Indoor Heat Strain Early Detection using Heart Rate Variability

Prosper Babon-Ayeng[1] and Wooyoung Jung, Ph.D., A.M.ASCE[2]

[1]Department of Civil and Architectural Engineering and Mechanics, The University of Arizona, Tucson, AZ 85719, USA; e-mail: pbabonayeng@arizona.edu
[2]Department of Civil and Architectural Engineering and Mechanics, The University of Arizona, Tucson, AZ 85719, USA; e-mail: wooyoung@arizona.edu

ABSTRACT

The increasing frequency and severity of heatwaves, exacerbated by climate change, pose significant health risks, particularly in underserved communities where high indoor temperatures are a growing concern. This study evaluates the applicability of root mean square of successive differences (RMSSD) in heart rate variability (HRV) as an indicator of heat strain, while highlighting inter-individual differences in autonomic responses. Eight healthy adults were exposed to controlled heat conditions ranging from 24°C to 40°C with relative humidity between 18% to 32% in a climate chamber. Non-invasive sensors recorded core temperature and HRV. K-Nearest Neighbors and Random Forest regressors were employed to predict RMSSD using lagged environmental and physiological features. Model performance varied among individuals, showing moderate to high performance, with adjusted R^2 values ranging from 0.67 to 0.89. These findings highlight the potential of RMSSD for enabling proactive building thermal management strategies to enhance occupant comfort and health during extreme heat events.

INTRODUCTION

The increasing frequency and intensity of heat waves, driven by climate change, has heightened concerns about comfort, health, and safety of underserved community members living in residential units with poorly insulated envelopes, inefficient air-conditioning units, and/or mechanical cooling failures (Sukanen et al. 2023). Addressing indoor heat strain in these environments requires improved monitoring techniques that can capture physiological responses in real time, facilitating timely interventions.

Heat strain is a series of non-specific responses produced by the human body in extremely hot environments, such as elevated body temperature, increased heart rate, and dehydration from acute sweating (Gotshall et al. 2001). Traditional approaches to assessing heat strain, such as measurements of heart rate, core body temperature, rectal temperature, and sweat rate (Malchaire et al. 2001; Moran et al. 1998), often do not detect early physiological changes and inadequately account for inter-individual variability in responses. These limitations emphasize the need for approaches that enable early detection of heat strain that accounts for individual variability, ensuring timely interventions to enhance occupant comfort, health, and well-being.

Heart rate variability (HRV), which quantifies the variation in time intervals between consecutive heartbeats, has been increasingly recognized as a promising tool for monitoring physiological responses to heat stress (Carrillo et al. 2024). The autonomic nervous system, which plays a central role in thermoregulation, exhibits distinct HRV patterns during heat exposure as the body attempts to manage thermal stress. Several studies have explored HRV in thermal strain contexts, such as its use in evaluating tolerance to physical activity under heat stress (De Barros et al. 2024), or predicting thermal comfort in older adults (Carrillo et al. 2024; Meade et al. 2024). However, these studies have primarily focused on physical work or specific population groups, leaving a critical gap in understanding HRV's role as an early indicator of heat strain in (sedentary) building occupants exposed to indoor heat stress.

Given these considerations, this study addresses the following research questions:

1) *How do individual autonomic responses, as captured by RMSSD, vary during exposure to increasing indoor temperatures?*
2) *Can RMSSD patterns be effectively estimated through environmental and physiological parameters in scenarios where direct HRV monitoring is unavailable?*

By incorporating continuous and feasible physiological monitoring (e.g., RMSSD as an indicator of autonomic responses to heat stress), we envision to enable building systems that can autonomously adjust thermal conditions to maintain occupant comfort and safety. This occupant-centric focus aligns with the essence of human building interaction, wherein the building and its occupants form a dynamic feedback loop whereby occupants influence building conditions, and buildings, in turn, adapt to occupants' physiological and even perceptional needs.

Heart Rate Variability (HRV)

In electrocardiography (ECG), the waves are conventionally labeled P, QRS, (a wave complex) and T (see Figure 1). The R wave is the large upward deflection in the QRS complex, which refers to the combination of three deflections (Q, R, and S waves) that collectively represent ventricular depolarization (Mirvis & Goldberger 2001). Since the R wave is typically distinct and easily identifiable, RR intervals offer a reliable way to quantify beat-to-beat fluctuations in heart rate.

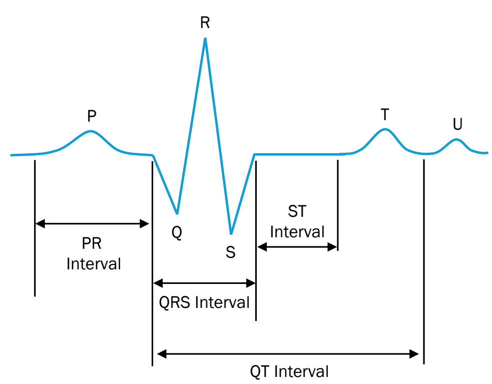

Figure 1.The basic pattern of electrical activity across the heart

where P wave is a small deflection wave that represents atrial depolarization; PR interval is the time between the first deflection of the P wave and the first deflection of the QRS complex; ST interval is the time between the end of the QRS complex and the start of the T wave; T waves represent ventricular repolarization.

HRV in Heat Strain Research

A variety of HRV metrics have been implemented throughout thermal stress and heat exposure studies including time-domain, frequency-domain, and non-linear metrics. Among HRV metrics, the Root Mean Square of Successive Differences (RMSSD) stands out as a time-domain measure that reflects parasympathetic activity and captures short-term (<5 minutes) variations in heart rate. RMSSD's sensitivity to rapid changes in autonomic regulation makes it particularly valuable for detecting early signs of physiological strain (Carrillo et al. 2016) before traditional indicators, such as heart rate or core temperature, exhibit significant changes (Liu et al. 2008).

The equation for RMSSD is provided below.

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(\text{RR}_{i+1} - \text{RR}_{i})^2}$$

Where, RR (R-to-R) refers to the interval between successive R waves in the electrocardiogram; RR_i and RR_{i+1} are consecutive RR intervals (in milliseconds), representing the time between successive heartbeats; N is the total number of RR intervals in the segment being analyzed.

HRV metrics have demonstrated significant potential as early indicators of heat strain across various contexts and populations. For instance, De Barros et al. (2024) found that RMSSD measurements during the first hour of heat exposure showed acceptable discriminative ability in predicting premature work termination due to heat strain. Their study revealed that reduced RMSSD early in heat exposure reflects increased sympathetic modulation and parasympathetic withdrawal before significant physiological deterioration occurs. Wu et al. (2021) established strong negative correlations between R-R intervals and thermal discomfort in mine workers, validating HRV metrics as biomarkers of thermal comfort capable of expressing physiological responses across different thermal conditions. Meanwhile, Carrillo et al. (2024) observed age-related differences in HRV responses during prolonged heat exposure, with older adults showing lower HRV indices (including RMSSD) that reflect changes consistent with vagal withdrawal compared to younger counterparts.

Despite these advancements, critical gaps remain in the application of HRV metrics for early heat strain detection in building occupants. Previous studies have primarily focused on physically active workers or specific populations like older adults, with limited attention to sedentary indoor occupants who represent a significant portion of building inhabitants. Furthermore, while existing research establishes HRV's value as an indicator of heat strain, few studies have developed predictive frameworks capable of accounting for the inter-individual variability in physiological responses observed across these studies.

This research addresses these gaps by leveraging RMSSD to detect early signs of heat strain among building occupants, likely to be sedentary, exposed to extreme indoor temperatures. By employing the K-Nearest Neighbors (KNN) and Random Forest (RF) regressor models, we aim to predict RMSSD patterns using environmental parameters (air temperature and relative humidity) combined with individual physiological data (core temperature).

RESEARCH METHODOLOGY

Data Collection: We exposed participants to increasing temperatures to examine how autonomic responses, particularly as measured by RMSSD, vary during heat stress conditions. The experimental protocol was designed to create environmental conditions classified as “extreme caution” according to the Heat Index Chart by the Arizona Department of Health Services (2011), allowing us to observe physiological responses that may not typically manifest in normal indoor conditions. The following were the three phases that we designed:

1) **Pre-exposure Phase (10 minutes):** Participants acclimated in a 24°C (75.2°F) room while baseline core temperature and HRV measurements were recorded via CALERA chest strap and CorSense finger sensors. Participants wore light clothing (0.5-1.0 clo).
2) **Heat Exposure Phase (120 minutes):** The main experimental phase involved controlled heat exposure in the climate chamber. The temperature was systematically increased from 24°C (75.2°F) to 40°C (104°F) in 1°C (1.8°F) increments every 10 minutes, while relative humidity was maintained between 18% and 32%. A peak indoor temperature of 40°C (104°F) was chosen based on evidence that buildings without air conditioning systems (free-running) in low-income neighborhoods can experience indoor temperatures up to this level during heatwaves (Sakka et al. 2012). Core body temperature was recorded at 1-minute intervals using the CALERA Research chest strap sensor, while HRV was measured via the CorSense finger sensor and aggregated to 1-minute epochs, yielding up to 1,200 data points per participant for each physiological measure. Environmental conditions were tracked at 5-minute intervals by the Awair Omni device. After data cleaning, these time-aligned measurements formed the basis for our predictive models. Participants remained seated throughout the phase to minimize activity-related variations in physiological measurements. Participants also had the option to consume water as much or as often as necessary throughout the experiment, and they were informed of their right to withdraw from the study at any time.
3) **Recovery Phase (20 minutes):** Following heat exposure, participants entered a recovery period in a controlled environment at 23°C (73.4°F), outside the climate chamber. Physiological monitoring continued during this phase to track the return of core temperature and HRV patterns toward baseline values.

Participants were recruited through targeted emails to university student, faculty, and staff mailing lists at the University of Arizona. A pre-screening survey was implemented to evaluate participants’ health history, specifically screening for cardiovascular diseases, renal insufficiency, and previous adverse reactions to heat exposure. The experiments were conducted in the SensorLab at the University of Arizona, a climate-controlled chamber measuring 3.35 meters by 5.18 meters (11 feet by 17 feet). The windowless chamber featured 100mm (3.94 inches) thick insulated walls with multiple external walls. Temperature control was achieved using five portable space heaters and two Honovos 17L/4.5Gal Ultrasonic Cool Mist Humidifiers for humidity regulation.

Given the intentional exposure to elevated temperatures, the study received approval from the University of Arizona Institutional Review Board (ID: STUDY00003790). All participants provided written informed consent after being fully informed about the experimental conditions, potential risks, and monitoring procedures.

Data Processing and Analysis: Data preprocessing was performed by removing outliers using a z-score method to eliminate extreme values that could bias model predictions. Additionally, time-lagged features were generated to capture temporal dependencies in RMSSD, with a lag of up to three previous intervals (15 minutes), enabling the models to consider short-term trends and patterns in physiological responses.

Initially, time series analysis was conducted to examine the relationships between environmental conditions and physiological responses. Afterwards, Pearson correlation coefficients were calculated to quantify the relationships between air temperature, relative humidity, core temperature, and RMSSD values.

Then, two machine learning (ML) models, detailed below, were developed and evaluated for their ability to predict RMSSD values 15 minutes ahead.

1) **KNN regressor:** a non-parametric model that predicts values based on the weighted average of the nearest neighbors in the feature space. Hyperparameter tuning included evaluating the number of neighbors (ranging from 1 to 20), weighting methods (uniform vs. distance), and distance metrics (Euclidean and Manhattan).
2) **RF regressor:** an ensemble-based model that uses multiple decision trees to capture complex relationships between features and the target variable. The RF regressor model was trained using 100 estimators (trees), a maximum depth of 10 to control tree size, and minimum samples split of 2, ensuring a balance between model complexity and overfitting prevention.

Both models utilized time-lagged air temperature, relative humidity and core body temperature features as predictors, with RMSSD serving as the target variable. Core body temperature was included as a predictor because it reflects a direct physiological response to heat stress, complementing environmental predictors in capturing the thermoregulatory dynamics of the body. Five-fold time series cross-validation was implemented, ensuring that the temporal dependencies in the data were respected by maintaining the sequential order of observations. Specifically, the dataset was partitioned into training (70%), validation (15%), and test (15%) sets, ensuring representative sampling across participants. Model performance was assessed using the adjusted R^2, and root mean square error (RMSE). This combination of metrics offers a balanced view of both the explanatory power (adjusted R^2) and predictive accuracy (RMSE) of the models.

RESULTS

The demographic characteristics of the participants are presented in Table 1.

Table 1: Demographic data

Subject	Gender	Age (years)	Weight (lb / kg)	Height (m/ ft)	Ethnicity
S1	Female	21	127.9 / 58.0	1.61 / 5.28	White
S2	Male	30	143.3 / 65.0	1.72 / 5.64	Black
S3	Male	28	136.0 / 61.7	1.70 / 5.58	Black
S4	Male	24	176.4 / 80.0	1.80 / 5.91	Other (Middle Eastern)
S5	Female	29	135.4 / 61.4	1.65 / 5.41	Black
S6	Female	35	125.7 / 57.0	1.71 / 5.61	Asian
S7	Non-binary	19	194.0 / 88.0	1.57 / 5.15	Hispanic or Latino
S8	Female	59	151.7 / 68.8	1.74 / 5.70	White

Among the participants, there were four females, three males, and one non-binary individual. Participants ranged in age from 19 to 59 years, with body weights varying from 125.7 lb (57.0 kg) to 205.0 lb (93.0 kg), and heights ranging between 1.57m (5.15ft) and 1.80m (5.91ft).

Figure 2 shows the temporal variations in environmental conditions during the two-hour experimental period for S3. The air temperature exhibited a steady increase from 24°C (75.2°F) at the start of the experiment to 40°C (104°F) by the end of the 120-minute period. Relative humidity levels fluctuated throughout the experiment, ranging between 17% and 33%.

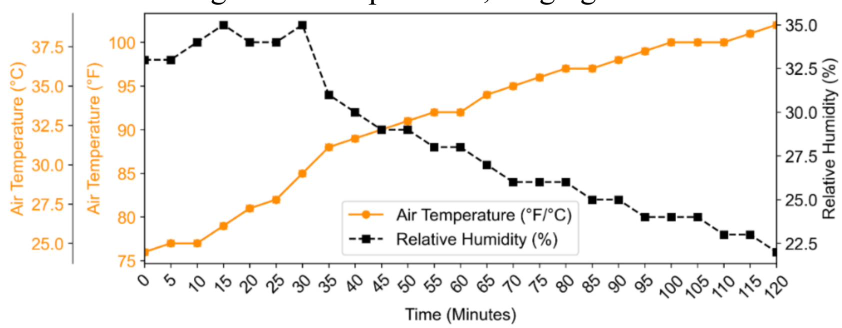

Figure 2. Room Temperature and Relative Humidity for the 120 Minutes of Heat Exposure

Figure 3 shows the physiological responses of three participants who showed very distinct patterns during heat exposure. Subject 4 began with a high baseline core temperature of 36.85C (98.3°F) that increased gradually to 37.79°C (100.0°F), while maintaining moderate RMSSD values that declined gradually over time. In contrast, Subject 6 exhibited a rapid increase in core temperature within the first 20 minutes from 37.0°C (98.6°F) to 37.58°C (99.6°F), followed by a more gradual rise to 38.09°C (100.6°F) by the end of heat exposure. Subject 8 displayed the most unique RMSSD pattern, starting with notably elevated values that dropped around the 25-minute mark before significant core temperature elevations were observed. This decline in RMSSD occurred while core temperature remained relatively low 36.19°C (97.1°F). These divergent patterns highlight the considerable inter-individual variability in thermoregulatory and autonomic responses to heat stress.

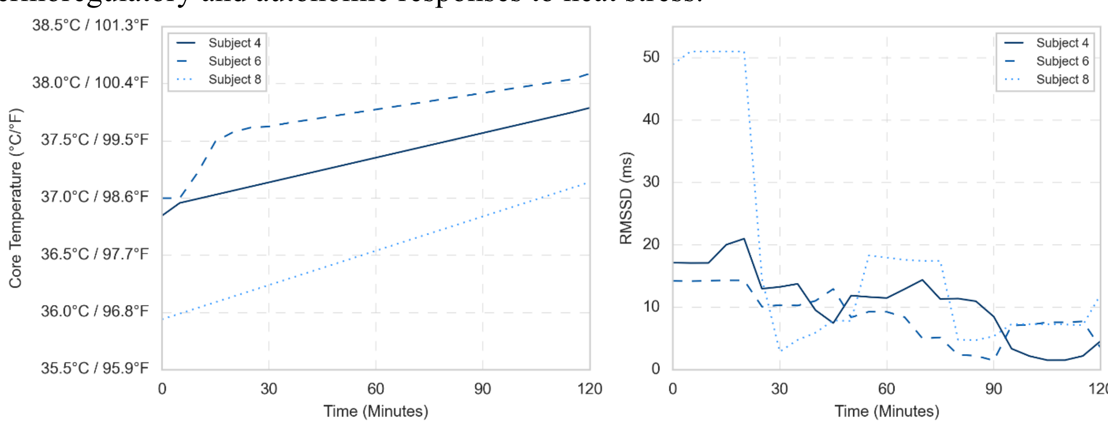

Figure 3. Variations in core temperature and heart rate variability during heat exposure

To quantify these relationships, Figure 4 shows correlation matrices for two participants (Subjects 7 and 8). These subjects were selected to represent the extremes of age range in our participant pool (S7: 19 years; S8: 59 years). For both participants, air temperature exhibits a strong negative correlation with RMSSD (r = -0.69 for Subject 7 and r = -0.85 for Subject 8), suggesting that as ambient heat increases, autonomic modulation reflected by RMSSD declines.

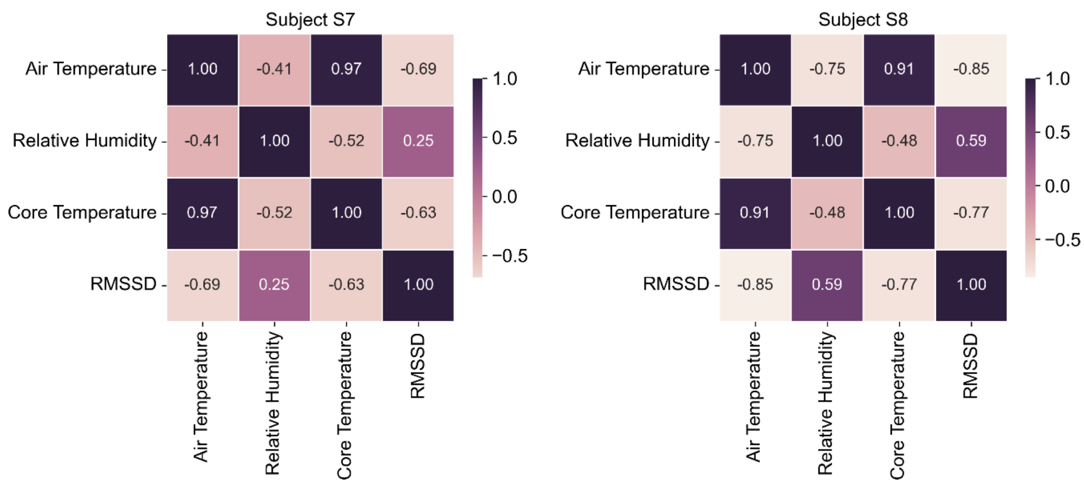

Figure 4. Correlation Heatmaps of S7 and S8

Figure 5 presents the performance metrics for the KNN and RF regressor models across all subjects. Overall, the KNN models demonstrated superior predictive capability with an average adjusted R^2 of 0.81 compared to RF's average of 0.76. The RMSE values similarly favored KNN (9.58) over RF (11.87) across subjects. However, notable exceptions to this pattern existed. For Subject 5, the RF model achieved its best performance with an adjusted R^2 of 0.89, outperforming the KNN model (0.80). Similarly, for Subject 8, RF (0.78) performed better than KNN (0.69). The most substantial performance gap favoring KNN occurred with Subject 4, where KNN achieved an adjusted R^2 of 0.82 compared to RF's notably lower 0.67. These variations suggest that individual physiological response patterns may be better captured by different modeling approaches, with KNN generally providing more accurate predictions for most subjects, while RF offers advantages for specific individuals.

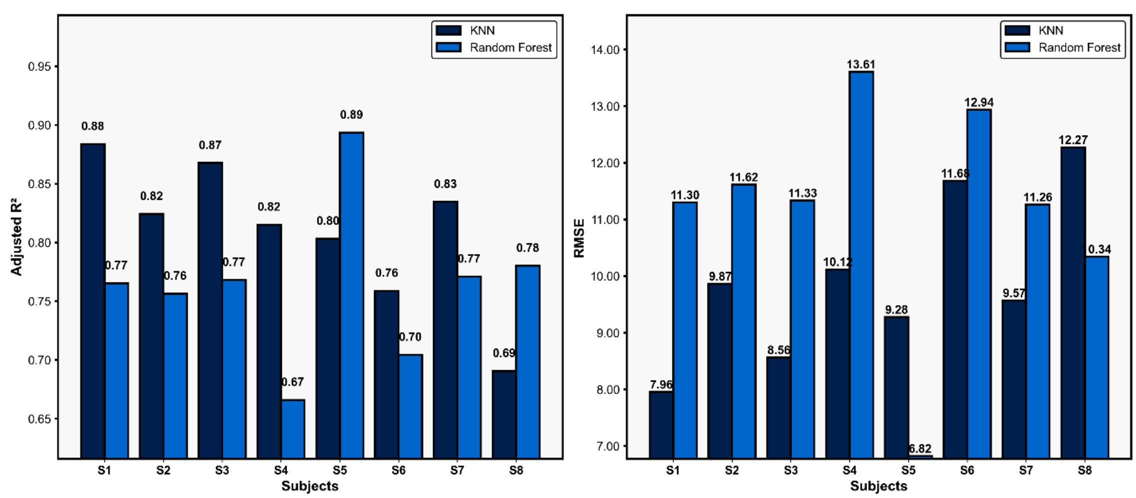

Figure 5. Adjusted R^2 values indicating goodness of fit; RMSE measuring prediction error in milliseconds

CONCLUSION

This study investigated the potential of HRV, specifically the RMSSD, as an early indicator of heat strain in indoor environments. By leveraging a controlled heat exposure experiment, we demonstrated the feasibility of using RMSSD to capture autonomic responses to thermal stress before traditional metrics, such as core body temperature, show significant changes.

Our findings reveal that RMSSD consistently responds earlier to heat stress than core temperature across subjects, providing a valuable physiological signal for early heat strain detection. The rapid decrease in RMSSD observed during the initial stages of heat exposure indicates that the autonomic nervous system responds promptly to thermal stress, potentially serving as an early warning system for heat-related stress. This early detection capability is particularly valuable because it occurs before core temperature rises significantly, creating a critical time window for preventive interventions. The KNN and RF regressor models exhibited varying performance in predicting RMSSD patterns across participants, reflecting the inherent inter-individual variability in physiological responses, but both confirmed the utility of RMSSD as a sensitive biomarker for heat strain assessment.

Importantly, our results emphasize the viability of using RMSSD as a non-invasive and feasible indicator of heat strain in building occupants. This early detection capability is especially relevant for occupant-centric applications in buildings, where proactive interventions such as localized cooling, adaptive ventilation, or occupant alerts could be deployed to mitigate discomfort and health risks before heat strain escalates. This approach moves beyond traditional one-size-fits-all strategies.

While this study demonstrates the potential of RMSSD in predicting heat strain in extreme indoor environments, several limitations must be addressed in future work. First, the study was conducted with a relatively small group of healthy adults. Expanding the dataset to include a larger, more diverse population, and varying health conditions would enhance the generalizability of the findings. Second, our 120-minute exposure protocol provided insights into short-term autonomic responses but did not capture possible long-term adaptations that may arise under prolonged or repeated heat exposure. Investigating these extended timescales would further strengthen and broaden the implications of our findings.

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