Decoding Indoor Comfort Models through Dynamic Physiological and Environmental Data Collection on Vehicles

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ABSTRACT

The concept of a smart environment stands for a significant shift in personalized comfort and intelligent indoors control. Key technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and multisensory data analysis, can be integrated to translate the preferences of occupants. This study aims to explore the intricate correlation between individual preferences and environmental conditions, adding dynamic physiological and environmental measurements during participants commuting activities. The central focus of our experiment lies in formulating personalized comfort models for commuters by exploring the combination of physiological signals, namely electrodermal activity, skin temperature and heart rate, and thermal environmental parameters. Data from eight different participants was collected during summertime in Perugia (Italy), for at least two entire weeks of their commuting activities to describe their thermal exposure. The data from physiological signals were gathered all the times the participant was driving. The collected data was employed to set up personalized comfort profiles, highlighting the impact of environmental fluctuations on subjects physiological measurements collectively (and individually). The investigation was not reliant on comfort survey application. In parallel, dedicated lab studies on thermal comfort and individual indoor comfort for commuters were conducted in the offices in order to analyse their preferences and attitudes in controlling in-vehicle HVAC with respect to their daily routine while in office. Our study aims to pave the way for innovative solutions that prioritize individual satisfaction and well-being, recognizing the personalized nature of comfort within varying environmental contexts. Additionally, this study could contribute to the development of tailored indoor comfort solutions by addressing individual physiological and environmental needs within dynamic indoor settings

Keywords: Indoor Comfort Profiling, Comfort Prediction Models, Human-Environment Interaction, Multisensory Data Analysis, Regression Models,

Nomenclature

- num_ibis: Number of Interbeat Intervals (IBIs).
- hrv_mean_nni: Mean of the NN intervals (IBIs).
- hrv_median_nni: Median of the NN intervals.
- hrv_range_nni: Range of NN intervals.
- hrv_sdsd: Standard Deviation of Successive Differences.
- hrv_rmssd: Root Mean Square of Successive Differences.
- hrv_pnni_50: Proportion of NN intervals differing by more than 50 ms.
- hrv_nni_20: Percentage of differences between consecutive NN intervals greater than 20 ms.
- hrv_pnni_20: Proportion of NN intervals differing by more than 20 ms.
- hrv_cvsd: Coefficient of Variation of Successive Differences.
- hrv_sdnn: Standard Deviation of NN intervals, reflecting overall HRV.
- hrv_cvnni: Coefficient of Variation of NN intervals.
- hrv_mean_hr: Mean Heart Rate.
- hrv_min_hr: Minimum Heart Rate.
- hrv_max_hr: Maximum Heart Rate.
- hrv_std_hr: Standard Deviation of Heart Rate.
- hrv_total_power: Total Power of the HRV spectrum.
- hrv_vlf, hrv_lf, hrv_hf: Power in Very Low Frequency, Low Frequency, and High-Frequency bands.
- hrv_lf_hf_ratio: Ratio of LF to HF power.
- hrv_lfnu, hrv_hfnu: Normalized LF and HF power, respectively.
- hrv_mean: Mean value of the HRV signal.
- hrv_std: Standard Deviation of the HRV signal.
- hrv_max: Maximum value observed in the HRV signal.
- hrv_ptp: Peak-to-Peak value, the difference between the maximum and minimum values in the HRV signal.
- hrv_sum: Sum of all values in the HRV signal.
- hrv_energy: Energy of the HRV signal.
- hrv_peaks: Count of local maxima or peaks in the HRV signal.
- hrv_rms: Root Mean Square of the HRV signal.
- hrv_lineintegral: Integral of the HRV signal.
- hrv_n_above_mean, hrv_n_below_mean: Number of data points above and below the mean HRV value.
- hrv_n_sign_changes: Number of times the HRV signal changes sign from positive to negative or vice versa.
- hrv_iqr: Interquartile Range of the HRV signal, measuring the spread of the middle 50
- hrv_iqr_5_95: Interquartile Range between the 5th and 95th percentiles of the HRV signal.
- hrv_pct_5, hrv_pct_95: Values at the 5th and 95th percentiles, respectively, of the HRV signal.
- hrv_entropy: Entropy of the HRV signal, a measure of randomness or disorder in the signal.
- hrv_perm_entropy: Permutation entropy, measuring complexity in the HRV signal using ordinal patterns.
- hrv_svd_entropy: Singular Value Decomposition (SVD) entropy, another measure of signal complexity using SVD.
- IoT: Internet of Things.
- AI: Artificial Intelligence.
- HVAC: Heating, Ventilation, and Air Conditioning.
- EDA: Electrodermal Activity.
- BVP: Blood Volume Pulse.
- ACC: Accelerometer.
- IBI: Inter Beat Interval.
- HR: Heart Rate.
- N1, N2, N3, N4, N5: Environmental Sensors.
- Participants IDs: S01, S02, S03, S04, S05, S06, S07, S08.

1 Introduction

Comfort is a fundamental aspect of human well-being and productivity, varying significantly among individuals and in diverse environmental contexts. Imagine embarking on a journey—a daily commute, a familiar routine. Now, envision this journey not just as a physical movement from one point to another, but as a dynamic interplay between you and your surroundings. This is where the crux of comfort lies, a concept so deeply ingrained in our daily lives yet intricately nuanced.

In the tapestry of human experience, comfort isn't a one-size-fits-all affair. It's a kaleidoscope, weaving together the threads of our physiology and the ever-shifting backdrop of our environment. What if we could decipher this intricate dance, understand the unique rhythm of comfort for each individual?

Enter the realm of indoor comfort models—a narrative that unfolds at the intersection of human physiology and environmental conditions. Our quest is to unravel the stories told by the body's signals and the whispers of the surroundings. It's an exploration where the protagonist is you, and the setting is the indoor space where your daily odyssey unfolds.

Picture this: a wrist-worn companion, Empatica E4, capturing the silent conversations within your body—heartbeat, skin's tales of arousal, temperature fluctuations, and the cadence of your movements. Now, add to this ensemble the ambient murmurs of the indoor world—a car, a controlled microcosm where you, as the protagonist, navigate through the ebbs and flows of temperature, humidity, and the gentle breeze.

This narrative comes to life through a symphony of data—physiological signals seamlessly blending with environmental cues. It's not just a collection of numbers; it's the brushstrokes painting a portrait of your comfort, a tapestry woven with threads of individuality.

But why embark on this journey? Because understanding these tales of comfort has the power to transform realms beyond the immediate. Our exploration reaches beyond the confines of this study—it holds the promise of revolutionizing automotive comfort systems, shaping user-centric smart buildings, and elevating wearable technology to new heights of well-being.

In the pages that follow, we invite you to traverse the chapters of our methodology, witness the unveiling of patterns in physiological and meteorological data, and delve into the realms of practical applications. We narrate not just a scientific endeavor but a story of potential impact on user satisfaction and well-being.

In conclusion, this research serves as an intricate bridge, seamlessly connecting the physiological symphony within the human body to the ever-shifting notes of the environment. The emergence of personalized comfort models heralds a paradigm shift—a user-centric approach designed not merely to decode comfort but to elevate the quality of life and satisfaction across diverse contexts. As we venture deeper into this narrative, each heartbeat and environmental whisper adds a stroke to the canvas of personalized comfort.

Sections 2 through 6 will systematically unveil the layers of our exploration—methodology, results, and discussions. These sections offer a guided journey through the scientific landscape of our research, shedding light on the nuances that underpin the development of personalized comfort models.

2 Methodology

In this section, we provide a detailed account of the procedures and techniques employed in our research to collect and analyze physiological and environmental signals for the development of indoor comfort models.

2.1 Data Collection

Eight participants, representing diverse demographics, were recruited for this study. Recorded participant details, including age, gender, and relevant health information, aimed to assess potential influences on comfort preferences. Informed consent was obtained, and participants were acquainted with the study's objectives and the use of wearable devices. To monitor physiological responses, participants wore wrist-worn Empatica E4 devices and additional strategically placed sensors. The Empatica E4 wristwatch recorded heart rate, skin conductance, temperature, and accelerometer data. Simultaneously, four tinytag sensors within the vehicle and one on the participant's carry bag captured environmental data, encompassing air temperature, humidity, and wind speed. This combined approach allowed the synchronized monitoring of individual physiological responses and environmental conditions, providing a comprehensive assessment of an individual's physiological state.

2.1.1 Data Acquisition Instruments

The Empatica E4 wristwatch served as the core element of the data collection setup, continuously recording heart rate, skin conductance, temperature, and accelerometer data. These parameters offered insights into cardiovascular responses, stress levels, thermal comfort, and physical activity.

The simultaneous use of tinytag sensors further enriched the dataset by capturing environmental parameters, providing a holistic understanding of comfort levels.

2.1.2 Experiment Design and Setup

Data collection occurred during the summer months (July to September 2023) in Perugia, Italy, focusing on the daily commuting activities of eight participants—two men and six women. Participants were instructed on the operation of Empatica E4 devices and adjusted controlled comfort parameters, such as ventilation and car wind, aligning them with personal preferences during commuting activities.

Physiological signals were exclusively collected during participants' commuting activities, ensuring a targeted focus. Simultaneously, strategically placed tinytag sensors within the vehicle recorded environmental parameters, providing a comprehensive snapshot of the indoor environment. This synchronized data collection facilitated a holistic understanding of the factors influencing personalized comfort preferences in indoor vehicle settings, forming the foundation for subsequent analyses and the development of personalized comfort models.

2.2 Data Preprocessing

The data processing phase of this research was pivotal in ensuring the accuracy, consistency, and readiness of the physiological and environmental data for analysis. The processing steps involved were designed to minimize noise, handle missing data, and prepare the datasets for meaningful correlations and personalized comfort model development.

2.2.1 Environmental Data

In the meticulous curation of environmental data, the initial step involved the cleaning of the raw dataset obtained from the five "tinytags" sensors, namely *N1, N2, N3, N4,* and *N5*. This process aimed at removing unnecessary values and information, ensuring a streamlined dataset for further analysis. Subsequently, the data was structured into a standardized format comprising DateTime, Temperature, Humidity, and Dew-Point columns.

To address temporal considerations, the original environmental data samples were initially recorded at a frequency of 45 seconds. To align with the experimental requirements and facilitate consistent analysis, the time series data underwent resampling. This resampling operation adjusted the frequency to 1 second, ensuring a uniform temporal resolution. This step is crucial for maintaining consistency across sensors and enabling meaningful comparisons.

Following resampling, the environmental data underwent interpolation to handle missing values. Given the shift in frequency, certain seconds within the time series were initially unrecorded. Interpolation involves estimating and filling in the missing values between existing data points. This process is essential for creating a continuous dataset, enabling a thorough exploration of environmental patterns and trends over time.

The final dataset, structured with DateTime, Temperature, Humidity, and Dew-Point columns, now provides a comprehensive and consistent representation of the environmental conditions recorded by sensors *N1, N2, N3, N4,* and *N5*. This refined dataset serves as the foundation for subsequent analyses related to indoor comfort, climate monitoring, and the development of personalized comfort models. The cleaning, resampling, and interpolation processes collectively contribute to the accuracy and reliability of the environmental data, ensuring its suitability for in-depth scientific exploration.

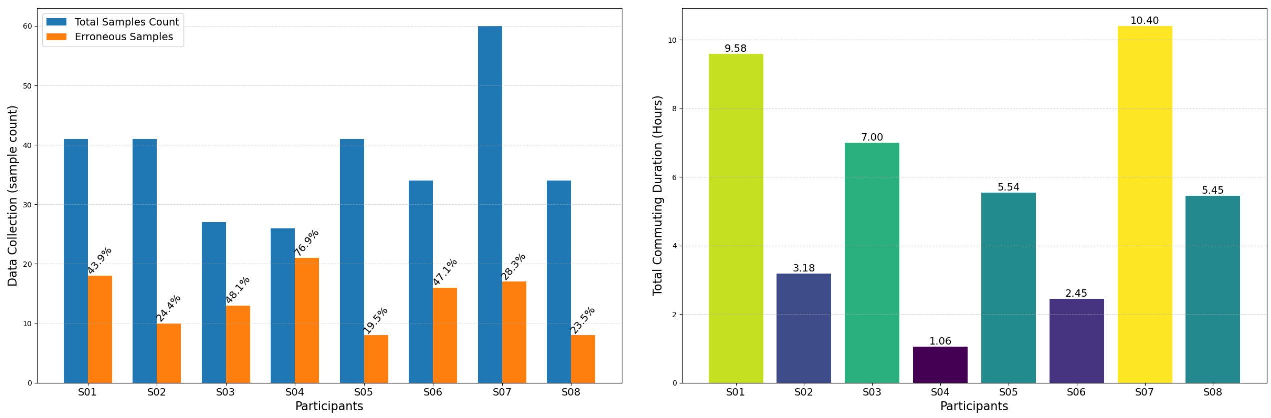

Figure 1: *(a) Erroneous samples in collected physiological data per participants. (b) Total commuting duration of considered samples for each participants*

2.2.2 Physiological Data

2.2.3 Data Cleaning and Quality Assurance

The initial step in data processing was to perform data cleaning and quality assurance on the physiological data collected using the Empatica E4 wrist watches. This process involved the following procedures:

- *Noise Reduction:* Physiological data often contain noise due to various factors, such as sensor inaccuracies or motion artifacts. To address this, we applied noise reduction techniques, including smoothing algorithms and median filtering, to attenuate outliers and smooth the data.

- *Missing Data Handling:* Missing data points are not uncommon in wearable sensor data due to various reasons, including sensor detachment or malfunction. We implemented a robust imputation strategy to estimate missing values by using interpolation techniques and considering the temporal patterns in the data.

- *Outlier Detection:* Outliers in the data, which could be caused by measurement errors or unusual physiological responses, were identified and addressed. Outliers were detected using statistical methods, such as z-scores and interquartile range (IQR) analysis.

Data Temporal Synchronization and Integration

To establish meaningful relationships between physiological responses and meteorological conditions, it was crucial to synchronize the timestamped physiological data with the corresponding meteorological data. This synchronization allowed for a precise alignment of physiological events and environmental conditions. After data cleaning and synchronization, the next step involved the fusion and integration of the physiological and meteorological datasets. This process aimed to consolidate the two streams of data into a single, unified dataset for analysis. Key considerations during data fusion included the temporal alignment of records and the removal of duplicate or redundant information.

3 Correlation Analysis

With the processed and integrated dataset in hand, we conducted a comprehensive correlation analysis to unveil patterns and relationships between physiological responses and environmental conditions. The primary goal was to identify significant associations that could be used to develop personalized comfort models.

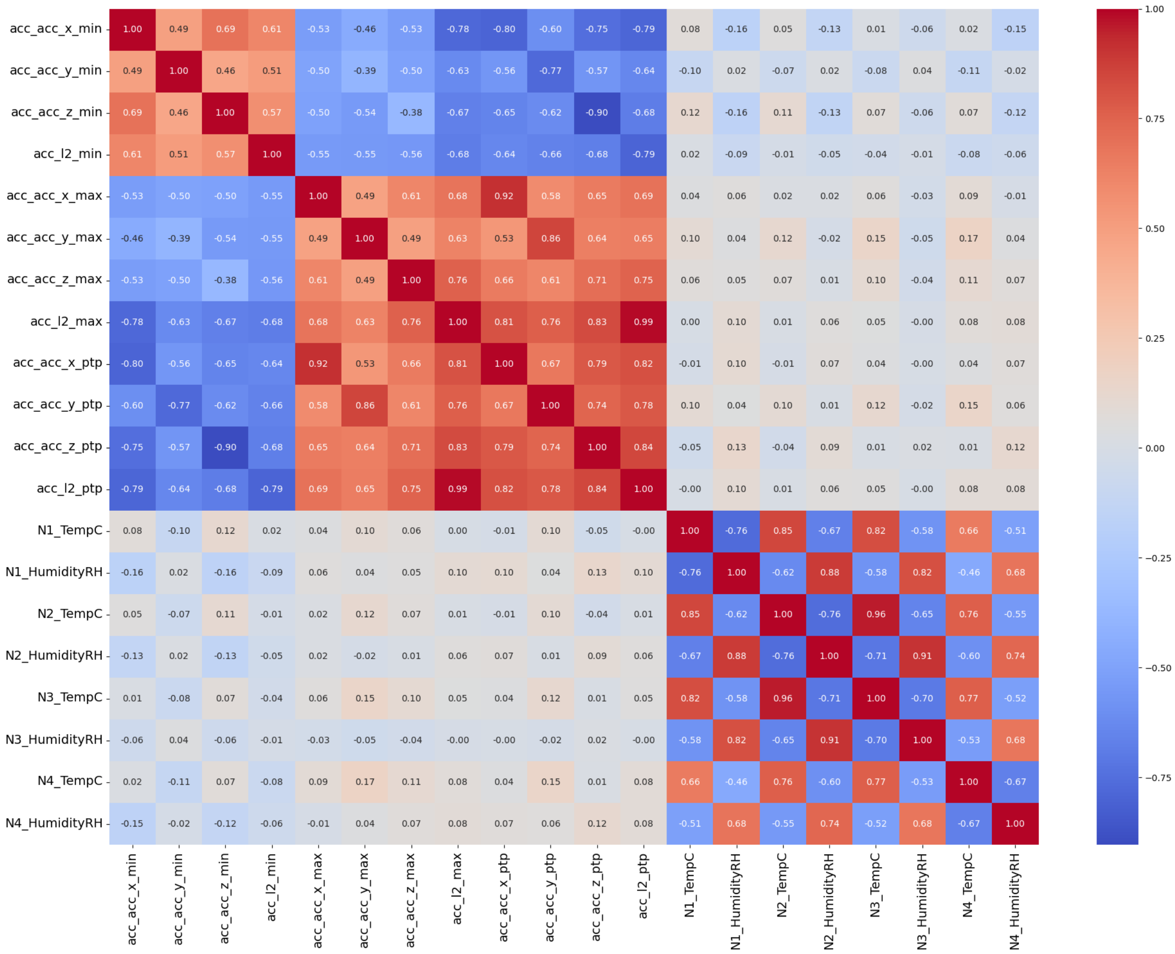

Figure 2: *Accelerometer features and environmental signals correlation heatmap*

Spearman Correlation Analysis

We delved into the intricate relationship between physiological measures of electrodermal activity (EDA) and environmental factors using Spearman correlation analysis. The results unveiled compelling insights into the associations between tonic electrodermal activity (`EDA_tonic_mean`) and various climate parameters. Notably, a substantial positive correlation (Spearman's $\rho = 0.372$, $p < 0.001$) was identified between `EDA_tonic_mean` and ambient temperature (`N1_TempC`), emphasizing the influence of temperature on tonic EDA levels. Conversely, a negative correlation was observed with humidity (`N1_HumidityRH`) (Spearman's $\rho = -0.265$, $p < 0.001$), signifying a potential inverse relationship between humidity and `EDA_tonic_mean`. These findings were consistently replicated with the inclusion of additional temperature and humidity variables (`N2_TempC, N2_HumidityRH, N3_TempC`), further substantiating the nuanced interplay between environmental conditions and tonic electrodermal activity. The significance of these correlations, coupled with the robust p-values ($p < 0.001$), underscores the relevance of climatic factors in shaping autonomic nervous system responses as reflected in electrodermal activity. This nuanced understanding has implications for research in psychophysiology and could inform the development of interventions tailored to specific environmental contexts. However, it is essential to acknowledge the multifaceted nature of these relationships, and further investigations, including potential moderating factors, are warranted to enrich our comprehension of the intricate dynamics between environmental conditions and electrodermal activity.

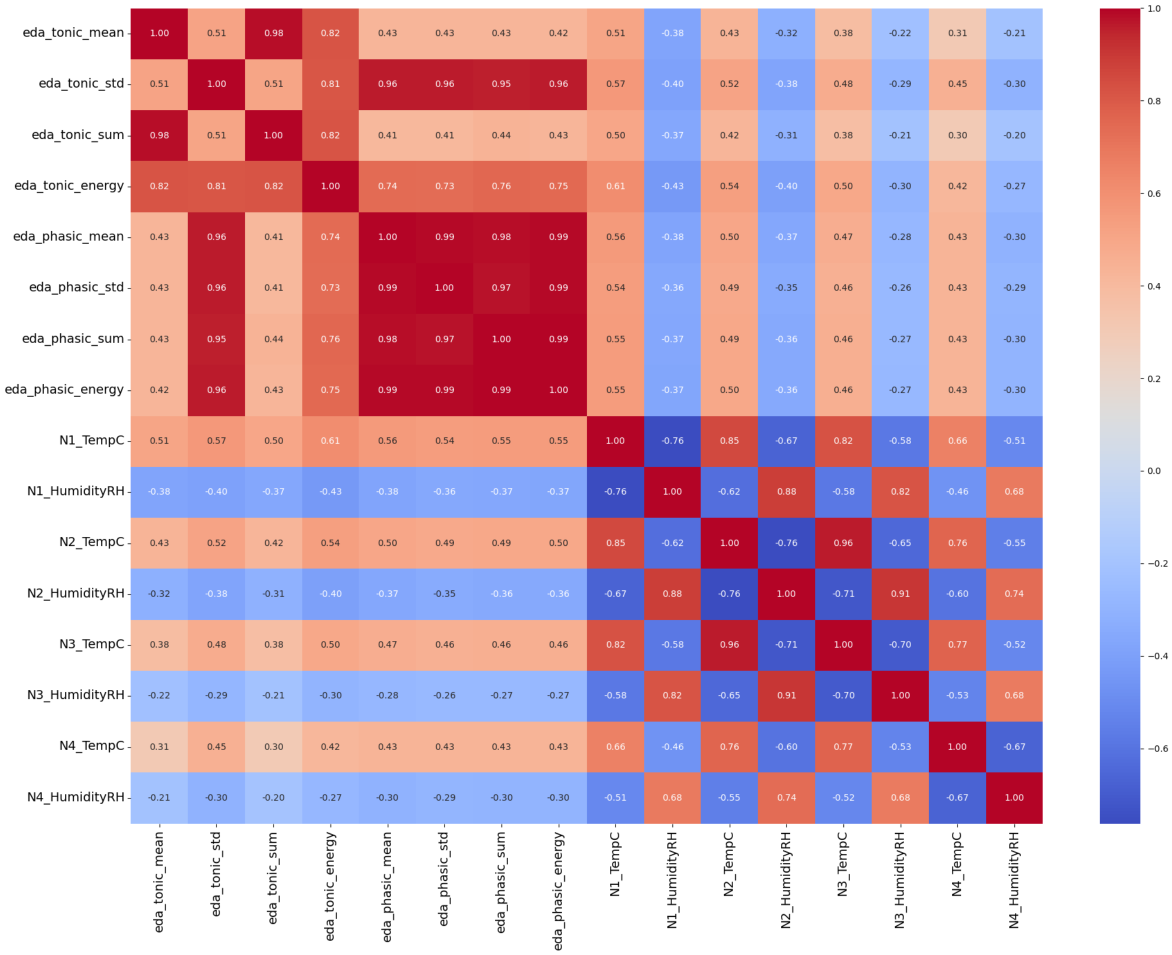

Figure 3: *Electrodermal activity features and environmental signals correlation heatmap*

Regression Analysis

In our analysis, we employed Ordinary Least Squares (OLS) regression to examine the relationship between the dependent variable, `eda_tonic_mean`, and the independent variable `N1_TempC`. The model demonstrated statistical significance, with an overall R^2 of 0.162, indicating that approximately 16.2% of the variance in `eda_tonic_mean` can be explained by the predictor variable. The F-statistic (3.090×10^4) was highly significant (Prob (F-statistic) < 0.001), supporting the validity of the model. The coefficient for `N1_TempC` was estimated at 0.5608 ($p < 0.001$), suggesting a positive relationship between the mean electrodermal activity and temperature. The 95% confidence interval for the coefficient (0.555 to 0.567) further supported the precision of this estimate. Notably, the intercept was -12.3328 ($p < 0.001$), representing the estimated value of `eda_tonic_mean` when `N1_TempC` is zero. The diagnostic tests, including the Omnibus, Durbin-Watson, and Jarque-Bera statistics, were conducted to assess the model's assumptions. While the results provide valuable insights, further exploration of residuals and potential sensitivity analyses will be essential for a comprehensive understanding of the findings.

In our comprehensive regression analysis, we investigated the relationship between the mean electrodermal activity (`eda_tonic_mean`) and various temperature variables (`N1_TempC, N2_TempC, N3_TempC, N4_TempC, N5_TempC`). Initially, we observed individual regressions for `N1_TempC` and `N2_TempC`. For `N1_TempC`, the model yielded an R^2 of 0.135, with a coefficient of 0.5296 ($p < 0.001$), indicating a positive association. The second model for `N2_TempC` exhibited an R^2 of 0.162, with a coefficient of 0.5608 ($p < 0.001$), also suggesting a positive relationship. Subsequently, a more complex model including `N1_TempC, N2_TempC, N3_TempC, N4_TempC, and N5_TempC` was considered. This extended model resulted in an R^2 of 0.310, indicating that

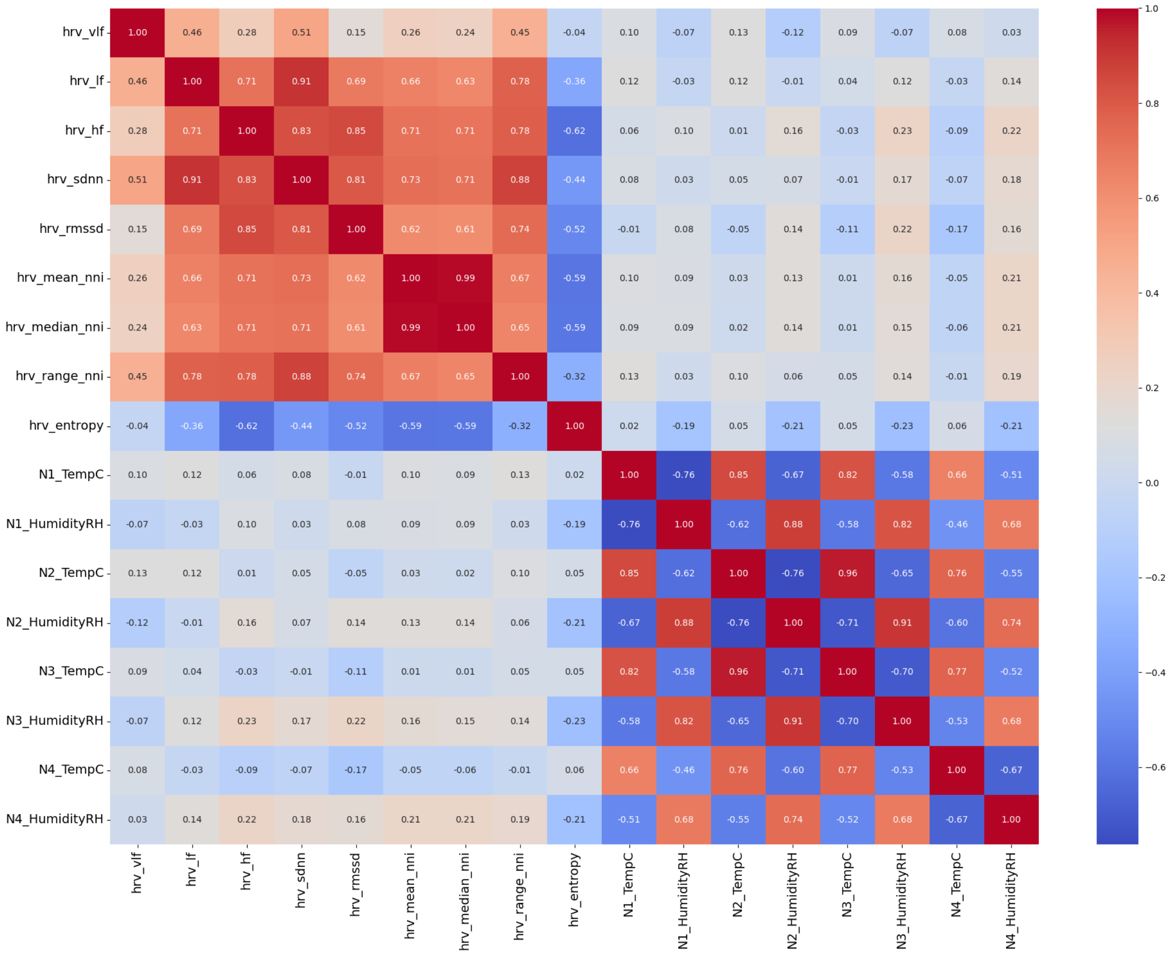

Figure 4: *Heart rate variation features and environmental signals correlation heatmap*

the inclusion of additional temperature variables substantially improved the explanatory power of the model. Individual coefficients for each temperature variable were estimated, and their significance varied, with `N2_TempC` and `N5_TempC` exhibiting strong positive associations with `eda_tonic_mean`, while `N3_TempC` showed a negative association. Additionally, similar analyses were performed for the dependent variable `eda_phasic_mean`, where temperature variables exhibited varying degrees of influence. These findings underscore the nuanced relationship between temperature and electrodermal activity, highlighting the importance of considering multiple factors in understanding physiological responses. Further examination of residuals and diagnostic tests will be conducted to ensure the robustness of these results.

4 Result and Discussion

5 Conclusion

References

Appendix A

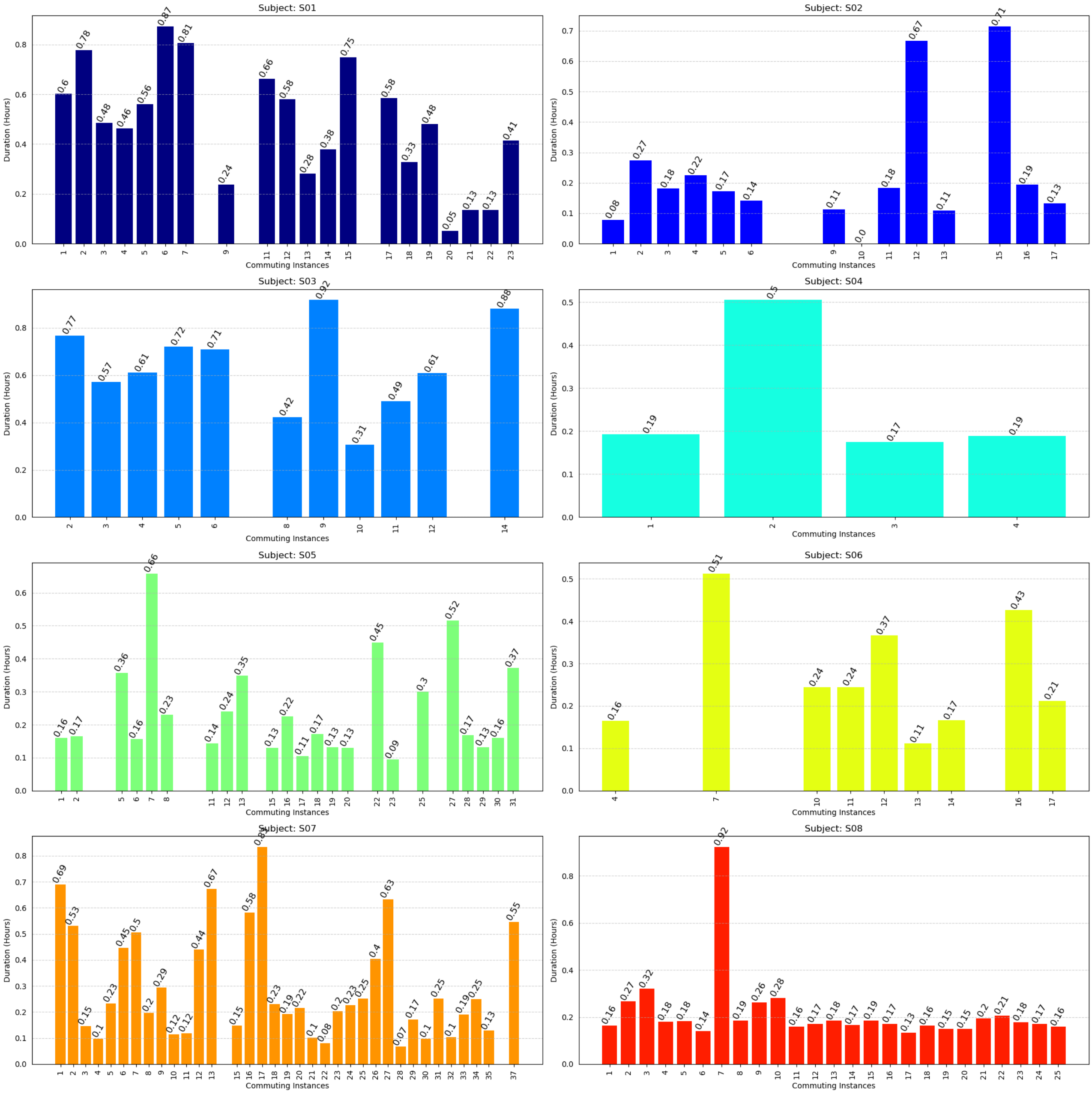

Figure 5: *Samples of each participants and duration of each sample instance*

Appendix B

Empatica Technical Specification

PPG Sensor

- Sampling frequency 64 Hz (Non customizabl
- LEDs: Green (2 LEDs), Red (2 LEDs) Photodiodes: 2units, total 15.5 mm2 sensitive area.
- Sensor output: Blood Volume Pulse (BVP) (variationof volume of arterial blood under the skin resultingfrom the heart cycle)
- Sensor output resolution 0.9 nW / Digit.
- Motion artifact removal algorithm:
- Combines different light wavelengths.
- Tolerates external lighting conditions

Infrared thermopile

- Sampling frequency: 4 Hz (Non customizable)
- Range:
- -40...85°C for ambient temperature.
- -40...115°C for skin temperature.
- Resolution: 0.02°C.
- Accuracy ±0.2°C within 36-39°C

EDA Sensor

- Sampling frequency: 4 Hz (Non customizable).
- Resolution: 1 digit 900 pSiemens.
- Range: 0.01 μSiemens – 100 μSiemens.
- Alternating current (8Hz frequency) with amax peak to peak value of 100 μ-Amps (at 100μ-Siemens).
- Electrodes: • Placement on the ventral (inner) wrist.
- Snap-on silver (Ag) plated with metallic core.
- Electrode longevity: • 4–6 months

3-Axis acceleromete

- Sampling frequency: 32 Hz (Non customizable).
- High sensitivity motion detection across 3 axes:X,Y, and Z.
- Default range ±2g.
- Ranges of ±4g or ±8g are selectable with custom.
- Resolution: 8 bits of the selected range.

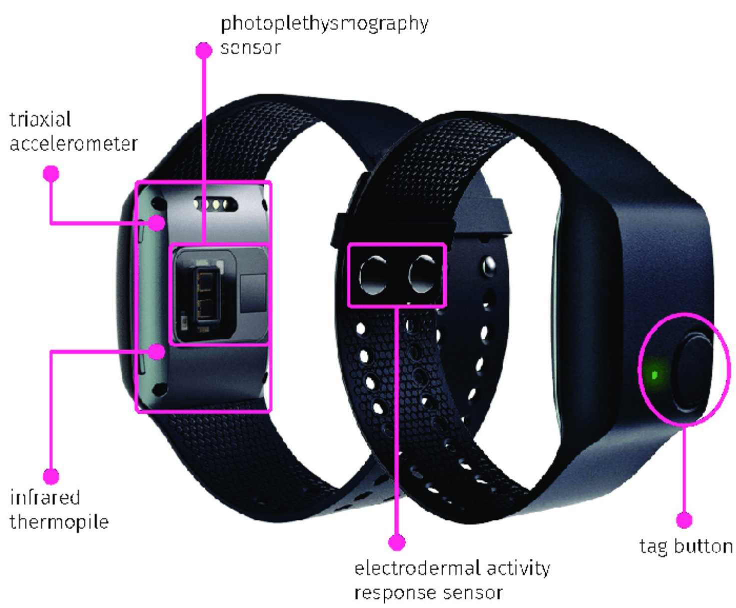

Figure 6: *E4 wristband, overview of sensors (adapted from Empatica.com)*