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Sensing Physiological Change and Mental Stress in Older Adults from Hot Weather

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ABSTRACT This study combines wearable sensors, weather data, and self-reported mood surveys to assess mental stress on older adults from heat experience. It is designed as a pilot and feasibility study in preparation for a large-scale experiment of older adults' mental wellbeing during extreme heat events. Results show that on-body temperatures from two i-Button sensors coupled with heart rate monitored from a smart watch are important indicators to evaluate individualized heat stress given a relatively uniform outdoor temperature. Furthermore, assessing their mood in their own environment demonstrates potential for understanding mental wellbeing that can change with varying time and location.

INDEX TERMS Wearable sensors, temperature, time factors.

I. INTRODUCTION

The use of sensors in health studies has blossomed in the past decade with the availability of low-cost wearable and mobile sensors for health monitoring [1]–[3]. These sensors generate precise and granular data on physiological, behavioral and affective states of individuals in a continuous and noninvasive manner [2]. They monitor health remotely, track and detect biophysical abnormalities, and evaluate activity monitoring. Burdensome wearing of sensor equipment on various parts of the body and the necessity of controlled experiments have been major obstacles to longer-term studies in one's natural environment. Recent developments in wearable sensor technology (e.g., smartwatches) make data collection easier and less expensive.

This paper uses sensors embedded and attached to a smartwatch to observe physiological changes in the daily life of older adults. The study measures heart rate, skin temperature, and near air temperature continually for a day to examine physiological change from exposure to heat during summer and resulting mental stress. Sensor data are combined with weather data and self-reported mood surveys using a dedicated mobile app and voice calls to understand the multi-faceted impacts of heat on the mood of older adults.

In addition, this study documents each person's momentary experience of heat in their environmental context. To examine whether variability in heat experience exists from changing indoor and outdoor temperatures, we also added weather data to evaluate against on-person temperatures and activity.

This study also serves as a pilot project in preparation for a large-scale experiment on the impacts of heat stress on aging populations in their natural environment. The large-scale natural experiment will employ sensors for longer duration to understand participants' experience of heat. As a feasibility study, this paper also sheds light on limitations arising from sensor data collection, data integration, and technology knowledge of participants. Results gained from the study will help improve the tools and techniques we employ to collect and analyze sensor data.

The first part of the paper discusses the current state of knowledge in the use of wearable sensors on older adults and advancements in combining wearable sensor data with other data sources. The second part of the paper explains each data source – wearable sensors, mobile app and voice phone-sourced ecological momentary assessments (self-reported surveys), and weather station. It also describes methods used to process and integrate these data. The third part of the paper presents and discusses results including limitations.

A. CURRENT STATE OF KNOWLEDGE

Use of on-person sensors in the aging population has increased at a rapid pace due to technological advancements combined with the benefits of continuous monitoring [4]. With increase of both the size of the aging population in the

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US and healthcare costs, sensors can be useful for ''aging in place'' programs that enable older adults to stay home and monitor their chronic conditions. They can be used to detect falls [5], cardiac arrest [3], and fatigues and depression [6], [7], among others. Sensor data can also help generate predictive algorithms that lead to an early diagnosis of diseases. They can contribute to preventive care when coupled with mobile phones to notify healthcare services to initiate immediate medical interventions [6], [7].

Despite rising interest and potential benefits of on-person sensors, their use has mostly been limited to research. In a review of 422 scientific articles on the use of wearable technology in patients aged 60 and above, Gordon [8] found that most were experimental in nature. To remedy the situation, he called for formal and randomized clinical trials. Recently, extensive research has been conducted to evaluate the effectiveness of wearable sensor technologies [9], [10]. For instance, activity monitoring in the home environment of older adults is a growing area of interest. Monitoring tools range from vision-based cameras, radio-based WiFi and radio frequency identification, and sensor-based tools such as accelerometers and smartwatches [11]–[13]. They can be attached to the trunk, limbs, wrist, or clothes to detect physical activities and mobility patterns [14].

Combining wearable sensors with other data sources to provide context has increased especially in the area of wellbeing. The MIT affective computing group pioneered a combination of physiological sensors with e-diaries, smart phone geolocation, and a phone application to assess stress and wellbeing of 201 college students [15]. Since then, several studies have examined affective states of individuals using a mix of wearable sensors and smart phone capabilities. Nalepa *et al.* [16] and Kanjo *et al.* [17], for example, speak to an integrated system of physical sensors, GPS coordinates, and ambient luminance; environmental data from weather and road traffic; and data stored in smart devices such as events in a calendar or current phone usage to assess context. Hayano *et al.* [18] targeted five participants for 10 weeks in their experiment using built-in sensors in the wristband to measure temperature, acceleration, pulse wave, environmental ultraviolet light, and sound to detect continuously physical activity along with options to record their strong emotion including happy, relaxed, sad, or angry every 30 minutes. Similarly, the Healthyoffice app in combination with wearable sensors asked participants at workplace to document their emotional state every two hours that ranges from excitement, happiness, calmness, tiredness, boredom, sadness, stress to anger [19].

In these novel combinations to denote affective states, physiological sensors such as galvanic skin response, heart rate and skin temperature integrated in smart wristbands are interpreted as proxy indicators of stress and mental wellbeing [20]. Ecological momentary assessments (EMAs) are often used to collect behavioral, physiological, or self-reported data in nearly real time and in a person's natural environment several times a day. They are less susceptible to recall bias and reflects the influence of contextual factors [21]. They employ a dedicated app to pose questions on people's smartphones. These combined data collection and analysis are done primarily for adolescents and younger adults thus far [22], and this study is first of its kind to combine physiological sensors, EMAs, and weather data and observe older adults.

TABLE 1. Participant information.

Participant	Gender	Age	Ethnicity	Level of education	Household size	Individual Income Level	Borough of residence
1	Female	70-74	White	Grad	Single person	Between $22411 and 37350	Manhattan
2	Female	85+	Black	High School	Single person	Less than $22410	Brooklyn
3	Female	75-79	White	Grad	Single person	Between $37351 and $59760	Manhattan
4	Female	65-69	White	College	Multiple person	Between $22411 and 37350	Manhattan
5	Female	65-69	White	College	Single person	Between $37351 and $59760	Manhattan
6	Male	65-69	White	Grad	Multiple person	Between $37351 and $59760	Manhattan
7	Male	65-69	Other	Undergrad	Multiple person	Between $22411 and 37350	Manhattan
8	Female	65-69	Hispanic or Latino	Undergrad	Multiple person	Between $22411 and 37350	Manhattan
9	Female	75-79	White	College	Multiple person	Less than $22410	Manhattan

II. MATERIALS AND METHODS

A. PARTICIPANTS

This study recruited participants using the city's network of senior centers affiliated with the Department for the Aging. There are more than 250 centers distributed in the five boroughs of New York City. This study used the Carter Burden Network to recruit three senior centers in East Harlem, Roosevelt Island and Brooklyn. We contacted the centers by phone and visited each location multiple times to recruit and collect data. This study is approved by the University of Kansas Institutional Review Board. Participants enrolled in the study included nine between the ages of 65 and 87 and without self-reported mental disorders. We conducted a survey to collect their demographic information, neighborhood of residence, and presence of air conditioner before initiating data collection. Eight participants live in Manhattan and one lives in Brooklyn, and seven participants have air conditioners installed at home. The income ranges between $22410 and $59760 (See Table 1). As a pilot study, cohort sample size is small and biased towards Caucasian female. The goal is to diversify and use representative sampling in a large-scale experiment. Weather on participant data collection days was relatively mild, with temperatures around 26.7° C, although at least one day registered temperatures exceeding 32.2°C.

B. WEARABLE SENSOR DATA

Each participant was given a Fitbit watch and two iButton sensors attached to the watch using a customized sensor holder to minimize potential discomfort while wearing the watch (Fig 1). Participants were instructed to wear the watch on their non-dominant wrist for a period of 24 continuous hours. They were asked to only remove the watch while taking a shower as the iButton sensors are not waterproof. Fitbit watches were fully charged when delivered to participants and were expected to last for three days.

Before deployment, we synchronized the time on the watch and iButton sensors with a designated computer used for the study. The synchronization disabled automatic time updates and ensured that the watch and sensors produced timestamps that could be compared and would represent nearly the same time window as the computer clock. This synchronization was necessary when using iButton sensors along with the watch to ensure that both sensors are getting nearly the same timestamp during the data collection period. Collection rate for iButton sensors was set to 0.07 Hz for a total of four samples per minute to ensure enough memory for 48 hours. When the collection rate was set to a higher rate of six to eight times per minute, these sensors can collect less than 12 hours of data. Biometric data collection included participant heart rate using an optical sensor embedded in the watch and step counts estimated through an accelerometer that was a proxy for physical activity. Frequency of data collection for heart rate and step count from the watch was 1 Hz and then downsampled for the data analysis process to 1 sample per minute, and sent directly to cloud storage. These records were downloaded from the equipment vendor via an application programming interface API. Recent studies [23], [24] have shown that optical heart rate sensors are reliable and accurate if ambient light, electromagnetic coupling with other sensors, and motion artifacts do not interfere with sensing heart rate [25]. One study, for example, [26] compared photoplethysmography (PPG) sensors from a smartwatch with a commonly used electrocardiagram, and found that they are highly correlated.

Given some limitations of sensing heart rate from wearable devices, we checked to assure limited interference from motion such as intense physical activities. Our step count assessment, for instance, showed that only two individuals exceeded 12,5000 steps per day. The continuous sensor measurement of heart rate also offered redundant information that provided a robust dataset to work with. There is a growing body of literature that shows mechanisms for improvement of heart rate datasets based on machine learning [27] and denoising algorithms [28]. We plan to use such algorithms in a larger study to improve the quality of the heart rate data.

Regarding on-body temperatures using two iButton sensors – skin and near air temperature sensors. These sensors were calibrated and used on the Fitbit watch previously by the Project Coolbit [29]. The skin temperature represents a heat exchange of the environmental temperature and body temperature [30], [31]. Wrist is also considered the best place to estimate subjective thermal sensation [32]. Given that skin temperature suffers from the influence of sweat or physical activities [33], [34], near air temperature serves as a better proxy indicator for assessing individually experienced ambient temperature.

C. SMART-PHONE BASED MOBILE SENSOR DATA

Ecological momentary assessments (EMAs) - self-reported surveys conducted multiple times a day - are used to assess the mood of participants. We used a mobile app, Ethica to prompt EMAs. In this study, participants received a notification from the app whenever EMA was conducted. We chose to do three times a day at 12 pm, 3 pm, and 6 pm for one day. We selected this time period to target the hotter parts of the day. Participants were requested to complete each survey before the next one came up, giving an expiration time of 180 minutes. Every time a participant sent a new survey the interaction was recorded, providing the exact time and location. Telephone surveys were used for the six participants with no technical knowledge of smartphone apps. From these six participants three provided a landline for the surveys while the rest provided a mobile phone number. Participants with mobile phones were asked for their location every time they completed the EMA survey. Phone survey followed the same procedure as the mobile app.

D. AIR AND SURFACE TEMPERATURE

In addition to on-person data sources, this study provided environmental context via the addition of outdoor weather data. Contrasts between temperature from the weather stations and wrist mounted equipment provided insight into adaptations each participant had available, such as air conditioning or shaded areas. Weather station data was extracted from NOAA's Automated Surface Observing Systems (ASOS) network, which includes four stations within NYC. Of the four stations, Central Park records observations at five minute intervals, while the rest do so hourly. To account for spatial variation of environmental conditions in the urban environment, we integrated land surface temperature estimated from the Landsat 8 satellite. Whenever a location was available for a participant, their coordinates were mapped to the closest 30m by 30m pixel in the Landsat 8 scene most recent to each participant record. During the study period, land surface temperatures for all participants varied between 55.6°C and 58.9°C, with those in the Roosevelt Island experiencing coolest values.

III. DATA PROCESSING/ANALYSIS

A. WEARABLE SENSORS

We imported CSV files of heart rate and step count from the Fitbit API, skin temperature from an iButton sensor that is in contact with the wrist of the participant, and near air temperature from an iButton sensor placed on the watch away from the skin contact. We converted all the data into time series and aligned them to generate measurements at one-minute interval for a 24-hour period. iButton sensors recorded data at 1 second intervals, which we downsampled by computing the mean value of each group of measurements

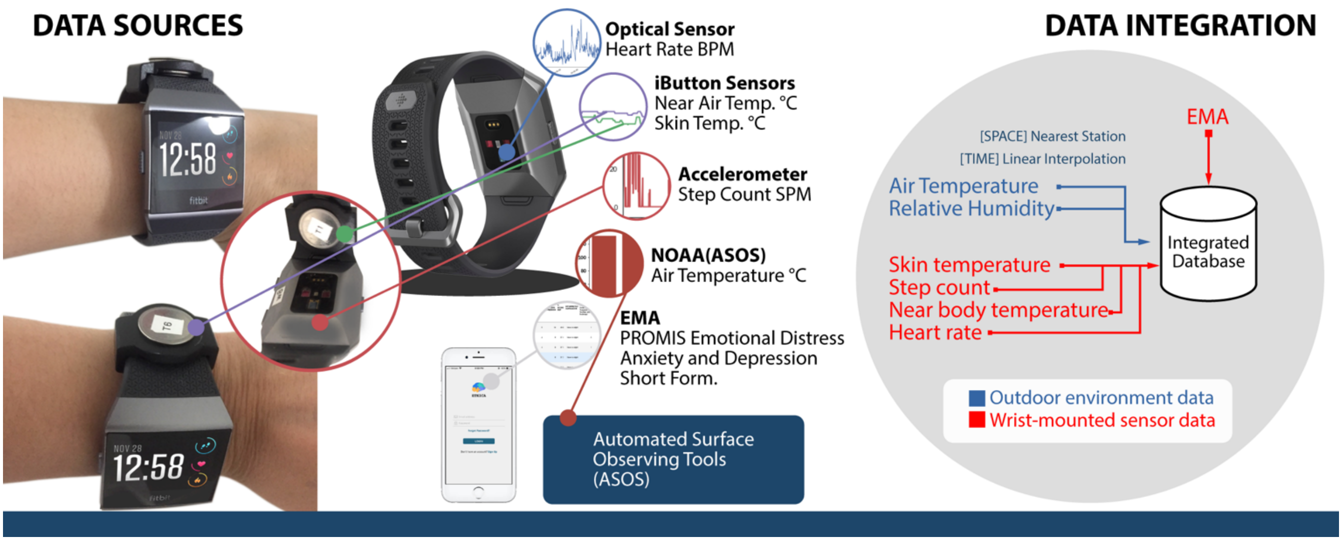


FIGURE 1. **Data sources and integration.**

within a 60 second interval. Step count was sampled at this same frequency.

We used time-series analysis to integrate all the data into a single dataset. This allowed us to visualize relationships among all the variables included in the study over the proposed period for each participant. We also created plots to illustrate within person variations by time.

B. EMAS

To analyze EMA survey data we used two validated tools, PROMIS Emotional Distress—Anxiety— Short Form and PROMIS Emotional Distress—Depression— Short Form. Each item on the measure was rated on a 5-point scale (1=never; 2= rarely; 3= sometimes; 4= often; and 5= always) with a range in score from 8 to 40 with higher scores indicating greater severity of depression or anxiety. We asked one question, 'How did you feel in the last three hours?' asking them to rate how fearful, anxious, or worried they felt, among others. Unanswered questions are prorated using the following formula:

$$score = raw \sum totalquestions \frac{}{answeredquestions} \tag{1}$$

We added the responses for each time of the day when we administered the survey on the Ethica mobile app. Then, we assigned the T-score for the corresponding measure. A lookup table was provided that mapped rounded total raw scores to a T-score, which was then mapped to anxiety levels as follows:

< 55: None to slight
55-59.9: Mild
60-69.9: Moderate
> 70: Severe

These categorical anxiety levels were then assigned a timestamp at the time they were finished and uploaded to a cloud-based service from which they were available for download to administrators.

We added two columns called 'INTERPRETED DEP' and 'INTERPRETED ANX' as shown in Figure 1. The values in this column associated the range and severity of depression or anxiety in a scale of, None to slight, Mild, Moderate and Severe. None of the participants in the study reported signs of depression beyond the Slight level during the EMA surveys, while five participants reported changes in their anxiety level going from None to Slight to Mild anxiety levels.

C. WEATHER

Because weather stations collect data less frequently than wrist sensors, they are resampled to the latter's one-minute interval via linear interpolation. Although this step potentially introduced uncertainty in outdoor conditions, air temperature and relative humidity were both known to exhibit large temporal autocorrelation, lessening the impact of the resampling. In addition, as weather stations were geographically static, each participant's location was used to map their nearest station using Euclidean distance:

$$D = \sqrt{(x_i - x_n)^2 + (y_i - y_n)^2} \tag{2}$$

where D is the distance between a weather station and a participant, x and y are the longitude and latitude respectively, while i and n subscripts denote the participant and weather station, respectively. The station with the smallest calculated distance was assigned to the participant whenever their location particular data record, the participant's previous coordinates were used for all computations.

The stations exhibit some variability in their distribution due to meteorological (e.g., sea breezes) and land cover. The warmest stations are LGA and JRB. JFK is located in

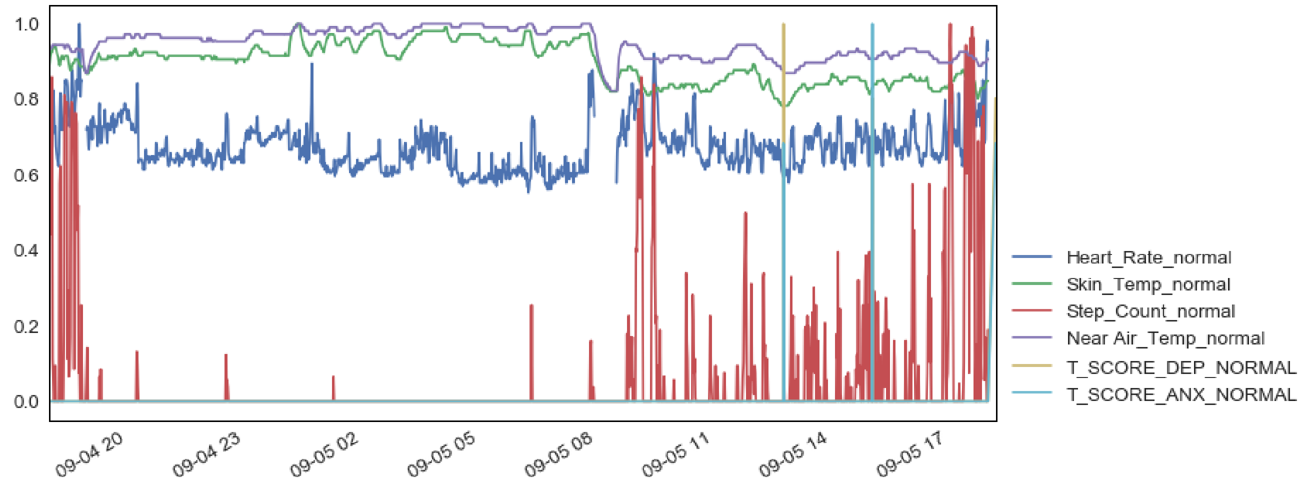
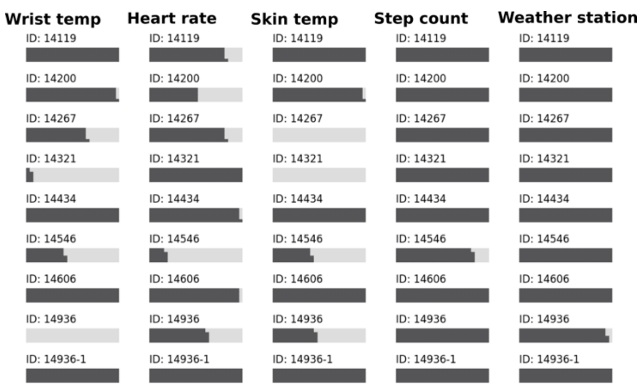


FIGURE 2. **Heat experience of participant 5.**

TABLE 2. **Inventory of data completeness.**



the southern coast of Long Island, which is often subject to land breezes that lead to cooler temperatures [35]. These differences are starker during the day when sea breezes form. An inventory of data collection was produced in order to asses completeness of sensor and EMA surveys across participants (Table 2). The ASOS weather stations, at least one of which has been operating for over 100 years, showed the least amount of missing data, for a single participant. On-person data collection proved less reliable, as three participants sometimes removed the wrist-mounted sensors before sleep. Sensors malfunctioned at least three times, such as wrist temperatures for participant 8 and skin temperatures for participants 3 and 4.

Missing data can prevent the inference of statistically significant results when they significantly impact the measurement sample size. However, significant correlations have been found between some of the measured data, opening the possibility of using multiple imputation (MI) techniques to fill in gaps [36]. However, if $> 50\%$ data from a sensor is provided, it will be tagged with a quality control flag so it may not be used in certain analyses.

IV. RESULTS

This section starts with a description of one participant's heat experience using on-person sensor data analysis (Fig 2). It is to illustrate holistically how environmental context affects the individual differently depending on the availability of air conditioning, time, and location. Participant #5 was a female, 67 years old without an air conditioner at home. She was active during the day while at a senior center. Because senior centers served as cooling centers during summer, they were air conditioned. At night when she returned home that had no air conditioning, her near air temperature increased on average to 33.9° C and skin temperature to 31.4°C. These temperatures were higher than during the day, which recorded on average 30.9 ° for near air temperature and 26.6°C for skin temperature. These temperatures were higher than during the day, which recorded on average 30.9°C. Skin temperature typically reflects the environment, and can drop to 17.7°C on average with ambient temperatures recording between 13.3°C and 23.9°C based on a study measuring hand temperature in moderately cold environments [37]. The heart rate also spiked while she was sleeping. The spikes were observed when the near air and skin temperatures increased to 35.6°C at 12:20 am, at 2:30 am and 4:00 am. Despite the absence of step counts, the periodic peaks in heart rate might have be caused by the higher night temperature at home without the air conditioner. Acute stress levels are known to elevate heart rates during sleep, increasing wakefulness [38]. Other reasons can be correlations between heart rate activity and various stages of sleep [39], [40], with peaks during the rapid eye movement stage (REM).

We also observed mood shifts with the increased on-person temperatures. Peaks in light blue and yellow indicate the times when the participant completed the survey that was requested and the T-Score on the depression and anxiety scale. There was no change in the level of depression as it stayed 'None' with a rise in on-person temperatures. There

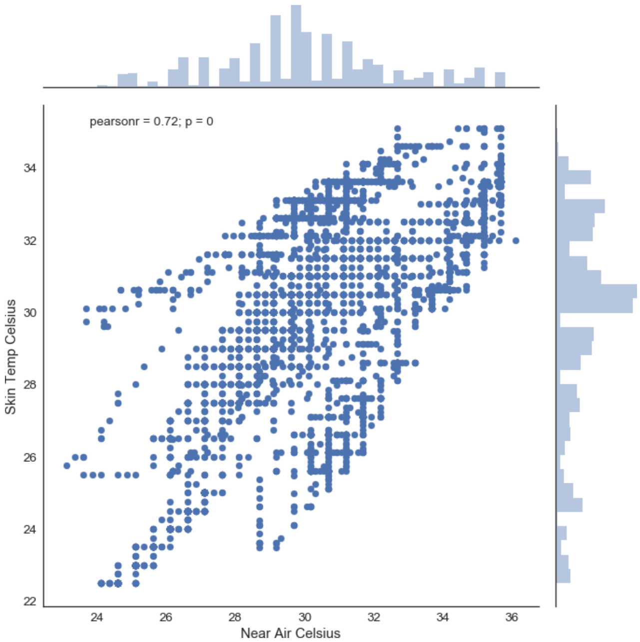


FIGURE 3. Scatter plot of skin temperature versus near air temperature. Marginal plots show histograms of each variable.

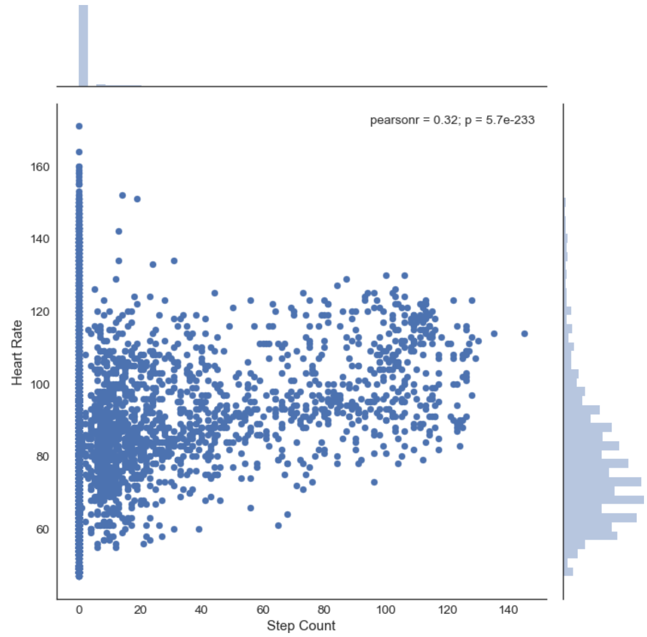


FIGURE 4. Scatterplot of heart rate and step count.

was, however, an increased level of anxiety from None to Slight to Mild.

A. COHORT CORRELATIONS

We analyzed correlations among variables generated by different data sources we measured at the group level. This is to demonstrate relationships among on-person and outside temperatures, stress, and activity. They also provided an opportunity to select one data source over the other if they are highly correlated. This will also cut down the cost of sensor purchase and processing time.

In Figure 3, we see a high correlation between skin and near air temperatures with a Pearson's coefficient value of 0.73. As the iButton sensors that measure skin and near air temperatures are located on the opposite sides of the watch (Fig 1), they may be exposed to a similar external environment. However, when both temperatures are examined in relation to heart rate, we see some difference in that near air temperature shows the Pearson's coefficient of -0.19 whereas skin temperature exhibits -0.03. This is partly due to the fact that the skin temperature sensing is in direct contact with the skin and can generate sweat that is not present in near air temperature sensor, which cools off the skin surface as it evaporates.

We also observe another strong correlation of 0.32 between heart rate and step count (Figure 4). When isolating times when participants moved (i.e., step count > 0), the correlation between the two increased to 0.45. This indicates that step count may be an important covariate to heart rate. As walking or running may not be the only source of physical activity for participants, additional insights may be gained from more granular data on speed of the participant movement. At the same time, we also observe that heart rate increases when there are no or little step counts. For instance, Participant 8 showed an increased heart rate up to 155 BPM when the steps amounted to 19 in a one minute period. The same participant showed a decreased heart rate around 115 BPM when there were 118 steps. These differences may be explained by heat stress or anomalies of the participant's heart condition. Two participants did not have air conditioning at home, and they showed a lower level of activity with a mean value of three steps per minute when compared to other participants with an average of 6.8 steps per minute. A lack of adaptive measures to combat heat (e.g., air conditioning) can be a barrier to physical activity by increasing discomfort among the participants.

There is little correlation between skin temperature and step count with a Pearson's coefficient of 0.053. Although Pearson coefficient is smaller than that of heart rate, it is nonetheless significant at the $p < 0.001$ level. Finally, results show nearly no relationship between near air temperature and heart rate.

B. PER-PARTICIPANT CORRELATIONS

Correlations among temperature related variables observed in each participant is useful in generating personal assessment of each individual's heat experience. The aggregated information on correlations discussed above is valuable in delineating important relationships that can be generalized with a large dataset. However, it has limitations in understanding how temperature-relevant factors interact and produce an individual-specific outcome. We selected two variables of considerable importance given past research on the topic. Mental stress has long been associated with heart rate [41], [42]. Studies have also shown that stress affects skin response. Sano et al [43] found that using heart rate and skin

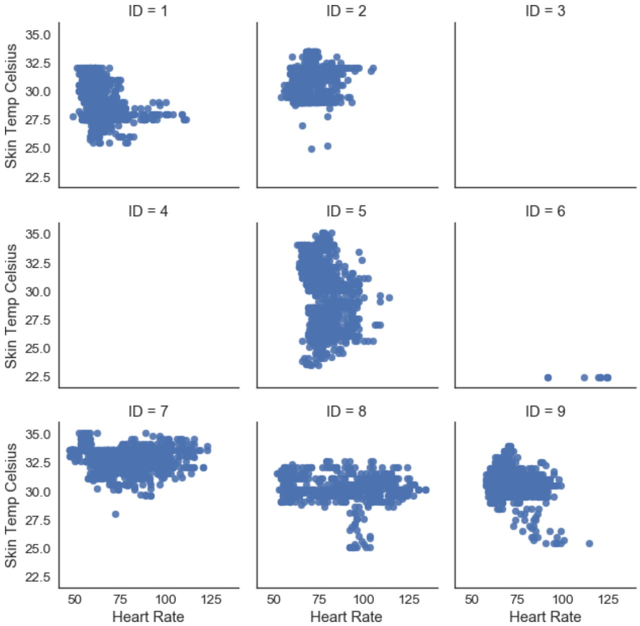


FIGURE 5. Scatter plot of skin temperature versus heart rate.

responses as features in a machine learning model resulted in 87% accuracy when classifying individuals into low and high stress groups.

For each individual, correlation coefficients of skin temperature and heart rate vary between −0.32 to −0.20. All participants exhibit a negative correlation coefficient, except for participant 2. The slope of the linear regression between these variables indicates decreases (increases) of −1.6°C (0.6°C) per unit increase of heart rate. Data from at least three of the participants show outliers in skin temperature, which may skew the linear regression coefficients towards lower values (ID = 2, 8, and 9). These outliers may be due to sensor mis-readings, a loose fit of the wrist strap on participants, or from participants temporarily removing their device. Participant 5 shows the largest variation of skin temperature, going from 23.9°C to 35°C, which may be due in part to their lack of air conditioning, different levels of physical stress, pre-existing medical conditions, or a combination of these. This participant has reported to not have air conditioning installed at home which corresponds to the highest reported temperature of 35.6°C at night. His on-body temperature at the 'cooled' senior center recorded the lowest temperature of 23.9°C around 1pm. Longer measurement records may help in attributing higher temperatures to lack of adaptive measures (e.g., air conditioning), different levels of physical stress, pre-existing conditions, or a combination of these factors.

In Figure 5, skin temperature sensors registered a failure for Participants 3 and 4 so data were not collected for them as they did not wear the watch immediately at the beginning of the study. This delay on the data collection at the beginning caused the iButton internal memory to fill up even before the collection started. iButton sensors were initially set up to collect data at a higher frequency (1 Hz: 60 times per minute) which means that sensors collected data 60 times per second. To address this issue the data collection rate was downsampled to 0.07 Hz (4 times per minute) to expand the duration of memory to 2-3 days and iButtons were programmed to delay start data collection for at least 240 minutes after configuration to guarantee successful data collection process. In general, step count showed a positive correlation with heart rate across all participants (Figure 6). The slope of the linear regression across participants varied from 0.10 to 0.9 when accounting only for timestamps where a step was registered. The correlation between these variables was also relatively strong, from 0.10 to 0.67. All these relationships were statistically significant at the 0.001 level, except for Participant 6, which only had 11 measurements available.

We checked the availability of AC with heart rate/step count, and it appears to not have a large effect on participant heart rate during the observation period (Figure 7).

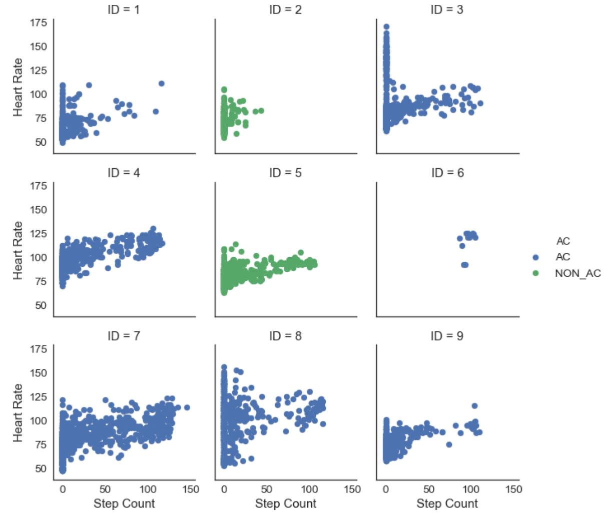


FIGURE 6. Scatter plot of heart rate versus step count by participant. Green markers denote participants without air conditioning.

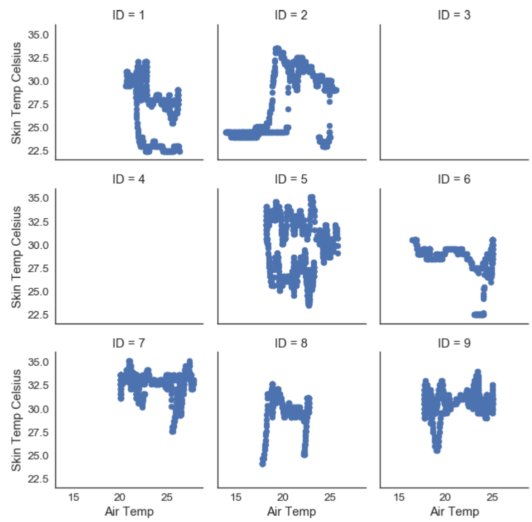


FIGURE 7. Scatter plot of skin versus outdoor air temperature by participant.

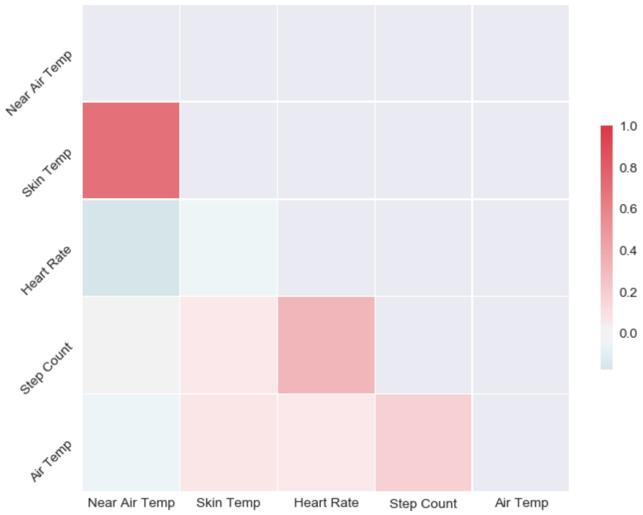


FIGURE 8. Cohort-level correlation coefficient heat map for biometric variables.

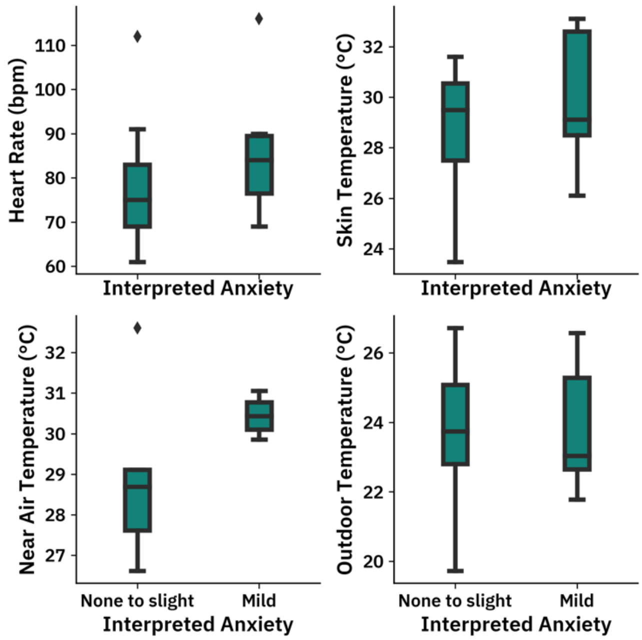


FIGURE 9. Box plot of heart rates and all temperature variables grouped by anxiety levels of all participants.

We included AC in this set of correlations because studies have associated weather and ambient temperature with heart rate [44], [45]. However, given the relatively less extreme weather during the study, a longer study during the summer months might yield more conclusive results. Moreover, indoor temperatures cool at slower rates than outdoor due to heat storage in buildings, leading to longer lasting warm conditions that extend into the night in rooms without air conditioning [46]–[48]. The availability of indoor cooling (i.e., air conditioning) may have a significant effect on heart rates and stress levels. Participant 5, for example, recorded the largest skin temperature variation, which could be due to the lack of AC. However, as data collection consisted of only a single day, which was not concurrent across all participants. A study with a longer period of time may be able to provide adequate results regarding the relationship between AC use and activity levels.

Finally, when looking at environmental factors, results show little to no correlation between outdoor air and near air temperature. Differences between these two values may be due to participants staying indoors or behaving in different ways as a function of outdoor temperatures. This highlights the importance of on-person sensing to capture the sample's experience of thermal comfort as it relates to mental and physical stresses. We summarize correlations among biometric variables in Figure 8 at the cohort level.

Results from EMA surveys are interpreted, with collected data across all participants only registering either None to slight or Mild anxiety levels without any depressive symptoms (Fig 9). Overall, participant heart rates, and both on-person and outside temperatures show higher values when patients experienced "Mild" levels of anxiety than "None to slight." Although the small amount of participant and short time period limits the total number of samples to 27 records, a larger cohort and time period may yield statistically significant results.

V. DISCUSSION

Measurements of sensor-based on-person temperatures have several benefits that previous research on heat stress lacks. They serve as proxy indicators for indoor temperatures often difficult to identify without installing temperature sensors inside homes and buildings. Although studies have installed sensors within homes, these efforts often have short time spans, or fail to distinguish between air conditioned and non-air-conditioned areas. Indoor temperatures can also be affected by building construction (e.g., materials, window size and placement, and roof treatments) as well as particular details of actual units (unit floor, air conditioning, insulation, and maintenance). For example, building materials play a large role, with bricks having a larger heat capacity than glass or wood, often leading to warmer temperatures that persist into the night or subsequent days. In addition, households may have air conditioners but do not use them because they do not want to pay for high utility bills [49]. Moreover, the fact that indoor temperatures stay warm several days after a heat wave poses higher risk for the elderly who tend stay indoors [47]. All these variations are difficult to capture without on-person temperature data.

We can correlate on-person data with outside temperature and location information to assess the micro environmental conditions that the person is situated in. This correlation addresses different types of indoor and outdoor environment ranging from home, senior centers, shopping malls to streets and parks. The wider the gap between the on-person temperatures and the outdoor temperature signifies the presence of an air conditioned surrounding or other types of adaptive environment to the heat.

The third benefit is the illustration of individual variations of heat experience despite similar environmental settings.

For example, participants without air conditioning recorded higher skin temperature variations than the rest of the cohort. On hot days, this might mean that these participants are at a higher risk of heat-related illness. What can strengthen the personalized assessment is a survey of pre-existing physical and mental health conditions. This will reveal the reasons for abnormal heart rate, step counts, or depression/anxiety levels that are not accounted for by extreme heat.

Moreover, group-level assessment of on-person data makes possible to test the relationship between variables that are not easily distinguishable at an individual scale. For example, group-level statistics show a slight positive relationship between activity level measured by step counts and skin temperature, although on an individual basis this relationship could be either positive or negative. Comparing on-person skin temperatures to outdoor temperature, the impact of individual behavior becomes more evident. For example, two participants without air conditioners experienced a larger variation of temperatures than their counterparts.

There may be other environmental factors related to physical activity not measured here. These may include meteorological hazards such as rainfall or high winds. Rainfall, for example, can prevent participants from being outside their home, in spite of how uncomfortable indoor conditions might be. Meanwhile, warm sunny days may prompt participants to be outdoors more often, potentially increasing their heat stress. One suggestion is to combine data at the person-level with outdoor factors to build a more useful model of mental stress by including factors that affect its indicators both directly (e.g., heat stress) and indirectly (i.e., behavior).

Collected data also yielded examples of adaptive mechanisms to warm conditions that were relatively counter-intuitive. For example, subjects with air conditioning available experienced warmer near air temperatures at night versus daytime. Participants reported difficulty sleeping and breathing when using AC at night in informal conversations after the study. These reports are consistent with studies that found air conditioning to be a significant risk factor in asthma patients, meaning that respiratory issues may influence behaviors that in turn impact heat stress [50], [51].

Given the results collected from this pilot study, useful additional data sources on the impact of heat exposure on the older adult include:

- Baseline biometric data: Establishing a baseline for participants' resting heart rates and near air temperature under thermal comfort conditions can establish a context to observed changes throughout the study.
- Pre-existing conditions: Participants' pre-existing health conditions may provide insight into patterns in sensed data either due to adaptive behaviors (e.g., turning off AC at night) or irregular biometric patterns (e.g., irregular heart rates).

Baseline biometric conditions can be established via a longer study period. Collecting data for enough days to capture both cool and warm conditions would allow for baselines to be established across all biometric data, and variables can then be expressed as departures from the baseline. Pre-existing conditions may be found via an initial survey administered directly to the participants.

In addition to these limitations, we address further constraints that can be improved in future studies. Due to participant and instrument availability, data collection among participants was not concurrent. No two participants were exposed to the same outdoor weather conditions. In addition, weather on participant data collection days was not considered extreme, with temperatures around 26.7°C to warrant a formal heat warning, although at least one day registered temperatures exceeding 32.2°C.

Finally, the use of smart technologies on older adults aged 65 and above was challenging. Wearable sensors on the wrist inconvenienced participants who suffered arthritis; some participants did not have smart phones or did not want to use them. Formal and personalized technology training needs to be built into the project of this nature. This will garner not only immediate benefit to the project but also raise their capacity to use technology in the long run.

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