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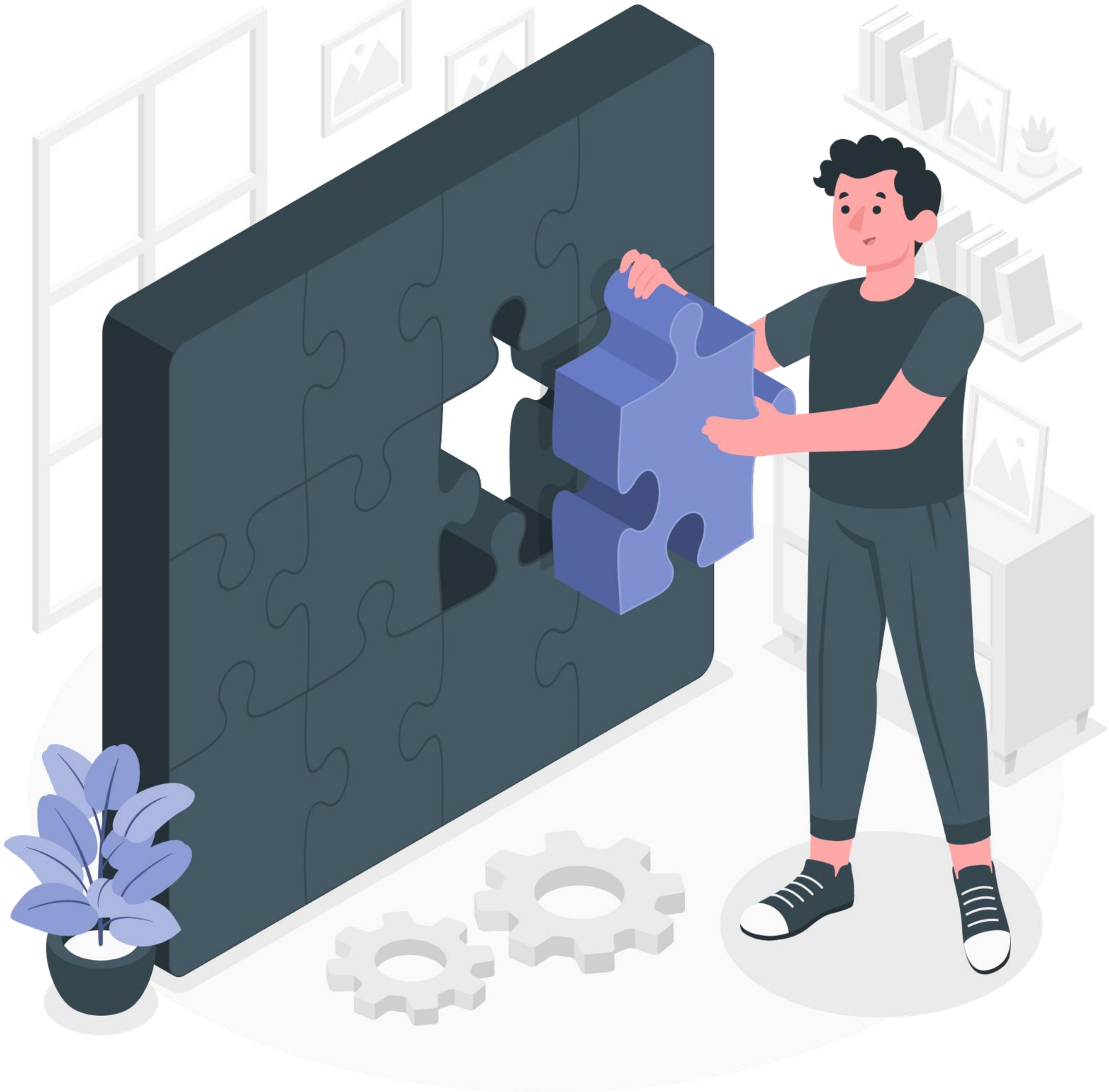

On the mismatch between measured and perceived sleep quality

Wellcomp 15/09/2022

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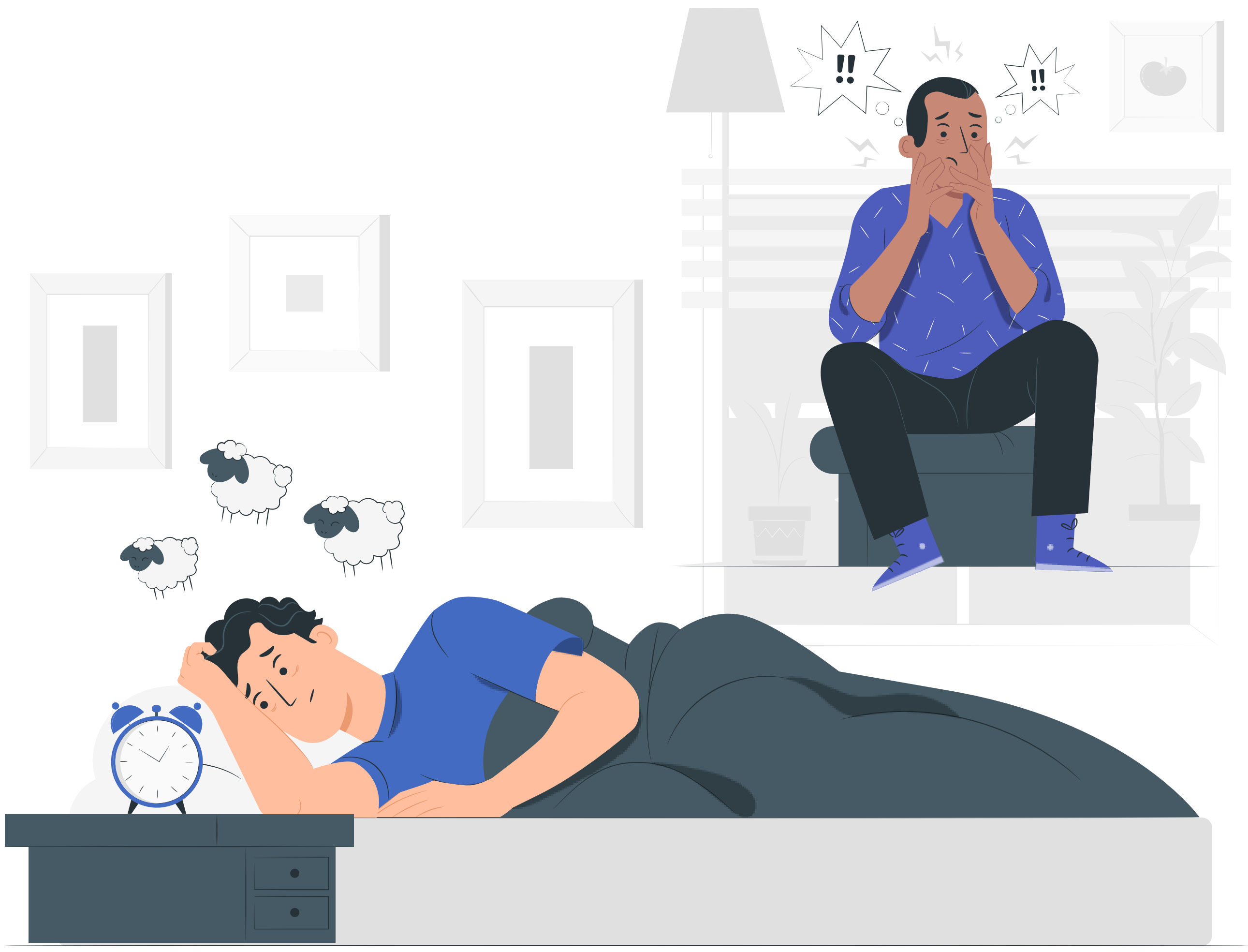
Motivation - Sleep

- Short term
  - Headache
  - Dizziness
  - Concentration
- Long term
  - Diabets
  - Cancer
  - Parkinson disease
  - Weakened immune system



Sleep Quality

"one's satisfaction of the sleep experience, integrating aspects of sleep initiation, sleep maintenance, sleep quantity, and refreshment upon awakening" [1].

[1] Christopher Kline. 2013. Sleep Quality. Springer New York, New York, NY.

Sleep Quality

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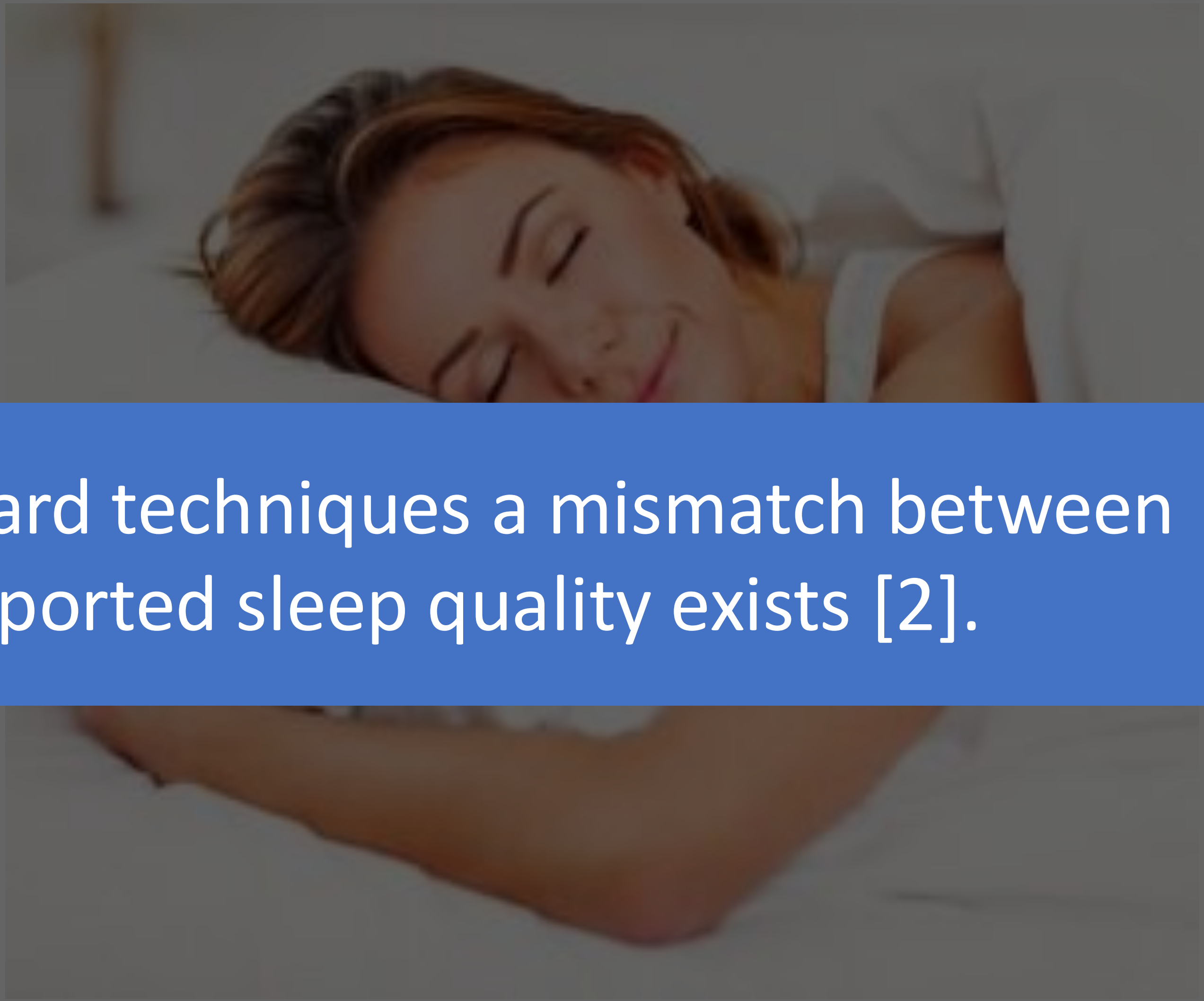

Even with sleep gold-standard techniques a mismatch between measured and self-reported sleep quality exists [2].

[2] Katherine A. Kaplan, Jason Hirshman, Beatriz Hernandez, Marcia L. Stefanick, Andrew R. Hoffman, Susan Redline, Sonia Ancoli-Israel, Katie Stone, Leah Friedman, and Jamie M. Zeitzer. 2017. When a gold standard isn’t so golden: Lack of prediction of subjective sleep quality from sleep polysomnography. Biological Psychology 123 (2017), 37–46.

[1] Christopher Kline. 2013. Sleep Quality. Springer New York, New York, NY.

Goal

Compare human self-reported scores of sleep quality with objective measurements provided by wearable devices.

Approach

Dataset (M2Sleep[8])

- Subjects: 16
- Self-reported data:
  - Daily:
    - Sleep start/end
    - Sleep quality
  - Day 0:
    - Demographics
    - Pittsburgh sleep quality index (PSQI)
    - Big five inventory (BFI)
    - Munich chronotype questionnaire (MCTQ)
- Days: 30
- Physiological data (wristband):
  - Accelerometer
  - Skin temperature
  - Electrodermal activty
  - Photoplethysmography (PPG)

[8] Shkurta Gashi, Lidia Alecci, Elena Di Lascio, Maike E. Debus, Francesca Gasparini, and Silvia Santini. 2022. The Role of Model Personalization for Sleep Stage and Sleep Quality Recognition Using Wearables. IEEE Pervasive Computing 21, 2 (2022).

Preprocessing and feature extraction

Sensor-based

Normalization: subtracting mean (subject-based)

Segmentation: before sleep (4 hours before sleep start), during sleep (between sleep start and sleep end), after sleep (4 hours after sleep end).

Non-sensor-based

Feature extraction:

- Self-reported: BFI (personality), PSQI, age, average sleep duration (MCTQ), weekly sleep loss (MCTQ).
- Quantitative sleep metrics: sleep duration, awakenings.
- Context metrics: day of week, weekend, lunar phase.

Feature Extraction – Sensors

Feature	Sensor	Description	Method
ACC	ACC	Magnitude	$\sqrt{x^2 + y^2 + z^2}$
HR	PPG	Heart rate	nk.ppg.process [3]
TEMP	TEMP	Raw TEMP	TEMP raw
EDA	EDA	Raw EDA	EDA raw
EDA Peak Epoch	EDA	5 peaks or more in a minute	Burch et al. [4]
EDA Storm	EDA	Peak epoch lasts 10 minutes or more	Sano and Picard [5]
Artifact	EDA	Abrupt rise, drop, peak drop rise quickly, peaks too close	EDArtifact [6]
EDA Filtered	EDA	1st order Butterworth low-pass filter, cut-off of 0.6 Hz	EDArtifact [6]
EDA Phasic	EDA	Quickly changing component of the raw EDA signal	cvxEDA [7]
EDA Tonic	EDA	Slowly changing component of the raw EDA signal	cvxEDA [7]

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For each feature we extracted statistic measures:

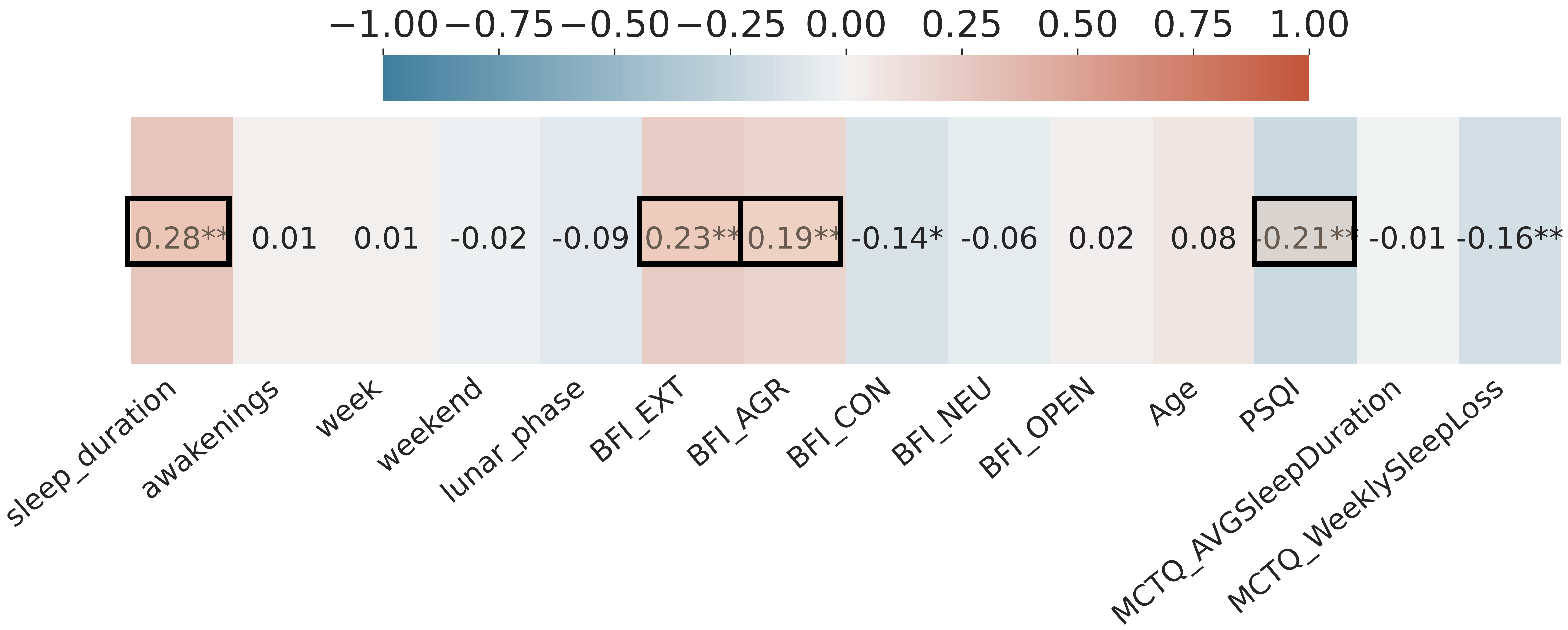
sum, mean, median, mean absolute deviation (mad), minimum, maximum, mode, standard deviation (std), difference between maximum and minimum, ratio between maximum and minimum, skew, kurtosis, and 10th, 20th, 30th, 40th, 60th, 70th and 80th percentile.

Results – Comparison commercial devices (MiBand)

User	Accuracy	Balance Accuracy	Recall	Precision
User 1	6.45%	**5.71%**	6.45%	47.31%
User 2	41.38%	**17.14%**	41.38%	23.17%

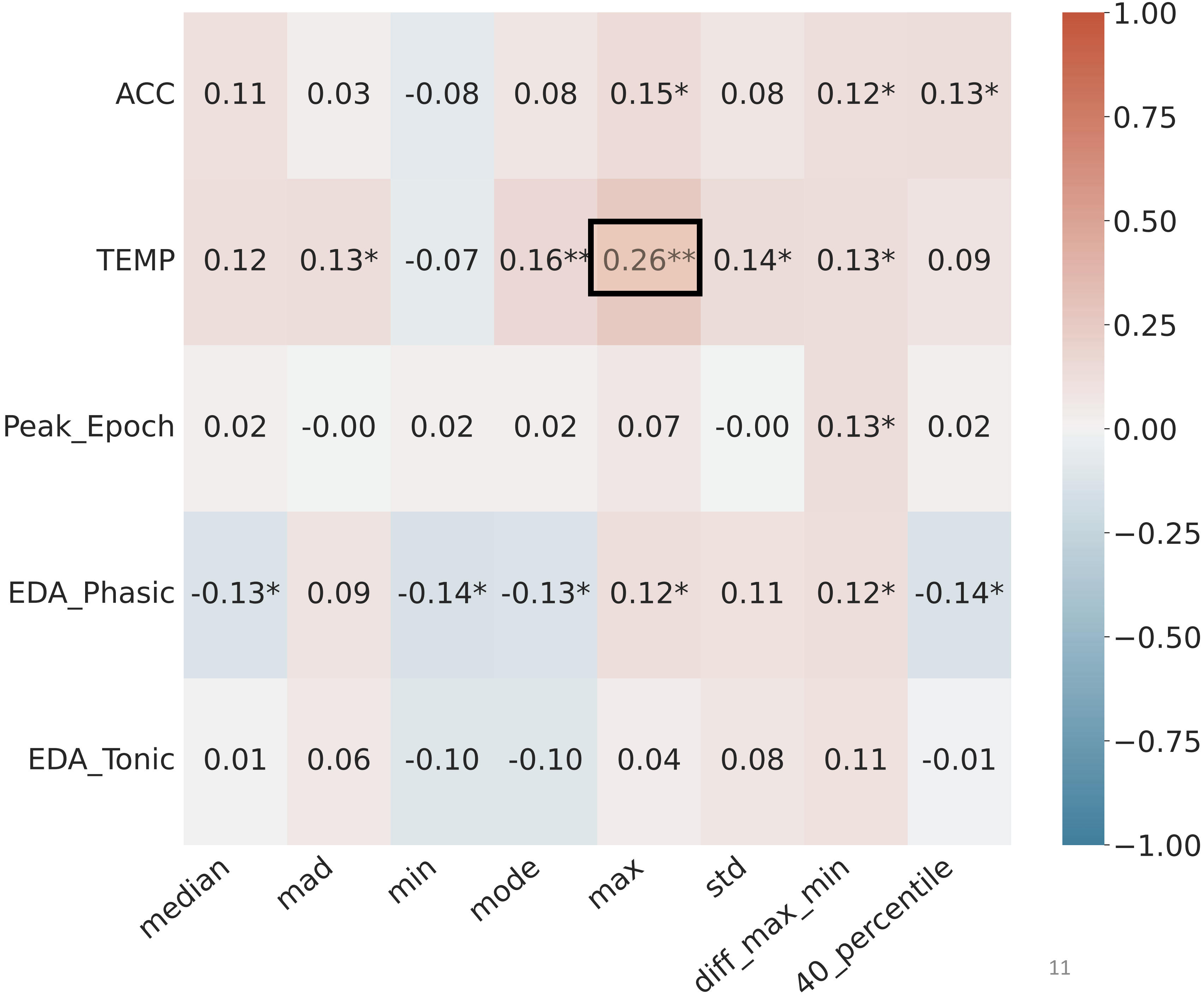
Sleep quality score on a 5-level Likert scale

Results – Correlation non-sensor-based



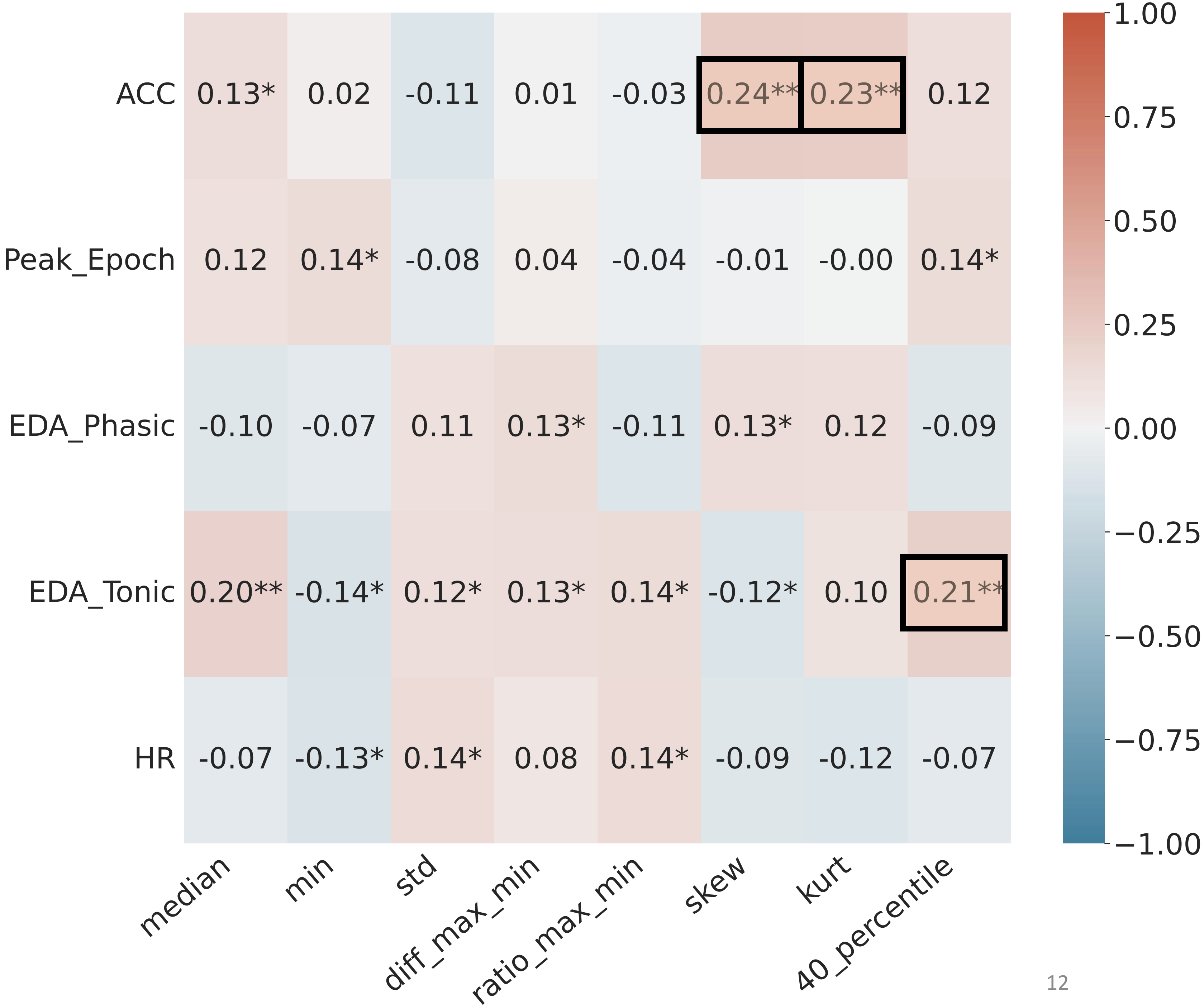
** p value < 0.001, * p value < 0.01

Results – Correlation sensor-based Before sleep



** p value < 0.001, * p value < 0.01

Results – Correlation sensor-based During sleep



** p value < 0.001, * p value < 0.01

Conclusion

- Self-reported sleep quality correlates weakly with sleep quality computed by commercial devices or sensor data traces or sleep metrics.
- No statistical significance between self-reported sleep quality and physiological responses after sleep.
- Max TEMP before sleep, ACC skew and kurt and 40 percentile EDA tonic > 0.20 Spearman’s correlation and statistical significance.
- Psychological traits correlate significantly with perceived sleep quality (suggesting bias).

Thank you!

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[1] Christopher Kline. 2013. Sleep Quality. Springer New York, New York, NY.

[2] Katherine A. Kaplan, Jason Hirshman, Beatriz Hernandez, Marcia L. Stefanick, Andrew R. Hoffman, Susan Redline, Sonia Ancoli-Israel, Katie Stone, Leah Friedman, and Jamie M. Zeitzer. 2017. When a gold standard isn't so golden: Lack of prediction of subjective sleep quality from sleep polysomnography. Biological Psychology 123 (2017).

[3] Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., & Chen, S. A. (2021). NeuroKit2: A Python toolbox for neurophysiological signal processing. Behavior Research Methods, 53(4), 1689–1696.

[4] Neil R Burch. 1965. Data Processing of Psychophysiological Recordings (Discussant: Harold W. Shipton). NASA Special Publication 72 (1965).

[5] Akane Sano and Rosalind Picard. 2011. Toward a taxonomy of autonomic sleep patterns with electrodermal activity. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2011.

[6] Shkurta Gashi, Elena Di Lascio, Bianca Stancu, Vedant Das Swain, Varun Mishra, Martin Gjoreski, and Silvia Santini. 2020. Detection of Artifacts in Ambulatory Electrodermal Activity Data. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 2, Article 44 (jun 2020).

[7] Alberto Greco, Gaetano Valenza, Antonio lanatà, Enzo Scilingo, and Luca Citi. 2016. cvxEDA: A convex optimization approach to electrodermal activity processing. IEEE transactions on biomedical engineering 2016 (04 2016).

[8] Shkurta Gashi, Lidia Alecci, Elena Di Lascio, Maike E. Debus, Francesca Gasparini, and Silvia Santini. 2022. The Role of Model Personalization for Sleep Stage and Sleep Quality Recognition Using Wearables. IEEE Pervasive Computing 21, 2 (2022).