Unobtrusive Sensing of Skin Temperature During Sleep Using a Mattress Sensor

Nikhil Makaram[1], Pavlo Chernega[2], Megha Rajam Rao[1], Sai Ashrith[1], Yehor Shcherbakov[2], Shawn Barr[1], Gary Garcia-Molina[1]

[1]Sleep Number Labs, San Jose, CA; [2]GlobalLogic, Kyiv, Ukraine

INTRODUCTION

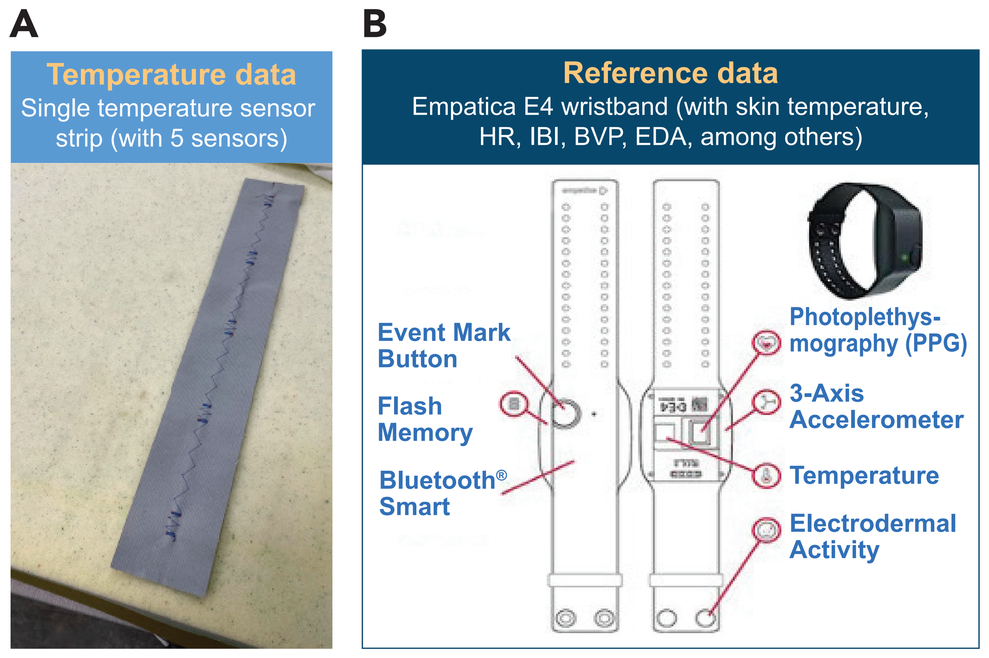
- Skin temperature is controlled by both environmental and endogenous processes, including central and autonomic nervous system functions, that actively regulate blood flow through the skin.[1]
- At sleep onset, distal (hands and feet) and proximal (abdomen) temperatures increase by about 1°C and about 0.5°C, respectively, forming a distal-to-proximal gradient that increases throughout the first half of a night's sleep.[2,3]
- During the same period, core body temperature decreases by approximately 1°C and heart rate decreases by approximately 5 bpm.[2]
- Few devices can measure these temperatures unobtrusively, yet quantification of skin temperature under real-world, ecologically valid conditions could enable a deeper understanding of temperature dynamics during sleep.
- Studies quantifying temperature during sleep have been limited in both the number of participants and sleep sessions due to the high burden associated with system setup, availability of resources, and cost.[4,5]
- Our study aim was to estimate distal skin temperature unobtrusively during sleep using a temperature sensor array on a mattress.

METHODS

Experimental design

- Thirteen volunteers (5 female, 8 male), with a mean age of 38.5 years (SD: 7.9 y), participated in a home-based study, which took place from February 6, 2022, to March 16, 2022.
  - A total of 120 sleep sessions were recorded (9.23 ± 6.0 sessions/participant).
- Skin temperatures were estimated using an array of 5 equally spaced thermistors (**Figure 1A**).
- Each participant wore an Empatica E4 wristband (Empatica, Boston, MA) to provide benchmark distal skin temperatures (**Figure 1B**).

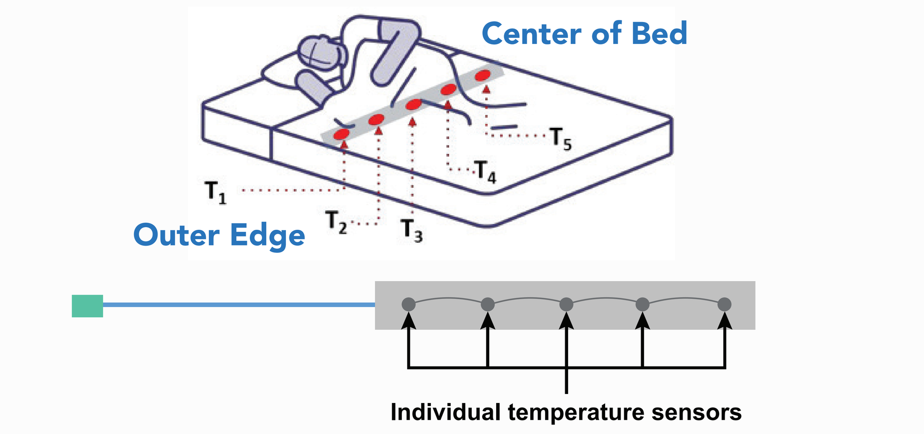
FIGURE 1: EXPERIMENTAL AND BENCHMARK TEMPERATURE SENSORS.



Experimental temperature data were collected by a temperature sensor strip (A). Benchmark data were collected using an Empatica E4 wristband worn by each participant (B). Images used with permission from Empatica, Inc. BVP, blood volume pulse; EDA, electrodermal activity; HR, heart rate; IBI, interbeat interval.

- **Figure 2** shows the position of the temperature sensor strip within the mattress and the configuration of the thermistors within the temperature sensor strip.

FIGURE 2: CONFIGURATION OF THE TEMPERATURE SENSOR STRIP WITHIN THE MATTRESS (A) AND TEMPERATURE SENSOR ARRAY WITHIN THE STRIP (B).

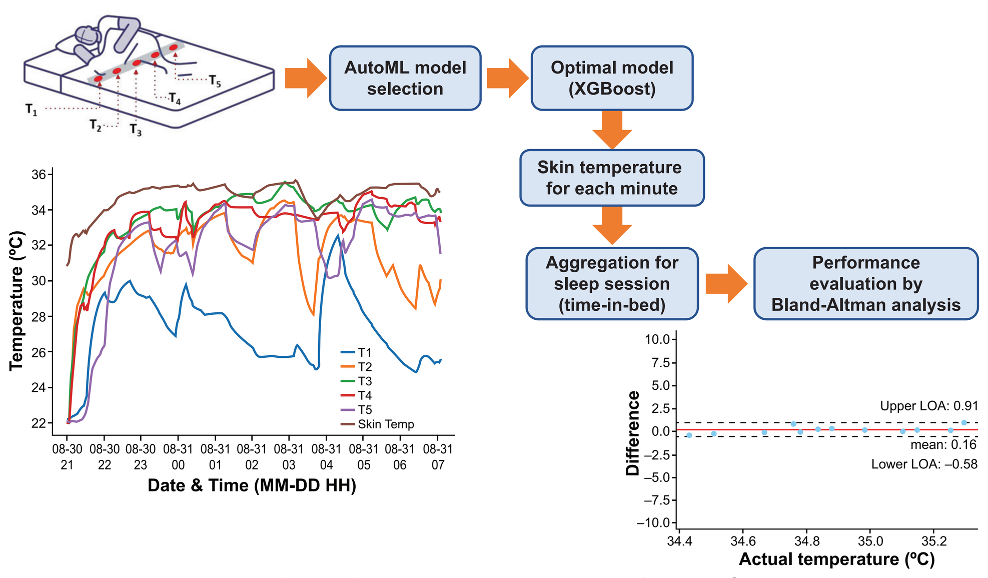


Panel A shows half of the mattress. The distance between the temperature sensors was 5.5 to 7 in, depending on the mattress size. T, individual thermistor positions on the temperature sensor strip.

Data collection, analysis and model development

- Temperature was recorded in Celsius at an approximate frequency of 0.2 Hz per sensor.
- Data were gathered from the temperature sensor strip and processed by a skin temperature estimation algorithm to produce a graphical representation of temperatures for each sleep session (**Figure 3**).
- After further processing and down-sampling, data from mattress-presence hours were used to build predictive models estimating distal skin temperature.
- The preprocessed data were grouped by participant and segmented into training and test sets (approximately 60%/40%, respectively), with earlier sleep sessions selected for model training and later sessions selected for testing.
  - The model was trained on 533 hours of data and tested on 388 hours of data.
- Using the Automated Machine Learning (AutoML) feature in Databricks,[6] a model was developed that optimized the coefficient of determination R^2 between the benchmark skin temperature provided by Empatica and our estimation.
- This model was applied to the test set and its performance evaluated by generating a Bland-Altman plot[7] to assess the limits of agreement (LOAs) between the averages of the predicted wearable temperature and actual wearable temperature readings (**Figure 3**).

FIGURE 3: DATA COLLECTION, ALGORITHM PROCESSING, AND BLAND-ALTMAN ANALYSIS TO EVALUATE THE PERFORMANCE OF THE SMART MATTRESS.



AutoML, Automated Machine Learning; LOA, limit of agreement; SD, standard deviation; T, thermistor.

RESULTS

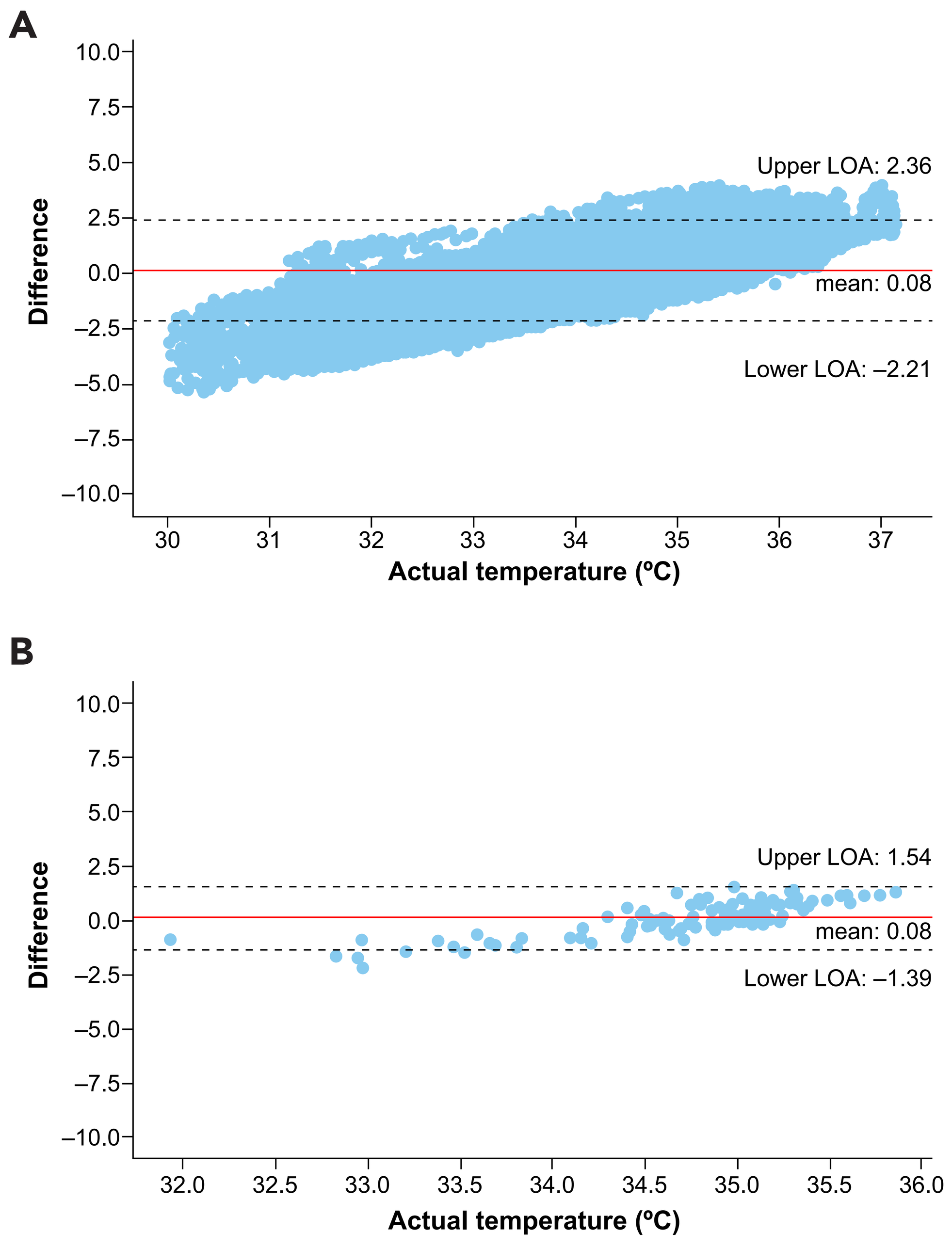
- The AutoML selected an XGBoost decision-tree model[8] to predict distal skin temperature for each minute.
- At the minute level, the mean difference in temperature between predicted and benchmark readings was 0.04°C, with lower and upper LOAs of -1.92 and 2.00 respectively (**Table 1**).
- Next, all minute-level data were averaged by sleep session, and model performance was re-evaluated across all sleep sessions.
- This approach resulted in narrower LOAs, with the same mean difference of 0.04°C (**Table 1**).
- Bland-Altman analysis using all cross-validation data combined confirmed that the system performed well at the minute level (**Figure 4A**) and at the sleep session level (**Figure 4B**).

TABLE 1: MEAN DIFFERENCE IN TEMPERATURE BETWEEN PREDICTED AND BENCHMARK READINGS.

Parameter	Minute-level analysis	Aggregate sleep-session level analysis
Mean difference, °C (CI)	0.04 (−0.42, 0.50)	0.04 (−0.41, 0.49)
Lower LOA, °C (CI)	−1.92 (−2.45, −1.39)	−0.55 (−1.06, −0.04)
Upper LOA, °C (CI)	2.00 (1.47, 2.53)	0.64 (0.23, 1.05)

CI, confidence interval; LOA, limit of agreement.

FIGURE 4: BLAND-ALTMAN ANALYSIS USING ALL CROSS-VALIDATION DATA, COLLECTED AT THE MINUTE LEVEL (A) AND AT THE SLEEP-SESSION LEVEL (B).



LOA, limit of agreement.

Limitations:

- Generalized model development across all participants likely led to broader LOAs and lower R^2 than individualized modeling would have produced because readings from the temperature array showed high interparticipant variability.
- Optimization of settings and occasional sensor failures restricted the number of sleep sessions that were suitable for analysis.

CONCLUSIONS

- These results suggest that a temperature sensor array, coupled with an optimized decision-tree model, can estimate distal skin temperature with an accuracy characterized by a 0.04°C bias for both 1-minute resolution and sleep-session mean. The LOAs were 3.9°C and 1.2°C wide for the 1-minute resolution and the sleep-session mean, respectively.
- Our system enabled unobtrusive, ecologically valid collection of distal skin temperatures during sleep and may be useful for future studies of overnight temperature dynamics.

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DISCLOSURES

NM, **MRR**, **SA**, **SB** and **GGM**: Employees of Sleep Number Corporation. **PC** and **YS**: Employees of GlobalLogic. GlobalLogic is a consultant under contract with Sleep Number Corporation.

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