices. Through this process, we also ensured that all participants have been in the same indoor environment for at least 30 min and have reached a physiologically stable condition before the start of the experiments. The profile of the participant group covered a body height range of 1.5–1.95 m (mean 1.71 m), weight of 42–102 kg (mean 72 kg), BMI of 18–32 (mean 23), and clothing insulation (iclo) of 0.34–0.44 (mean 0.36). Participants were then directed outdoors and asked to walk on a predefined path for approximately 40–50 min while wearing the modified wearable devices (figure 2). The path was chosen to cover a range of different built environment characteristics, including an indoor environment, a semi-covered outdoor environment, covered outdoor locations (distinguished by a presence or lack thereof of a ceiling fan), and fully exposed locations with different sky view factors. Along this path, participants passed two sets of fixed environmental sensors: (1) temperature and relative humidity sensors (Hobo MX2302 data logger) and (2) WBGT Heat Stress tracker (Kestrel 5400) to collect a comprehensive set of environmental data. The participants were then asked to answer the questionnaire at five pre-selected locations (i.e. survey stations equipped with environmental sensors). The survey asks participants to rank their thermal comfort satisfaction, sensation, and preference during the experiment using ASHRAE's 7-point sensation and satisfaction scales as well as 3-point scale preference votes for various microclimate parameters (temperature, humidity, wind speed, and radiation). Additionally, we continuously monitored participants' heart rate, skin temperature, skin humidity, air temperature and humidity at wrist, location, and walking speed during this experiment.

3. Results

3.1. Physiological data collection and prediction of body core temperature

Here, we evaluate the physiological data collection using wearable sensors and their correlation with heat strain (indicated by body core temperature). First, we compared the skin temperature obtained at

Figure 3. Controlled-environment experiment at NUS Department of Physiology. A participant is walking on a treadmill while wearing the wrist-mounted sensor arrangement (figure 2), chest-wrapped heart rate monitoring (Polar A300), and iButton sensors for recording skin temperature at various body parts. The environmental parameters in the climate chamber as well as ratings of thermal sensation (ASHRAE's 7-point scale) and RPE are continuously monitored throughout the experiment. Data from the ingested telemetric capsules were collected by the wireless data-recording devices and the body core temperature is monitored closely such that the experiment is ceased if the threshold of 40 °C is reached.

the wrist with temperature distribution at different body locations as well as air temperature (figure 6). Chest and thigh exhibit the highest skin temperature (∼31 °C–37 °C), but also resemble body areas that were mostly covered by participants. Skin temperature at the wrist ($T_{s,w}$) shows the lowest median and minimum value compared to other body parts, while being consistently higher than the air temperature at wrist in the studied conditions. We observe that although the variability in ambient air temperature (T_a) is very small (∼28 °C–30 °C), air temperature at the wrist ($T_{a,w}$) varies significantly during the experiment (∼26 °C–34 °C). This variation is due to the sensor being placed at the proximity of the human body that acts as a heat source. This indicates that air temperature at the wrist, alone, cannot determine the ambient air temperature in the built environment as it exhibits the combined effect of environmental conditions (T_a) and physiological responses (T_s). However, it is worth noting that it may be feasible to predict ambient air temperature using air and skin temperature at the wrist considering the heat exchange between human skin surface and thermal environment [43, 44]. Additionally, we compared wrist skin temperature with mean skin temperature [41] for each participant (figure 6—right) and found a linear relationship for all participants. The majority of participants, however, showed lower wrist temperature compared to mean skin temperature, as temperatures at body extremities are usually lower. Nonetheless, we observed that wrist (skin and air) temperatures ($T_{a,w}$ and $T_{s,w}$) better describe the thermal comfort sensation of individuals (section 3.2) and therefore these parameters are used for further analyses. Further monitoring relative humidity at the wrist (RH_w), we observe that for some participants, RH_w reaches saturation during the experiments (in both controlled and semi-controlled settings). Although this value may be higher than RH reported in other body parts due to the rubber wristband, we note that the onset of sweating in different individuals (a critical determinant for the physiological strain and acclimatization) is captured using the wearables which can be the subject for future research on personalized heat exposure.

We further compared the wrist-mounted heart rate data with highly accurate measurements obtained from chest strap sensors (figure 7—left) as well as body core temperature obtained from telemetric capsules (figure 7—right). The comparison is in agreement with previous studies that deemed Fitbit satisfactory for heart rate monitoring [36]. We observed that 83% of heart rate data falls within the desired ±5 bpm accuracy level, with significantly smaller error observed for $HR > 120$ that is particularly of interest for heat strain assessments. Additionally, it is found that a significant majority of the error is attributed to two participants. After evaluating temperature measurements at the wrist for these participants (not shown), we find that this error has been introduced due to the way the smartwatches were worn during the experiment. This is particularly important for future deployments and motivates means to ensure that wearables are worn correctly. An example of such interventions can be a smartwatch function that monitors the wearable pressure on the wrist and triggers an alarm on the smartwatch in response.

Lastly, we focused on non-invasive prediction of body core temperature (T_c) using physiological and environmental data by the wrist-mounted sensors. We observed that core temperature is positively correlated with heart rate data (figure 7), which is in close agreement with the reported role of metabolic rate on heat strain [46]. However, given (i) potential errors in heart rate monitoring using Fitbit watches (figure 7—left) and (ii) moderate performance in T_c prediction when only heart rate data are used [47, 48], we revisited the core temperature predictions using sequential air and skin temperature at wrist ($T_{a,w}$ and $T_{s,w}$). A Kalman filter (also known as linear quadratic estimation [49]) was employed to estimate core temperature (T_c) using the variables obtained from wearable sensors. The KF model (further explained

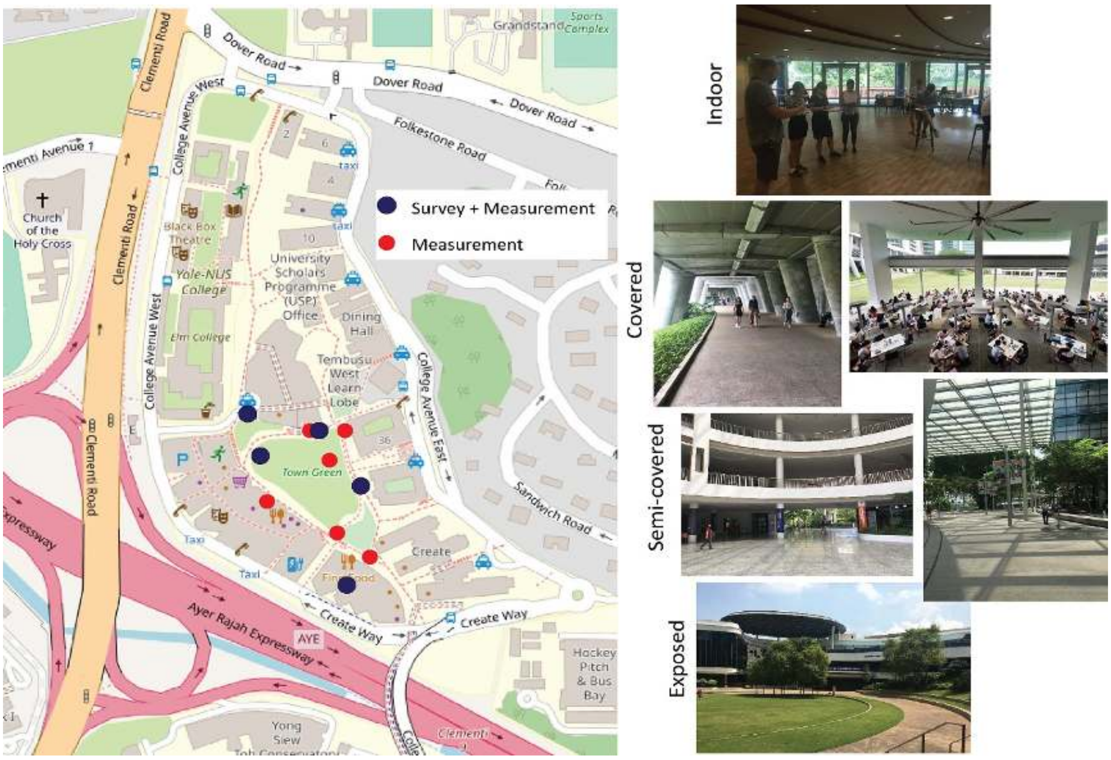

Figure 4. Map and photos of sensor network in the semi-controlled experiment. Left: map of the studied area at NUS UTown Campus with location of sensors and survey stations identified. Right: different characteristics of built environment selected for the experiment. Five survey stations were selected among an indoor (air-conditioned) environment, a semi-covered outdoor environment, covered outdoor locations (distinguished by a presence or lack thereof of ceiling fan), and fully exposed locations with different sky view factors.

Figure 5. From left: sensor calibration in indoor laboratory; Hobo MX2302 temperature and humidity logger installed on site with a radiation shield; Kestrel 5400 Heat Stress Tracker at survey stations; and participants answering survey questions while wearing modified wearable devices. We ensured that the participants have been in Singapore for the week preceding the experiment (i.e. no overseas travels to hotter or colder climates that can affect their thermal sensation) and are well-rested to undertake a walk on flat terrain (40–50 min duration). Fixed environmental sensors are placed at the height of wearables at wrist (1.1–1.2 m).

in appendix A) is used extensively for T_c estimation using non-invasive measurements, mainly heart rate [47, 50–52].

Figure 8 shows the schematic of physiological measurements for the core temperature prediction, as well as the comparison between estimated and observed T_c data. Compared to using HR as the only indicator ($R^2 = 0.52$, not shown), core temperature estimation is significantly improved when sequential skin and air temperature observations at wrist are used as input parameters ($R^2 = 0.81$). Figure 9 shows the distribution of error and level of agreement with observations for predicted T_c. We find that 95% of the predicted core temperature falls within 0.27 °C of the measured data, which is among the best performances observed in the literature [47, 48, 52]. The mean bias and mean absolute error (MAE) are 0.008 °C and 0.1 °C, respectively, with a maximum error of no more than 0.44 °C. For male participants, we observe that a prediction tends to underestimate T_c, which is due to lower core temperature during the experiment as the training data. Lastly, we observe that minimum of 12–13 participants are needed to train the prediction algorithm with percentage of target attainment rate of higher than 80% (when target set as 0.3 °C) and MAE lower than 0.25 °C. Overall, this analysis

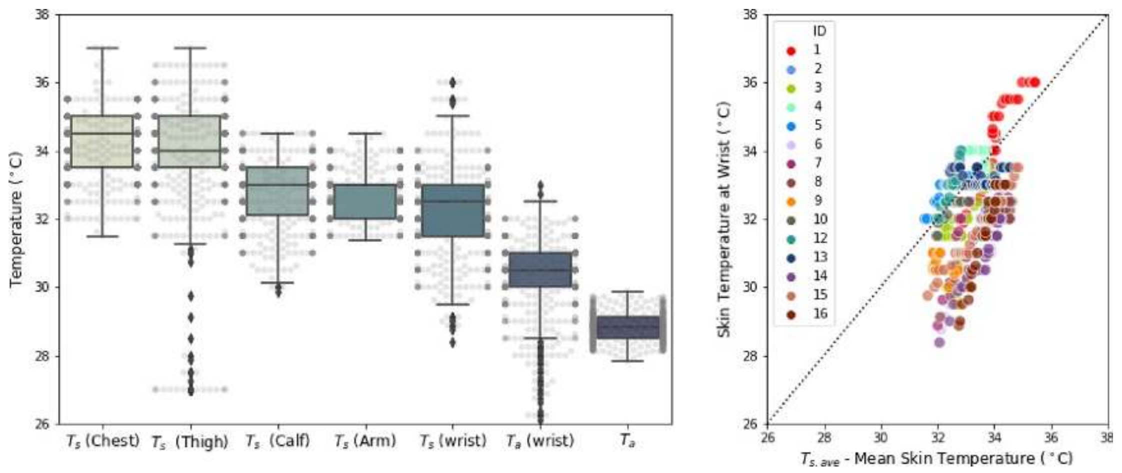

Figure 6. Left: Boxplots of observed skin temperature (1 min average) at five body areas (chest, thigh, calf, arm, and wrist) compared with air temperature measurements (near-wrist and ambient). Right: Distribution of skin temperature at wrist compared to mean body skin temperature for each individuals [41, 45]. Each ID represents a unique participant in the controlled-environment experiment and the 1:1 relationship is represented by a dashed line.

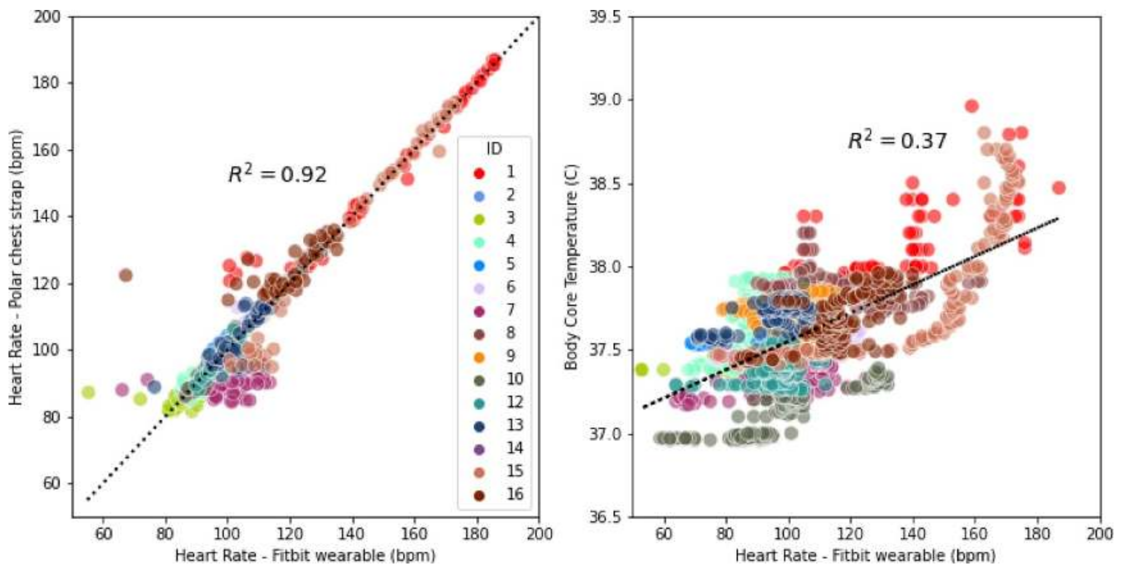

Figure 7. Left: Comparison of heart rate data (1 min average) obtained from Fitbit wearables (figure 2) with high-accuracy chest strap sensors (Polar A300). The 1:1 relationship is represented by a dashed line. Right: Distribution of observed core temperature as a function of heart rate. Each ID represents a unique participant in the controlled-environment experiment.

demonstrates the ability of wrist-mounted sensing for non-invasive prediction of core temperature and further inferring heat strain [47] and can be extended to include a larger sample size and testing with different population groups.

3.2. Prediction and impacts of thermal sensation vote

Comparing participants' thermal sensation with local microclimate parameters (such as WBGT obtained from fixed monitoring stations) yielded similar results to findings of Yang *et al* [53] and Heng and Chow [54], indicating a linear relationship between thermal comfort indices and aggregated thermal sensation vote (TSV). Here, we extend the analysis to compare thermal sensation and satisfaction votes, TSV and TCV respectively, with data obtained from wearable devices such as skin and air temperature at the wrist (figure 10). We observe that TSV (figure 10—right, ranging from 'Very Cold' to 'Very Hot') exhibits a positive correlation with the air and skin temperature at wrist and a stronger correlation compared to ambient air temperature. For thermal comfort vote (TCV) (figure 10—left, ranging from 'Extremely Satisfied' to 'Extremely Dissatisfied'), the median and distribution of air temperature measured at the wrist exhibit the most significant correlation with thermal satisfaction, which indicates the ability of $T_{a,w}$ for predicting comfort. Additionally, figure 10 shows that as TSV moves towards hotter sensations or TCV moves to higher dissatisfaction, the difference between temperatures at the wrist and ambient air

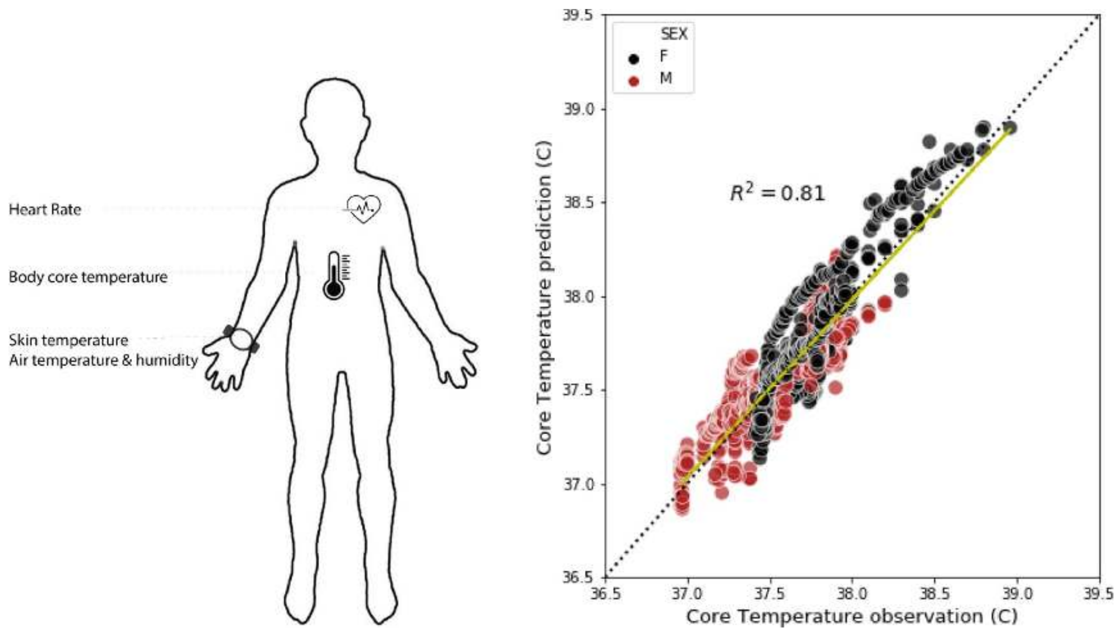

Figure 8. Left: schematic of various physiological and environmental parameters used to predict body core temperature, including heart rate, wrist skin temperature ($T_{a,w}$) and wrist air temperature ($T_{s,w}$). Skin humidity (RH_w) was also considered in the prediction algorithm but did not increase the accuracy of results. Right: prediction of body core temperature (30 s average) for different genders (red: male, black: female) using a Kalman filter compared with measurements in the climate chamber.

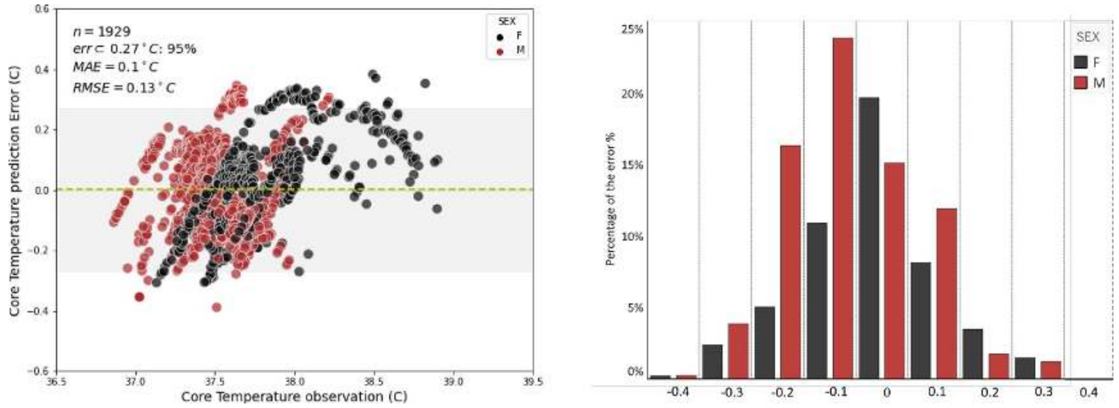

Figure 9. Distribution of error for predicted core temperature using a Kalman filter and sequential observed data for heart rate, air temperature, and skin temperature at wrist. Left: Bland–Altman plot of agreement between observed and predicted core temperature. 95% confidence interval is met at the target temperature error of 0.27 °C. The dashed yellow line represents the bias of prediction. Right: Normalized histogram of percentage error for all training data shown based on different gender.

temperature decreases. This difference dominates the rate of sensible heat transfer from the skin, which is critically important for human comfort and satisfaction [55].

Next, to analyze and predict the respondents' thermal sensation and comfort, we binned the data based on wrist air temperature ($T_{a,w}$) into 0.5 °C intervals [14] and calculated the mean TSV and TCV in each bin (figure 11). We observe that the correlation between heart rate and TSV is weak, but skin temperature and particularly air temperature at the wrist are linearly correlated with thermal sensation. Combining measured relative humidity with air temperature obtained at the wrist [56] improved the accuracy of thermal comfort prediction (yielding $R^2 = 0.74$—not shown) and TSV is predicted with MAE = 0.3 for this dataset. However, although such prediction provides a valuable assessment of collective comfort sensation and can help to assess the impact of urban characteristics on collective dwellers' comfort, the predictive ability of such regression models for individualized response remains at ∼35%–40%, in line with a range of thermal comfort indices assessed in previous studies [57]. This further motivates the development of personal comfort models [58] based on long-term data collection and consideration of behavioral and subjective factors, which is a focus in future developments of Project Coolbit.

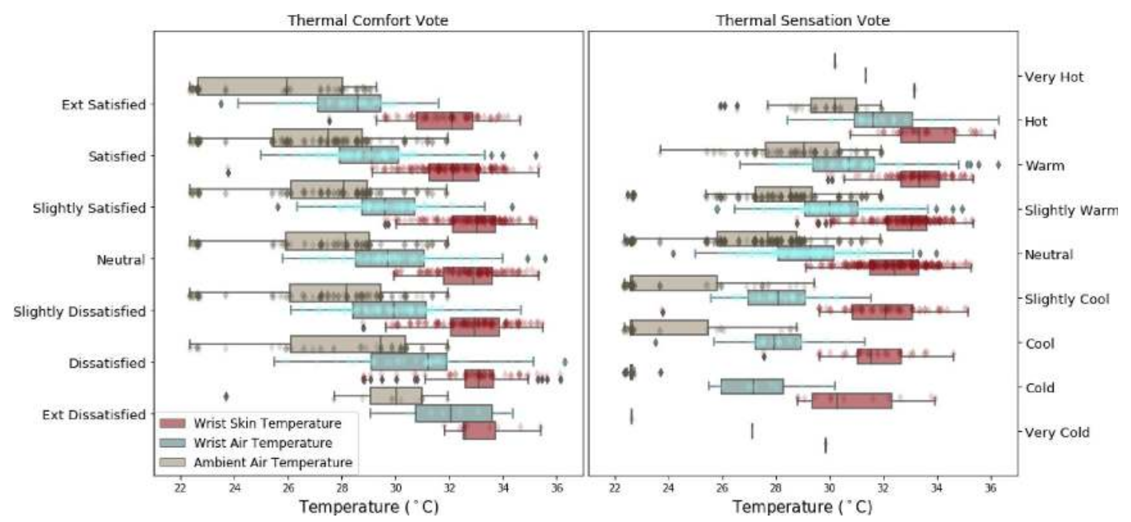

Figure 10. Boxplots of wrist skin temperature (red), wrist air temperature (green) and ambient air temperature (grey) categorized by Thermal Comfort Vote and Thermal Sensation Vote of participants. The boxplots are overlaid with scattered data points in each vote category. Data points represent 726 responses collected from 62 participants over 15 sessions.

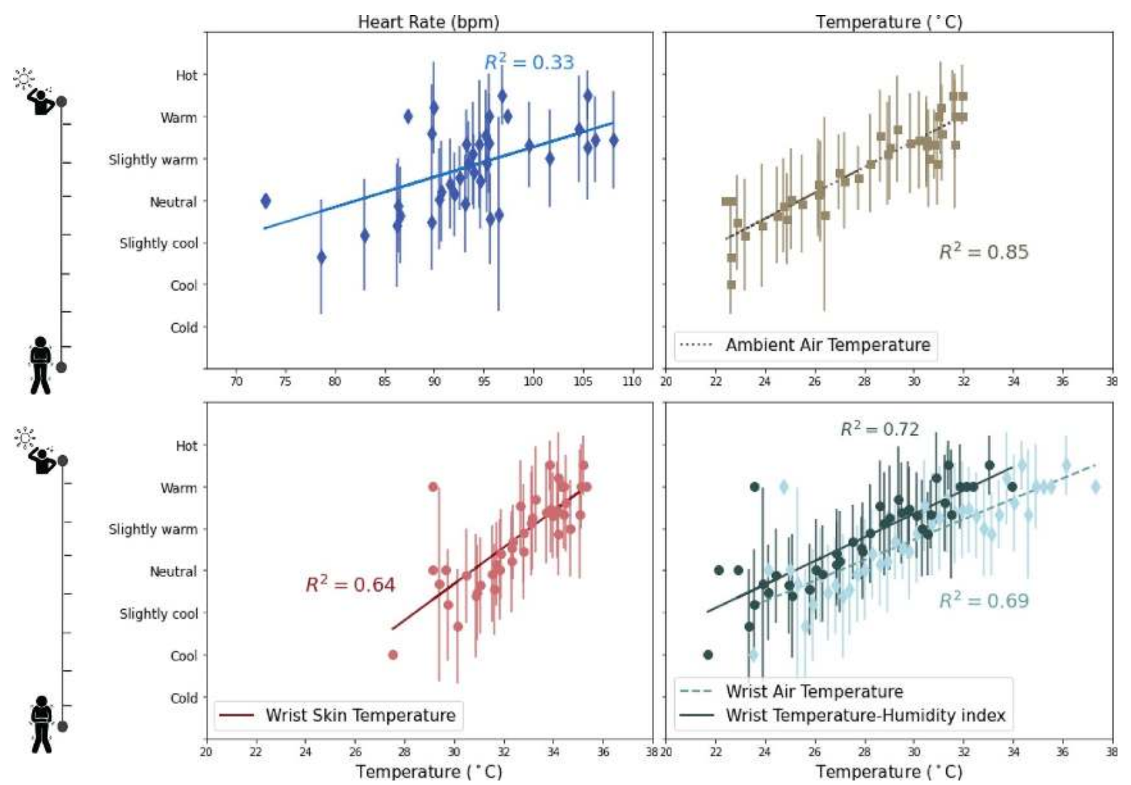

Figure 11. Distribution of thermal sensation vote as a function of wearable data (binned based on wrist air temperature). Pearson regression coefficient and errorbars (indicating the standard deviation of TSV for the binned data) are also presented for each variable. The temperature-humidity index is adopted from Steadman [59] to combine air temperature and relative humidity monitored at the wrist.

To extend our assessment regarding the relationship between thermal sensation and satisfaction and the consequent impact on human life, we show the correlations between TCV, TSV, and perceived activity vote (PAV) obtained in our experiments (figure 12). PAV is introduced here to assess the impact of the thermal environment on human activity and lifestyle, which is a critical factor indirectly contributing to heat-related health outcomes. For example, an uncomfortable thermal environment can result in less desire to perform physical activity, which further contributes to health challenges such as obesity, mental health, and high blood cholesterol and pressure level. Identifying such links between the thermal environment and activity level is, therefore, considered as one of the motivations and

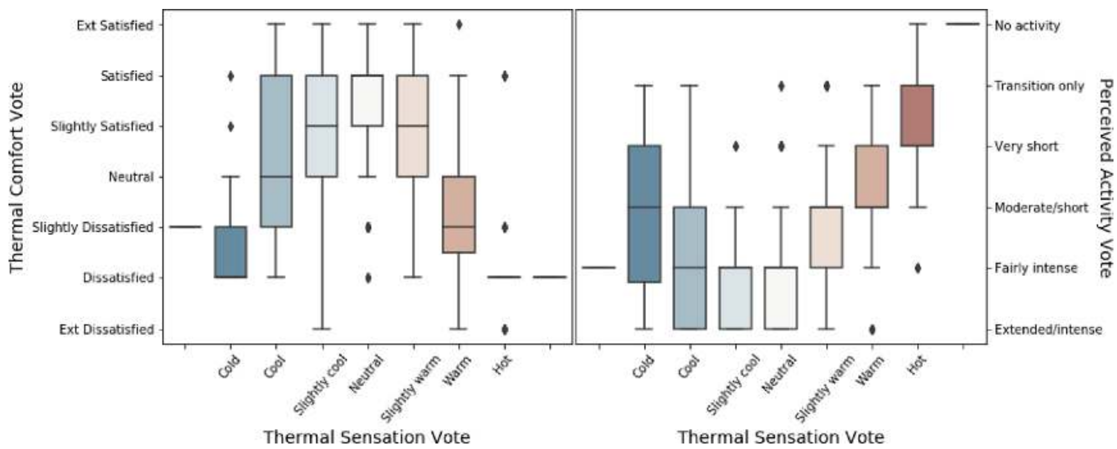

Figure 12. Bar charts of thermal comfort votes (TCVs) as varied by thermal sensation vote (TSV) and perceived activity vote (PAV). Results are obtained based on 720 responses of 62 participants in indoor/outdoor environments with a range of activities and built environment characteristics. For PAV, participants are asked to rank the level of activity that they perceive suitable based on the thermal environment. For example, 'Extended/intense' activity vote indicates that participants are comfortable to perform intense activities or stay for an extended period in this thermal environment while 'No activity' indicates that participants find this thermal condition extremely uncomfortable or unhealthy for any activity.

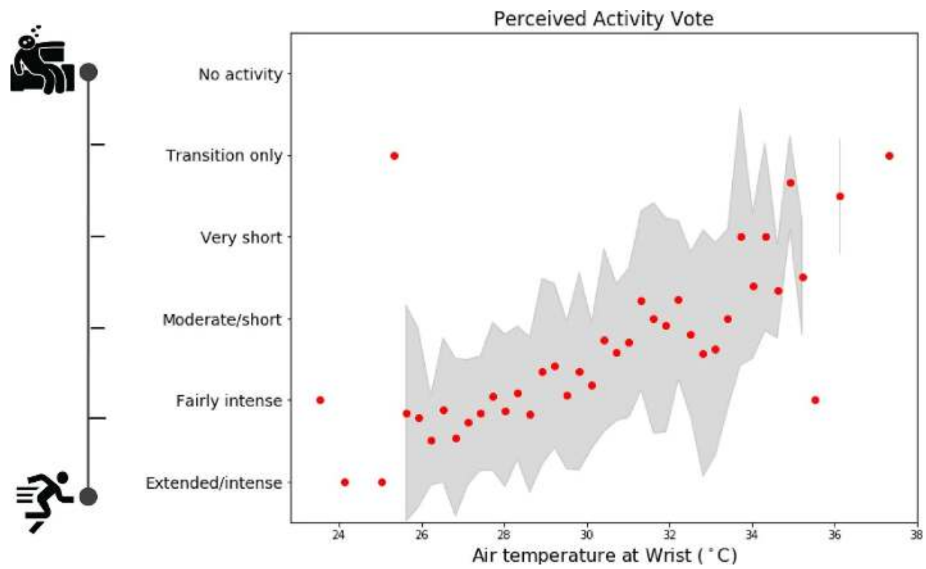

Figure 13. Distribution of perceived activity vote as a function of air temperature at wrist obtained from wearable sensors.

advantages of using activity-tracker wearables in this study. Assessing the PAV enables us to not only analyze and predict thermal comfort but also quantify the implications on health and wellbeing in the built environment.

In figure 12 (left), we observe that for the climate of Singapore, TSV corresponding to 'cool', 'Slightly Cool', 'Neutral' and 'Slightly Warm' can lead to satisfaction of the thermal environment. This is in line with previous studies that demonstrated that (a) 'Neutral temperature' does not necessarily indicate thermal comfort and satisfaction [14] and (b) Singapore residents tend to have a higher tolerance to colder indoor conditions, especially considering the high humidity level outdoors.

More importantly, by comparing the PAV with TSV (figure 12—right), we find that the desire to do an activity is significantly affected by the thermal environment. Participants may be willing to do an extended activity in cold thermal sensations but a warm condition directly translated to shortened or lack of activity in our experiments. Moreover, using the binned data (figure 13), we can draw a direct connection between the air temperature at the wrist and perceived activity level: with increased $T_{a,w}$, the desire for physical activity is significantly reduced, reaching 'Transition only' PAV level at 36 °C. This is the first quantification of thermal comfort impact on human activity and demonstrates the ability of this methodology to not only predict the overall thermal comfort, but further contribute to quantification of the indirect impact on health through the loss of activity and change in lifestyle.

4. Conclusions and future work

Heat exposure has a wide range of adverse effects on the human body and is considered a public health hazard [5, 60]. Additionally, thermal discomfort in urban spaces has been associated with loss in productivity, cognitive performance, and wellbeing of individuals [1]. However, despite decades of climatological, epidemiological, and physiological research on this topic, little is known about actual thermal conditions people experience as they go about their daily lives [61]. The personalized and real-time assessment of urban heat exposure, which further provides comprehensive assessments of impacts on human life, is yet to be achieved.

Such knowledge gaps and methodological limitations motivated the present study. Here, we proposed wearable sensing for human-centric heat exposure assessments, such that we connect humans with their immediate environment. We introduced an integrated personalized methodology, i.e. wearable weather stations, that in one wrist-mounted sensing unit can record environmental parameters, physiological responses, and human activities and feedback. We then addressed the feasibility of this methodology using two sets of experiments: (1) controlled-environment experiments in a climate chamber focused on physiological responses and (2) semi-controlled experiments in the built environment focused on thermal comfort. The objectives were to answer two questions: *(1) can this wearable sensing predict heat strain?* and *(2) what information regarding thermal sensation can be derived using personalized monitoring?*

We demonstrated that body core temperature (T_c) can be predicted non-invasively with high accuracy: using data from 15 participants, T_c was predicted using heart rate, skin temperature, and air temperature at wrist (obtained from wearable devices) and 95% of predicted results fell within 0.27 °C of measurements obtained from telemetric capsules. This is among the best performances seen in the literature and presents the most viable option as smartwatches are easily worn and carried on the wrist at all times. However, it should be noted that due to the limited number of participants in this study (15 in total), it was not statistically meaningful to train the data using a segment of the sample size for testing and more importantly, a relatively homogeneous participant profile is considered here. Accordingly, it is critical that measurements and testings are extended to increase the number of participants with diverse profiles (such as age, gender, BMI, acclimatization status, fitness, and health conditions). We further plan to extend the measurements to higher T_c and HR ranges in collaboration with the NUS Department of Physiology and by studying healthy adults that can complete maximum physical activity tests in experimental settings.

Using environmental and physiological data obtained from the watch, we were also able to predict the overall sensation of participant groups. However, when regression models are applied to individualized responses, only ∼35%–40% of responses are accurately predicted which is similar to previous thermal comfort models [57]. This is due to the subjective nature of thermal comfort that includes individual preferences based on behavioral, cultural, and climatic backgrounds. To account for these, we aim to extend the data collection period and employ machine learning techniques that incorporate individualized behavioral patterns to train personal comfort models [58]. More importantly, we demonstrated that this methodology can quantify the indirect impact of heat on health through the change in physical activity level and lifestyle. To the best of our knowledge, this is the first study that quantified the impact of urban heat on activity level, which opens new doors for heat-health assessments. We plan to extend this study to quantify the impacts of more realistic thermal environments on perceived and actual activity levels of individuals.

This study represents the first methodology to monitor personal heat exposure in a non-intrusive yet quantitative way, which enables us to better determine the links between climatic variables and human health and wellbeing, design effective mitigation and adaptation strategies, and prepare emergency responses to extreme conditions. Such knowledge can ultimately transform the way we understand and design for optimized exposure. However, we note the deployment of wearable sensors is done for a limited number of participants so far. To fully realize the impact of this methodology, the sensor array needs to be further developed and extended in real-time and realistic conditions in the built environment, which presents a challenge regarding sensor cost and effective communication of data. Additionally, to translate this understanding to establishing climate-resilient cities, large scale deployments are needed to cover large spatial and temporal distributions in cities.

Appendix A. Fundamentals of Kalman filter used for core temperature prediction

The Kalman filter is known for its capability of estimating unknown variables from indirect measurements that contain statistical noise and other inaccuracies. The *KF* model is comprised of a state-transition and an observation model, and the noise allied to each model. All the *KF* parameters were learned from the dataset gained in this study via linear regression. The state-transition model illustrates how the hidden variable $T_{C,t}$ transferred from the previous time point status $T_{C,t-1}$, which can be defined as:

$$T_{C,t} = A \times T_{C,t-1} + A_0 + w_t \tag{A1}$$

$$w_t \sim N(0, Q_t) \tag{A2}$$

Where A and A_0 are the weights learned by the linear regression of $T_{C,t}$ against $T_{C,t-1}$ with the 15 s time step. w is the transition model noise with a zero mean normal Gaussian distribution with covariance Q. In this case, Q is the standard deviation of minute difference of T_c.

The observation model was defined as a linear model of observed variables against the hidden variable $T_{C,t}$. Here we used heart rate (HR_t), skin temperature at wrist ($T_{sw,t}$), and air temperature at wrist ($T_{aw,t}$) as inputs. The observation models of these two models can be represented as follows:

$$\begin{Bmatrix} HR_t \\ T_{sw,t} \\ T_{aw,t} \end{Bmatrix} = H \times T_{C,t} + H_0 + v_t \tag{A3}$$

$$v_t \sim N(0, R_t) \tag{A4}$$

Where H and H_0 are the weight matrix learned by linear regression of T_c against HR , T_{sw}, and T_{aw}. v is the observation model noise with a zero mean normal Gaussian distribution with covariance R. R is the covariance matrix of 15 s difference of HR, T_{sw}, and T_{aw}.

In our analysis, at each new 15 s time step (t), the KF provided a new estimate of $T_{C,t}$ and its error variance $P_{C,t}$ based on the observed HR_t, $T_{sw,t}$ and $T_{aw,t}$ by iteratively calculating equations (A1)–(A6). First, a preliminary estimated $T_{C,t}$ was computed using equations (A1)–(A2). The associated error variance was calculated as

$${P_t}^T = A \times P_{t-1} \times A^T + Q_t \tag{A5}$$

where the initial P_t was set as 0 and the superscript T means the transposed matrix. The Kalman gain K_t was then estimated by

$$P_t = {P_t}^T H^T (H {P_t}^T H^T + R_t)^{-1}. \tag{A6}$$

The final estimate of $T_{C,t}$ was calculated with the preliminary estimate ($T_{C,t-1}$), the error between the observed variables (HR_t, $T_{sw,t}$, and $T_{aw,t}$) and the estimated ones using the $T_{C,t-1}$:

$$T_{C,t} = T^T_{C,t} + K_t\left(\begin{Bmatrix} HR_t \\ T_{sw,t} \\ T_{aw,t} \end{Bmatrix} - (H \times T^T_{C,t}) + H_0\right). \tag{A7}$$

Finally, the current core temperature estimate error variance is computed as

$$P_t = (1 - K_t H){P_t}^T. \tag{A8}$$

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

ORCID iDs

Negin Nazarian https://orcid.org/0000-0001-9839-7234
Jason K W Lee https://orcid.org/0000-0003-4042-795X
Winston T L Chow https://orcid.org/0000-0003-1819-597X
Sharifah Badriyah Alhadad https://orcid.org/0000-0002-1391-7681
Alberto Martilli https://orcid.org/0000-0002-7795-5871
Leslie K Norford https://orcid.org/0000-0002-5631-7256

References

[1] Zhang F, de Dear R and Hancock P 2019 Effects of moderate thermal environments on cognitive performance: a multidisciplinary review *Appl. Energy* **236** 760–77
[2] Santamouris M 2019 Recent progress on urban overheating and heat island research. Integrated assessment of the energy, environmental, vulnerability and health impact. Synergies with the global climate change *Energy and Buildings* **207**
[3] Perkins S E, Alexander L V and Nairn J R 2012 Increasing frequency, intensity and duration of observed global heatwaves and warm spells *Geophys. Res. Lett.* **39** L20714
[4] Steffen W, Hughes L and Perkins S 2014 *Heatwaves: Hotter, Longer, More Often* (Climate Council of Australia)
[5] Sari Kovats R and Hajat S 2008 Heat stress and public health: A critical review *Annu. Rev. Public Health* (Palo Alto, CA: Annual Reviews) **29** 41–55
[6] Stewart I D 2019 Why should urban heat island researchers study history? *Urban Clim.* **30** 100484
[7] Price Waterhouse Coopers 2011 Protecting human health and safety during severe and extreme heat events: a national framework *Department of Climate Change, Commonwealth Government* (https://www.pwc.com.au/publications/pdf/extreme-heat-events-nov11.pdf)
[8] Borden K A and Cutter S L 2008 Spatial patterns of natural hazards mortality in the united states *Int. J. Health Geographics* **70** 64
[9] Ali-Toudert F and Mayer H 2007 Thermal comfort in an east–west oriented street canyon in Freiburg (Germany) under hot summer conditions *Theor. Appl. Climatol.* **87** 223–37
[10] Middel A and Scott Krayenhoff E 2019 Micrometeorological determinants of pedestrian thermal exposure during record-breaking heat in Tempe, Arizona: introducing the MaRTy observational platform *Sci. Total Environ.* **687** 137–51
[11] Cheng V, Ng E, Chan C and Givoni B 2012 Outdoor thermal comfort study in a sub-tropical climate: a longitudinal study based in Hong Kong *Int. J. Biometeorol.* **56** 43–56
[12] Johansson E, Thorsson S, Emmanuel R and Krüger E 2014 Instruments and methods in outdoor thermal comfort studies - the need for standardization *Urban Climate* **10** 346–66
[13] Salata F and Golasi I 2016 Roberto de Lieto Vollaro and Andrea de Lieto Vollaro. Outdoor thermal comfort in the mediterranean area a transversal study in rome, italy *Build. Environ.* **96** 46–61

[14] Middel A, Selover N, Hagen B and Chhetri N 2016 Impact of shade on outdoor thermal comfort—a seasonal field study in Tempe, Arizona *Int. J. Biometeorol.* **60** 1849–61
[15] Ali-Toudert F and Mayer H 2006 Numerical study on the effects of aspect ratio and orientation of an urban street canyon on outdoor thermal comfort in hot and dry climate *Build. Environ* **41** 94–108
[16] Lin B, Li X, Zhu Y and Qin Y 2008 Numerical simulation studies of the different vegetation patterns' effects on outdoor pedestrian thermal comfort *J. Wind Eng. Ind. Aerodyn.* **96** 1707–18
[17] Nazarian N, Fan J, Sin T, Norford L and Kleissl J 2017 Predicting outdoor thermal comfort in urban environments: a 3D numerical model for standard effective temperature *Urban Clim.* **20** 251–67
[18] Nazarian N, Sin T and Norford L 2018 Numerical modeling of outdoor thermal comfort in 3D *Urban Clim.* **26** 212–30
[19] Nazarian N, Acero J A and Norford L 2019a Outdoor thermal comfort autonomy: performance metrics for climate-conscious urban design *Build. Environ.* **155** 145–60
[20] Nikolopoulou M, Baker N and Steemers K 2001 Thermal comfort in outdoor urban spaces: understanding the human parameter *Sol. Energy* **70** 227–35
[21] Höppe P 2002 Different aspects of assessing indoor and outdoor thermal comfort *Energy Build.* **34** 661–5
[22] Chen L and Ng E 2012 Outdoor thermal comfort and outdoor activities: a review of research in the past decade *Cities* **29** 118–25
[23] Song X, Wang S, Hu Y, Yue M, Zhang T, Liu Y, Tian J and Shang K 2017 Impact of ambient temperature on morbidity and mortality: an overview of reviews *Sci. Total Environ.* **586** 241–54
[24] Chapman L, Bell C and Bell S 2017 Can the crowdsourcing data paradigm take atmospheric science to a new level? A case study of the urban heat island of london quantified using netatmo weather stations: crowdsourcing the London UHI *Int. J. Climatol.* **37** 3597–605
[25] Nakayoshi M, Kanda M, Shi R and de Dear R 2015 Outdoor thermal physiology along human pathways: a study using a wearable measurement system *Int. J. Biometeorol.* **59** 503–15
[26] Liu S, Schiavon S, Das H P, Jin M and Spanos C J 2019 Personal thermal comfort models with wearable sensors *Build. Environ.* **162** 106281
[27] Takada S, Matsumoto S and Matsushita T 2013 Prediction of whole-body thermal sensation in the non-steady state based on skin temperature *Build. Environ.* **68** 123–33
[28] Sim S Y, Koh M J, Joo K M, Noh S, Park S, Kim Y H and Park K S 2016 Estimation of thermal sensation based on wrist skin temperatures *Sensors* **16** 420
[29] Buller M J *et al* 2013a Estimation of human core temperature from sequential heart rate observations *Physiol. Meas.* **34** 781–98
[30] Abdallah M, Caroline C, Tam V and Anh N 2016 Sensing Occupant Comfort Using Wearable Technologies *Construction Research Congress*
[31] Int. Data Corporation 2015 Worldwide quarterly: wearable device tracker
[32] Sawka M N and Friedl K E 2018 Emerging wearable physiological monitoring technologies and decision aids for health and performance *J. Appl. Physiol.* **124** 430–1
[33] Friedl K E, Buller M J, Tharion W J, Potter A W, Manglapus G L, and Hoyt R W 2016 Real Time Physiological Status Monitoring(RT-PSM) Accomplishments, Requirements, and Research Roadmap - *Report* (Natick, MA: United States Army Research Institute of Environmental Medicine)
[34] Buller M J, Welles A P and Friedl K E 2018 Wearable physiological monitoring for human thermal-work strain optimization *J. Appl. Physiol.* **124** 432–41
[35] Fitbit, Inc. Fitbit official site for activity trackers accessed 9 July 2019 (available at: www.fitbit.com/au/home)
[36] Bai Y, Hibbing P, Mantis C and Welk G J 2018 Comparative evaluation of heart rate-based monitors: Apple Watch vs Fitbit Charge HR *J. Sports Sci.* **36** 1734–41
[37] Haghayegh S, Khoshnevis S, Smolensky M H and Diller K R 2019 Accuracy of purepulse photoplethysmography technology of Fitbit Charge 2 for assessment of heart rate during sleep *Chronobiol. Int.* **36** 927–33
[38] Maxim Integrated Overview of ibutton® sensors and temperature/humidity data loggers—application note—maxim accessed 9 July 2019 (available at: www.maximintegrated.com/en/app-notes/index.mvp/id/3892)
[39] Jayathissa P, Quintana M, Sood T, Nazarian N and Miller C 2019 Is your clock-face cozie? A smartwatch methodology for the in-situ collection of occupant comfort data *J. Phys.: Conf. Ser* **1343** 012145
[40] Philips Respironics. VitalSense Telemetric Physiological Monitoring System (www.actigraphy.com/solutions/vitalsense/) (accessed 10 July 2019)
[41] Ramanathan N L 1964 A new weighting system for mean surface temperature of the human body *J. Appl. Physiol.* **19** 0531–33
[42] Borg G 1990 Psychophysical scaling with applications in physical work and the perception of exertion *Scand. J. Work Environ. Health* **16** 055–58
[43] Nazarian N, Miller C, Norford L, Kohler M and Chow W 2019b Jason Lee Kai Wei, Sharifah Badriyah Alhadad, Matias Quintana, Lindsey Sunden and Alberto Martilli. Project coolbit updates: personal thermal comfort assessments using wearable devices *Geophys. Res. Abstr.* **21** 1
[44] Pharo Gagge A and Nishi Y 2010 Heat exchange between human skin surface and thermal environment *Comprehensive Physiology* pp 69–92
[45] Liu W, Lian Z, Deng Q and Liu Y 2011 Evaluation of calculation methods of mean skin temperature for use in thermal comfort study *Build. Environ.* **46** 478–88
[46] Lee J K W, Nio A Q X, Lim C L, Teo E Y N and Byrne C 2010 Thermoregulation, pacing and fluid balance during mass participation distance running in a warm and humid environment *Eur. J. Appl. Physiol.* **1090** 887–98
[47] Buller M J *et al* 2013b Estimation of human core temperature from sequential heart rate observations *Physiol. Meas.* **34** 781
[48] Looney D P *et al* 2018 Estimating resting core temperature using heart rate *J. Meas. Phys. Behav.* **10** 79–86
[49] Kalman R E 1960 A new approach to linear filtering and prediction problems *J. Basic Eng.* **82** 035–45
[50] Buller M J, Tharion W J, Hoyt R W and Jenkins O C 2010 Estimation of human internal temperature from wearable physiological sensors *Proc. of the 24th AAAI Conf. on Artificial Intelligence* 1763–8
[51] Seng K-Y, Chen Y, Chai K M A, Wang T, Fun D C Y, Teo Y S, Tan P M S, Ang W H and Lee J K W 2016 Tracking body core temperature in military thermal environments: an extended Kalman filter approach *2016 IEEE 13th Int. Conf. on Wearable and Implantable Body Sensor Networks (BSN)* (IEEE) pp 296–9
[52] Welles A P, Xu X, Santee W R, Looney D P, Buller M J, Potter A W and Hoyt R W 2018 Estimation of core body temperature from skin temperature, heat flux and heart rate using a Kalman filter *Comput. Biol. Med.* **99** 1–6
[53] Yang W, Wong N H and Jusuf S K 2013 Thermal comfort in outdoor urban spaces in singapore *Build. Environ.* **59** 426–35
[54] Heng S Li and Chow W T L 2019 How 'hot' is too hot? Evaluating acceptable outdoor thermal comfort ranges in an equatorial urban park *Int. J. Biometeorol.* **630** 801–16
[55] Arens E A and Zhang H 2006 The skin's role in human thermoregulation and comfort *Thermal and Moisture Transport in Fibrous Materials* (Chelmsford: Woodhead Publishing Ltd) (https://doi.org/10.1533/9781845692261.3.560)

[56] Thom E C 1959 The discomfort index *Weatherwise* **12** 57–61

[57] Ruiz Mia Aélica and Correa E N 2015 Suitability of different comfort indices for the prediction of thermal conditions in tree-covered outdoor spaces in arid cities *Theor. Appl. Climatol.* **1220** 69–83

[58] Kim J, Zhou Y, Schiavon S, Raftery P and Brager G 2018 Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning *Build. Environ.* **129** 96–106

[59] Steadman R G 1979 The assessment of sultriness. part i: a temperature-humidity index based on human physiology and clothing science *J. Appl. Meteorol.* **18** 0861–873

[60] Bi P, Williams S, Loughnan M, Lloyd G, Hansen A, Kjellstrom T, Dear K and Saniotis A 2011 The effects of extreme heat on human mortality and morbidity in Australia: implications for public health *Asia. Pac. J. Public Health* **23** 027S–36

[61] Kuras E R *et al* 2017 Opportunities and challenges for personal heat exposure research *Environ. Health Perspect.* **125** 085001