Philipps Universität Marburg

Associations between ecological momentary assessment and passive sensor data in a large student sample

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Digital Phenotyping in Mental Health Research

- Many **promises** of wearable sensor data: Scalable forms of assessment, high temporal resolution, more “objective”(?) measurements

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- Focus on three **transdiagnostic markers**:
    - **Stress** (transdiagnostic marker)
    - **Sleep** (common in DSM-5, robust contributor to psychopathology)
    - **Tiredness** (indicator of sleep problems, related to depression and other disorders)

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- Continuous physiological monitoring

Sensor-EMA Features

Self-report variable	Sensor variable

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Self-reported stress *"I feel stressed right now"*	Mean sensor stress Based on HR, HRV, & activity; scored 0-100 (0-25: resting, 26-50: low, 51-75: medium, 76-100: high stress).

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Self-reported sleep quality *"Last night, I slept well"*	Sensor total sleep duration Total sleep duration in hours

Note: All self-report variables measured on 1-7 Likert scale ("not at all" to "very much")

Methods

Multilevel models in `nlme` with maximum likelihood estimation:

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$$\underset{\text{Sensor outcome}}{y_{it}} = \overset{\text{Fixed intercept}}{\beta_0} + \overset{\text{WP effect}}{\beta_1} (x_{it} - \bar{x}_i) + \underset{\text{BP effect}}{\beta_2} \bar{x}_i + \overset{\text{Time-of-day}}{\beta_3} d_{it} + \underset{\text{Random intercept}}{u_{0i}} + \overset{\text{Random slope}}{u_{1i}} (x_{it} - \bar{x}_i) + \underset{\text{Error}}{e_{it}}$$

Additional Analyses

Analysis	Stress	Tiredness	Sleep
Interaction with Age, Gender, Depression, Cohort	✓	✓	✓
Change of Residual Correlation Structure	✓	✓	✓
Informed “Binning” of Outcome	✓	✓	✗
Alternative Outcome Operationalization	✓	✓	✗
Different Lags & Aggregations	✓	✓	✗

Main Results: EMA-Sensor Associations

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	Stress	Tiredness	Sleep
WP association	0.49	-1.55	0.33
95% CI	(0.35, 0.63)	(-1.68, -1.42)	(0.31, 0.35)
R^2 (conditional)	0.22	0.42	0.28
RMSE	21.66	20.46	1.33

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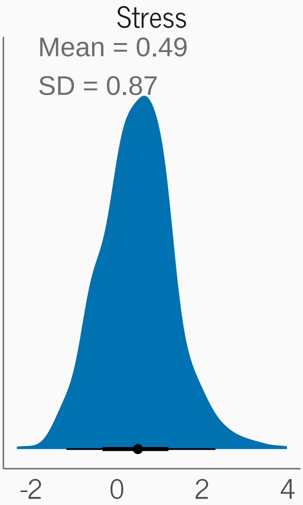
Additional Findings

Cohort Differences: Stress weaker in cohorts 2 & 4 (summer); Tiredness & Sleep stronger in cohorts 2 & 4

Demographics: No significant effects of age, gender, or depression on associations

Individual Estimates



Regression Estimate

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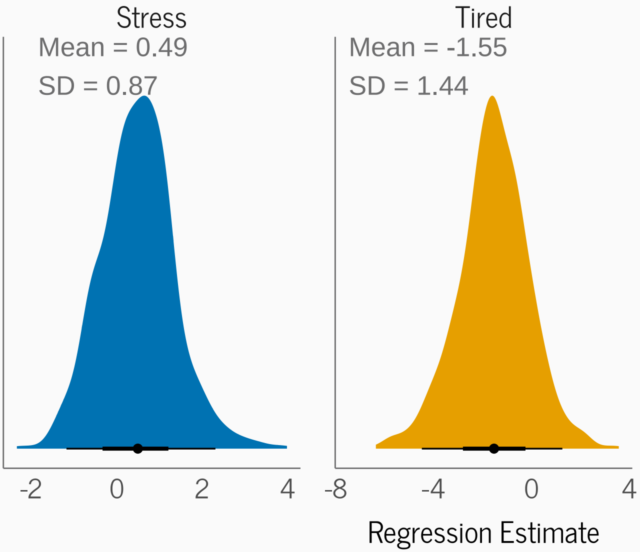

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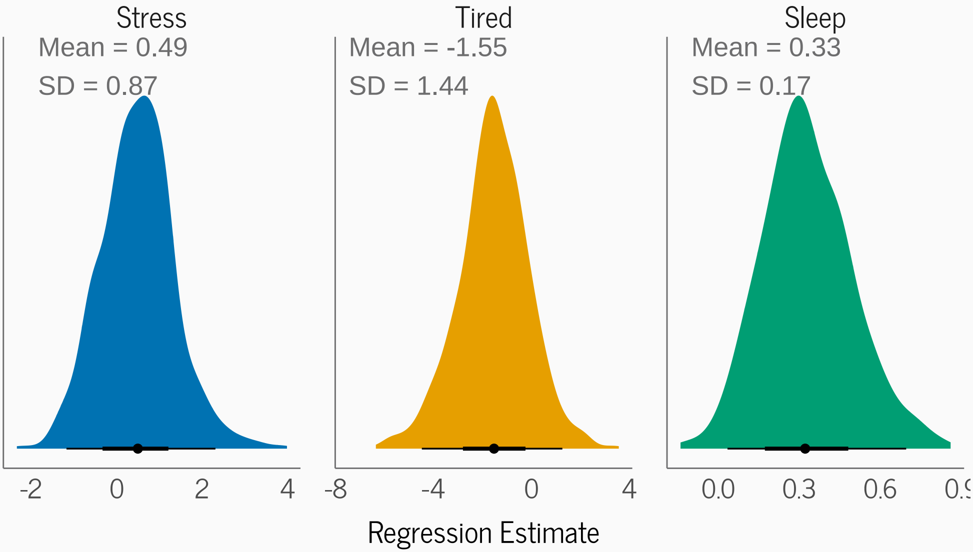
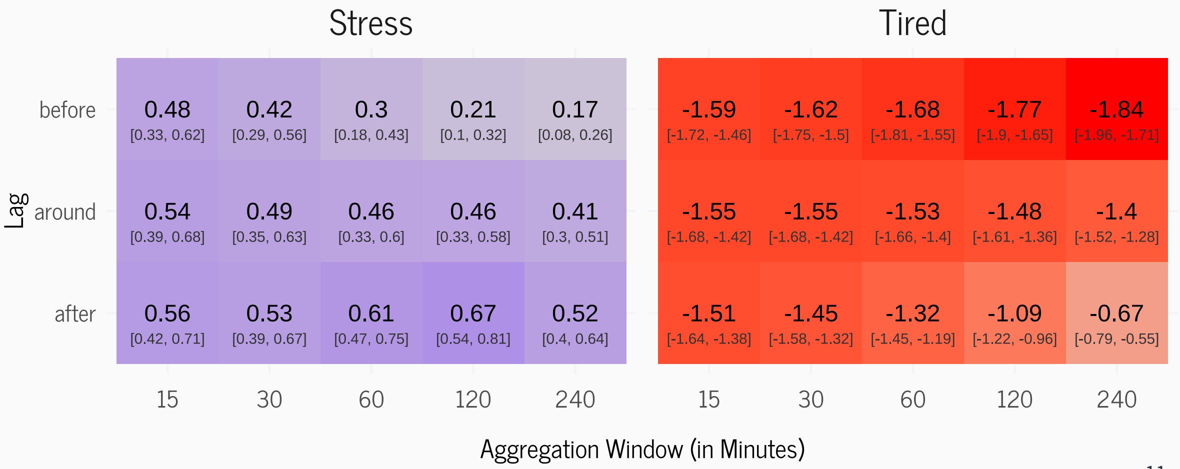
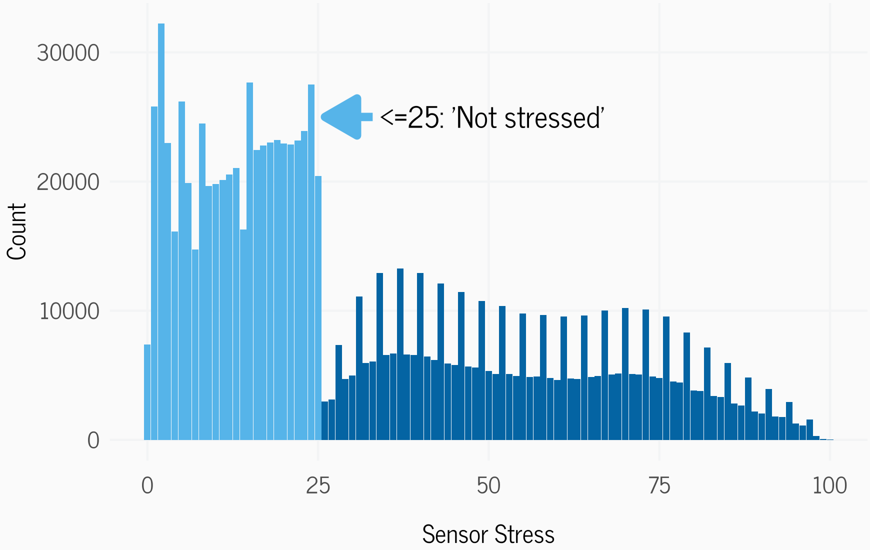


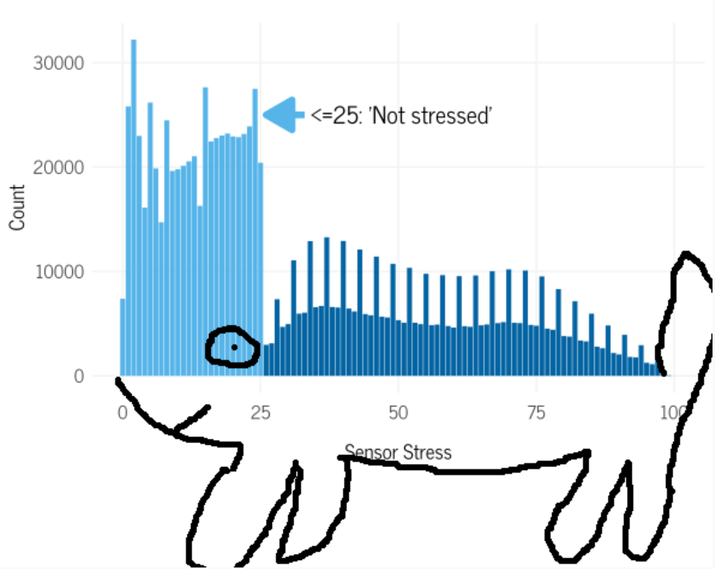
Sensitivity Analysis



Raw Stress Distribution



Stress Dinosaur



Key Takeaways

Findings:

- **Stress:** Weak to no associations

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Image credit: Advnture/Future

Thank you

WARN-D TEAM

Get In Touch

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- BlueSky: bsiepe
- https://bsiepe.github.io/

Paper & Slides

References i

Image Source

Garmin Watch:
https://www.advnture.com/news/
if-your-garmin-watch-is-giving-you-strange-stress-warning-dont-ignore-them