DPK2025 - Bergfest in Berlin

Uncovering daily symptoms: **long-term digital phenotyping and EMA** in patients undergoing cognitive behavioral therapy for internalizing disorders (SP6)

M.Sc. Leona Hammelrath, Dr. Annette Brose, Prof. Dr. Christine Knaevelsrud

Department of Clinical Psychological Intervention,

Freie Universität Berlin, Germany

FOR 5187 PREACT

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FOR SP6/ PREACT-digital

Can we depict symptoms in everyday life and predict therapy non-response using digital phenotyping and EMA?
→focus on emotion regulation

FOR SP6/ PREACT-digital

Can we depict symptoms in everyday life and predict therapy non-response using digital phenotyping and EMA?

- ⇒ Digital Phenotyping and EMA in Mental Health
- ⇒ PREACT-digital study (SP6)
- ⇒ DP in Psychotherapy? Feasibility and Engagement
- ⇒ Ongoing study

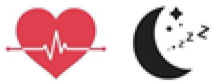
Background: DP & EMA in Mental Health

Background

Collect data in the patients' **everyday life**

Digital Phenotyping (DP)

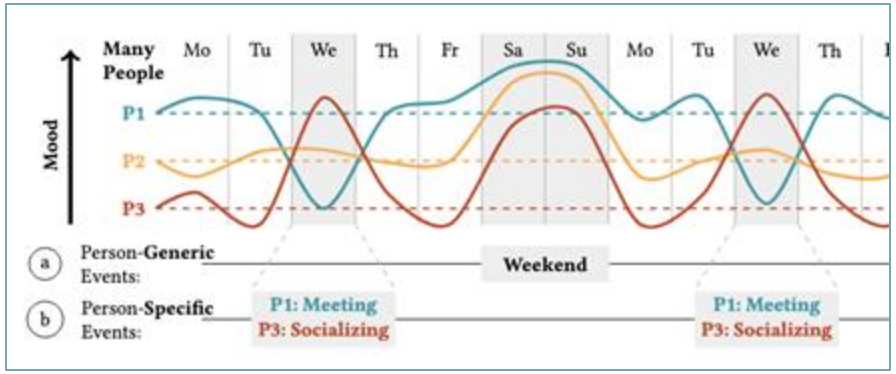
→ **passive**
→ via wearables (i.e. Smartwatch) or smartphones



→ low burden
→ allows long-term continuous, real time data collection

EMA *(Ecologically momentary assessment)*

→ **active**, i.e. user input required
→ short, repeated self-reports on the smartphone
→ high temporal resolution, no retrospective bias
→ catches fluctuations in real time (i.e. mood)



Wörtwein et al., 2023

Background

Uncover **daily symptoms** in internalizing disorders using **DP** and **EMA**

Internalizing Disorders

→most common: diagnosis of depression (i.e. RADAR study)
→ i.e. time at home predicts change in PHQ-8 scores (Zhang et al., 2022)

→ Large heterogeneity in study designs and outcomes; many shortcomings

→ **DP** in its **infancy**!

Psychotherapy

→ no studies predicting **psychotherapy outcomes** using DP!

→ De Angel et al (2023): feasibility of DP in patients doing psychotherapy
→ good adherence; declines when therapy starts; but small sample

→ need for more studies on DP during psychotherapy in internalizing disorders!

PREACT-digital

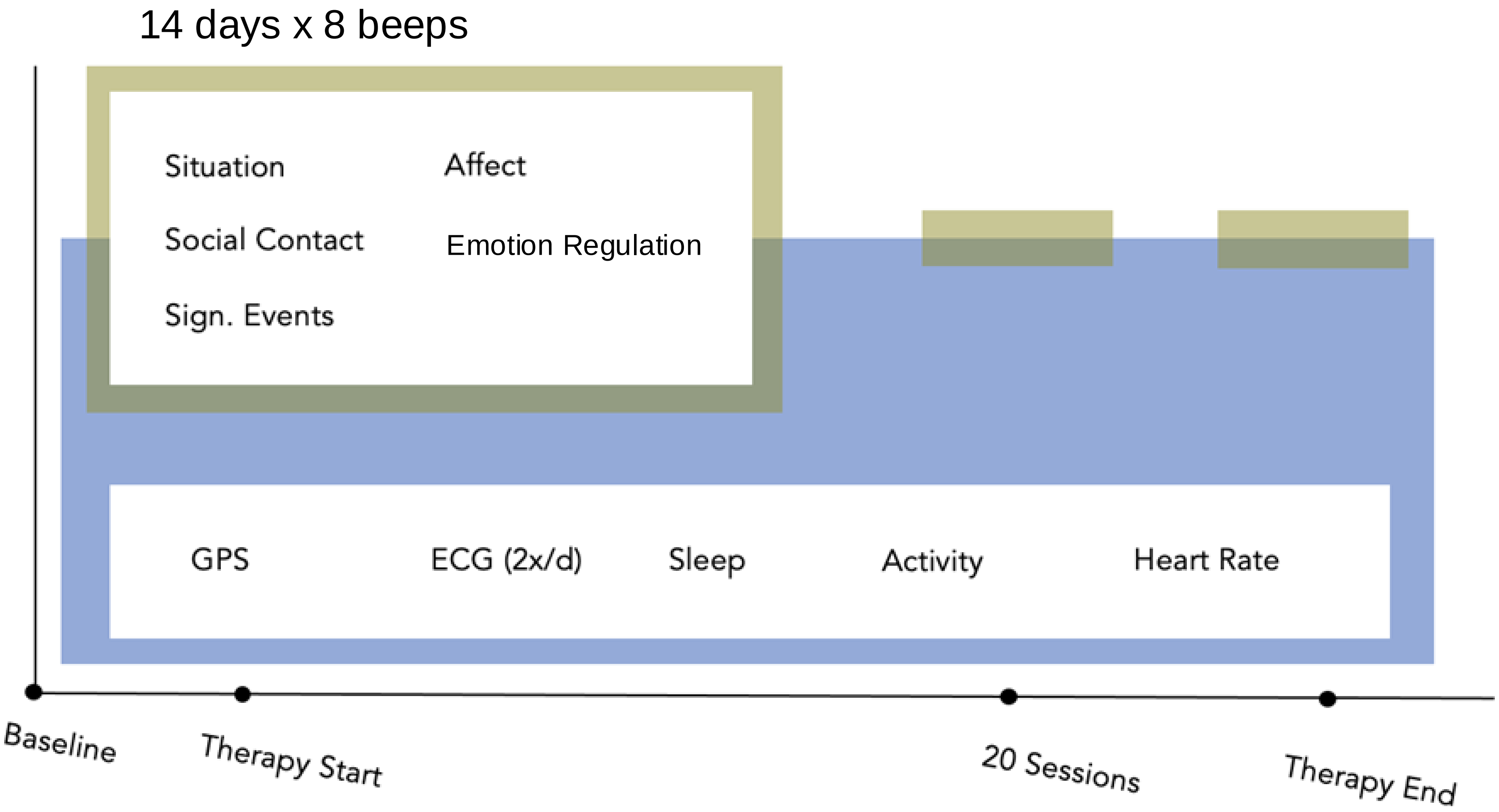
Study procedures

TIKI App

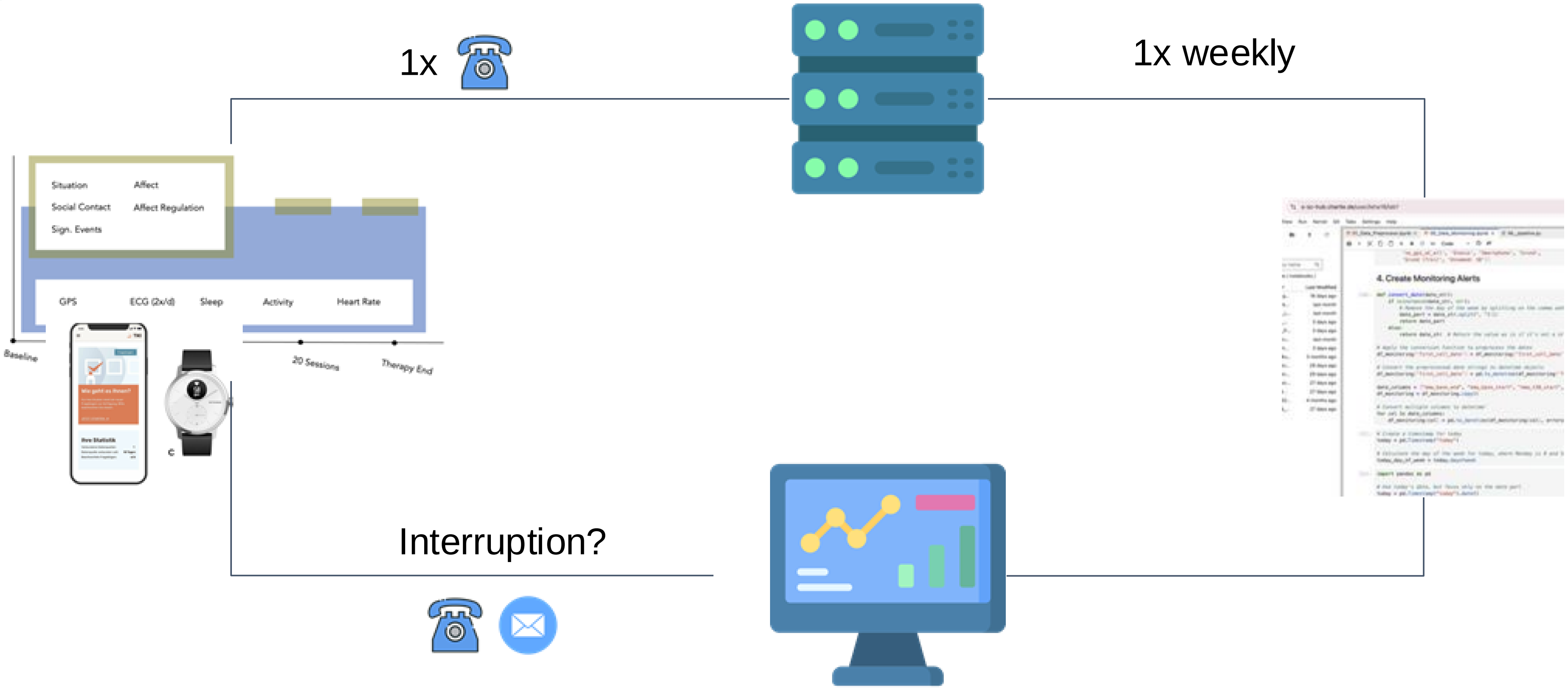
C

Withings Scanwatch

Study procedures



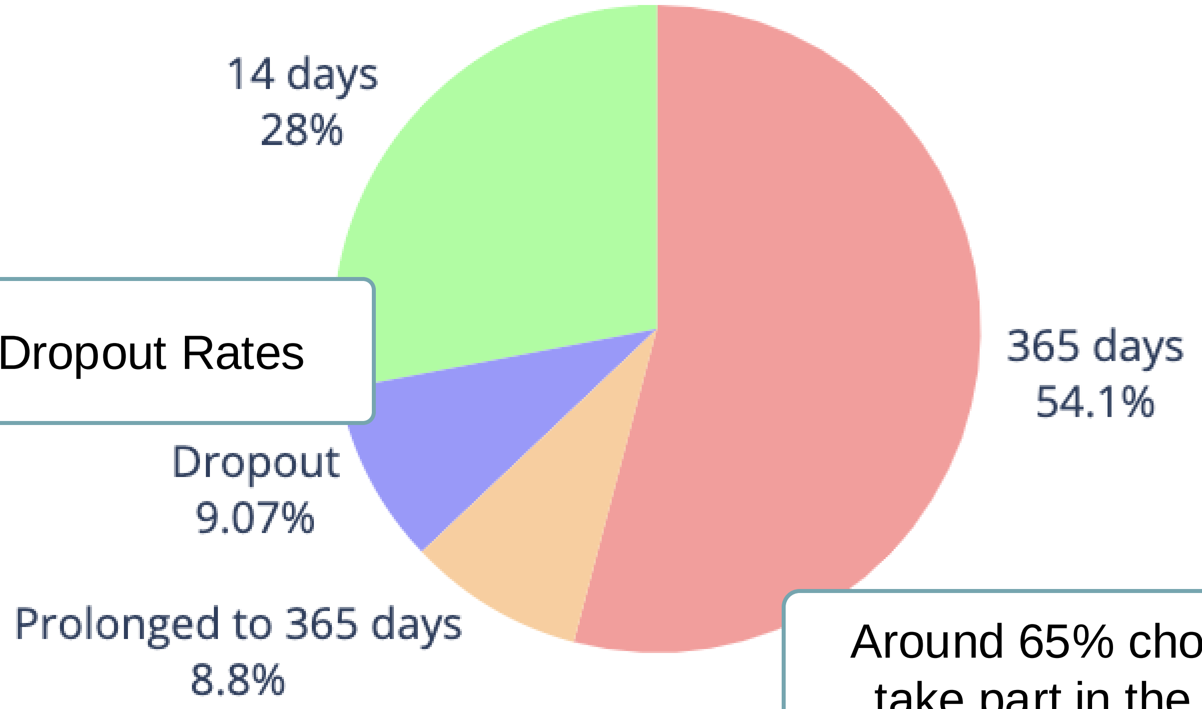
Study procedures



Feasibility & Adherence

Retention Rates

N= 372 patients
(72%)



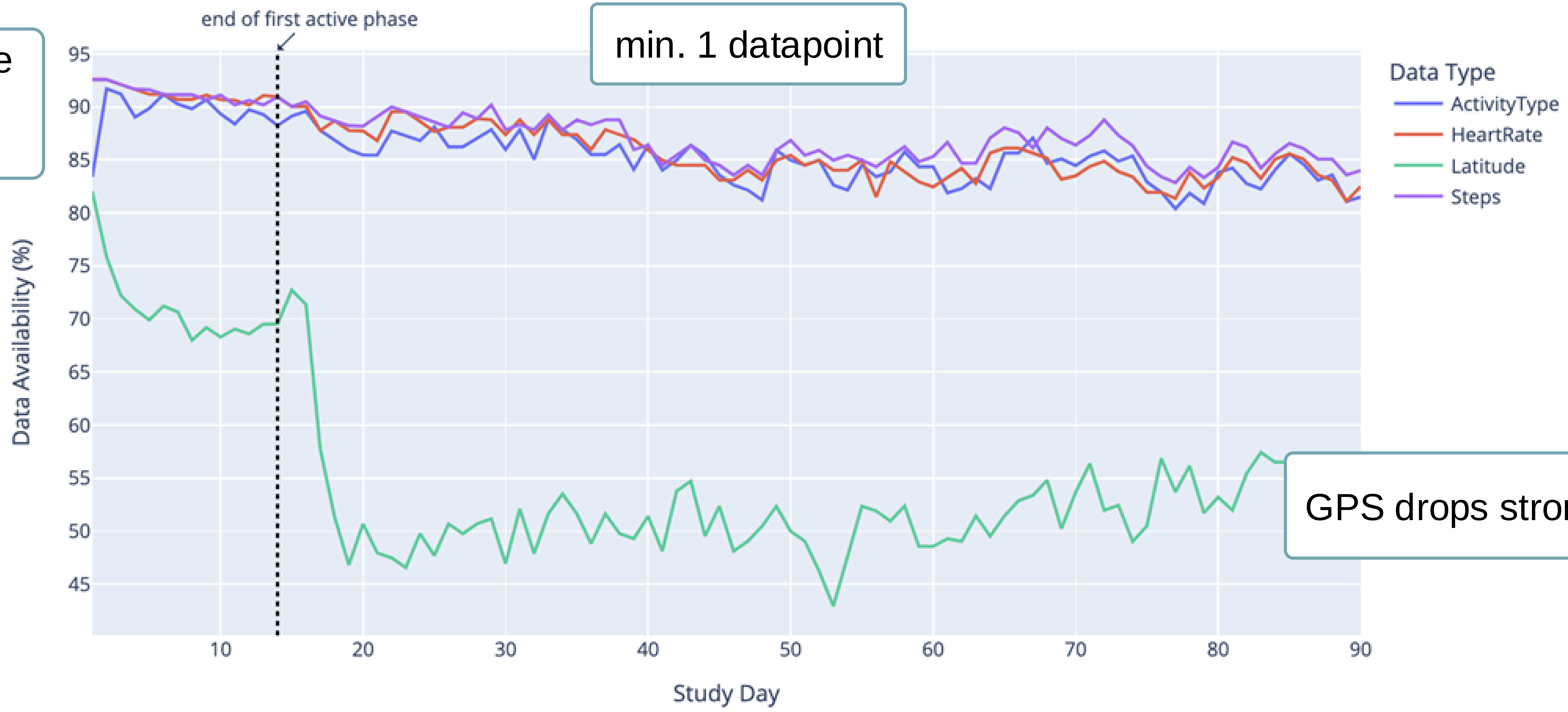
Low Dropout Rates

Around 65% choose to take part in the Long Version

Adherence: DP

slight decrease for wearable data

min. 1 datapoint

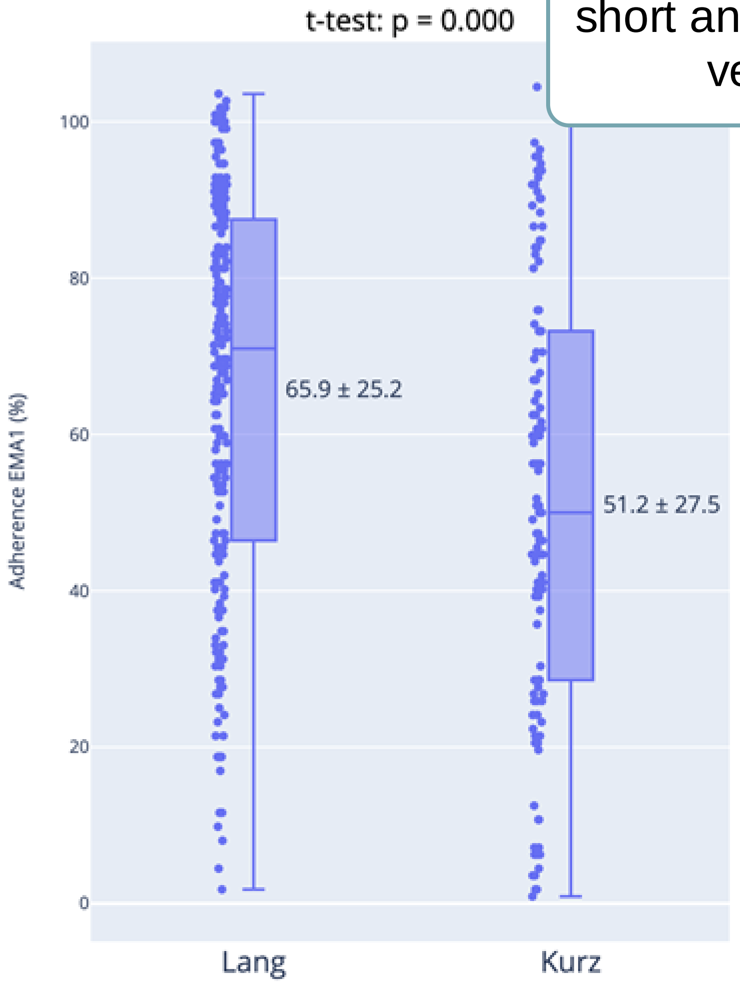


GPS drops strongly

Engagement: EMA

EMA compliance declines over time, but still satisfactory

significant difference between short and long study version



Discussion Feasibility

Conclusion

→ lessons learned: choose study-app with better maintenance-service

→ but: Long-term DP and EMA are feasible in clinical populations, also during psychotherapy!

Passive

↑ High long-term adherence for Smartwatch-derived data; adherence comparable to previous studies

↓ Lower adherence for GPS data due to technical constraints

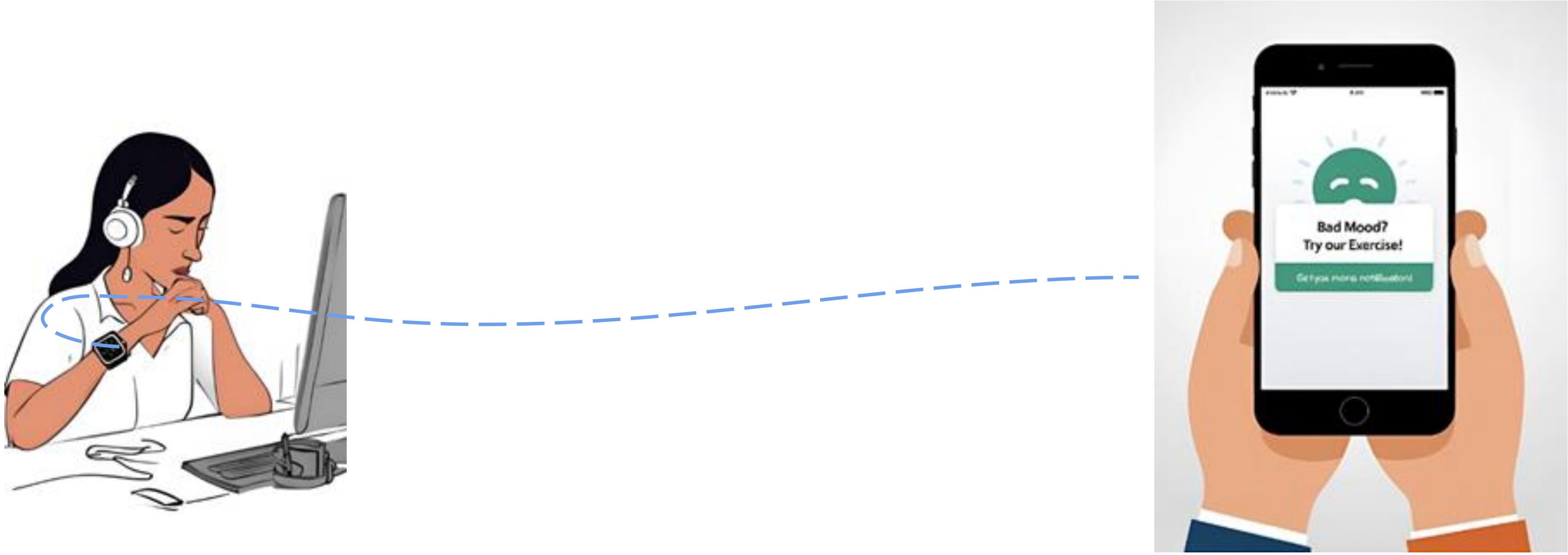
Active

→ Sufficient adherence across study phases

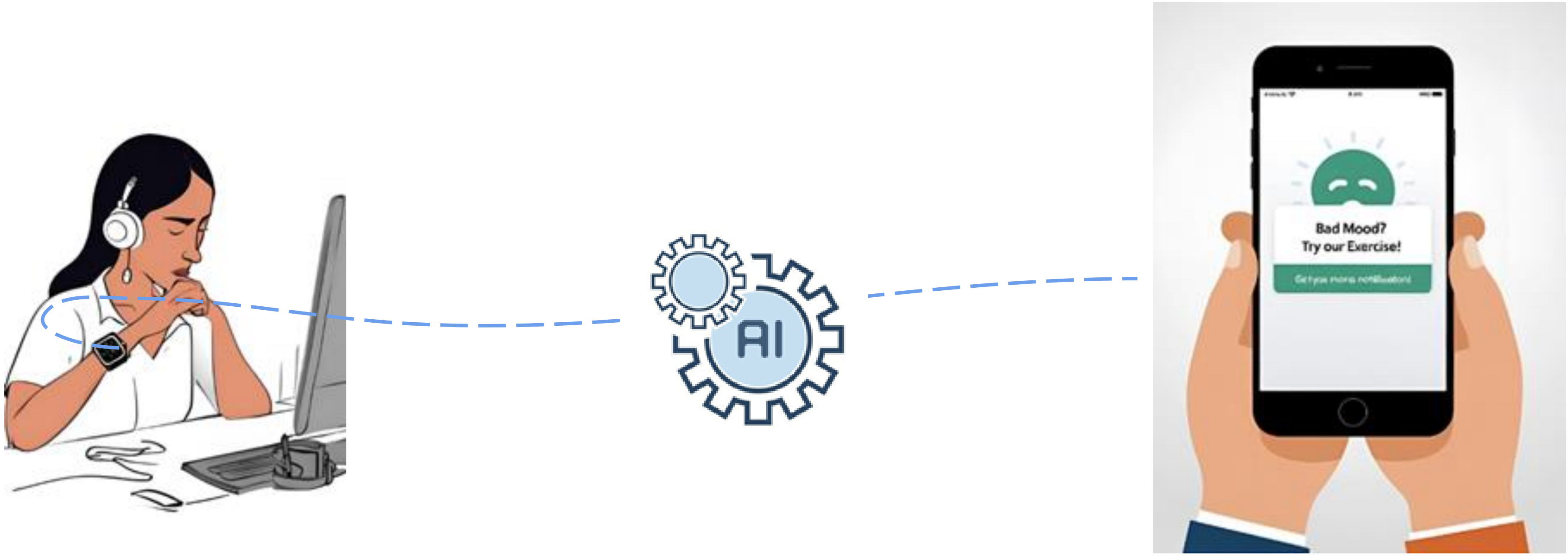
→ difference between short vs. long version = therapy motivation?

Ongoing study

Towards JITAI



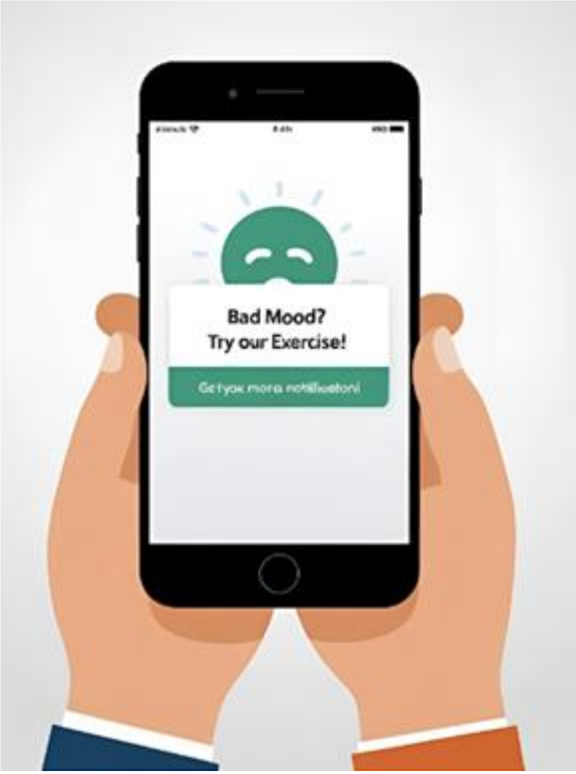
Towards JITAI



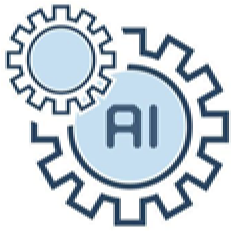
Towards JITAI

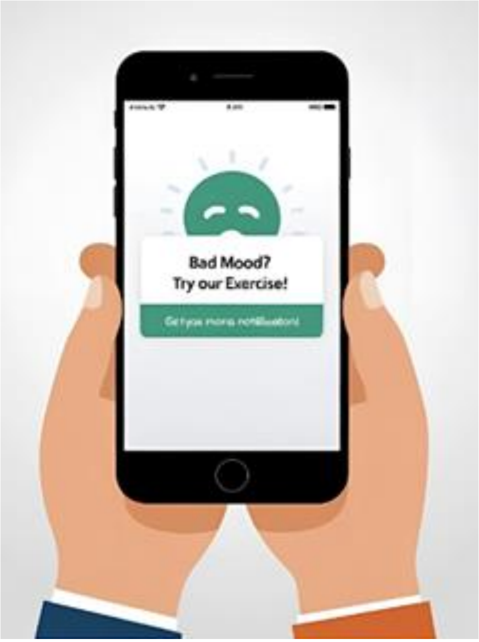
Can we predict **short-term** fluctuations in negative affect with **entirely passive data**?

→compare **subject-independent** with **subject-dependent** machine learning (“personalized ML”)



Towards JITAI





2 hours,
passive data

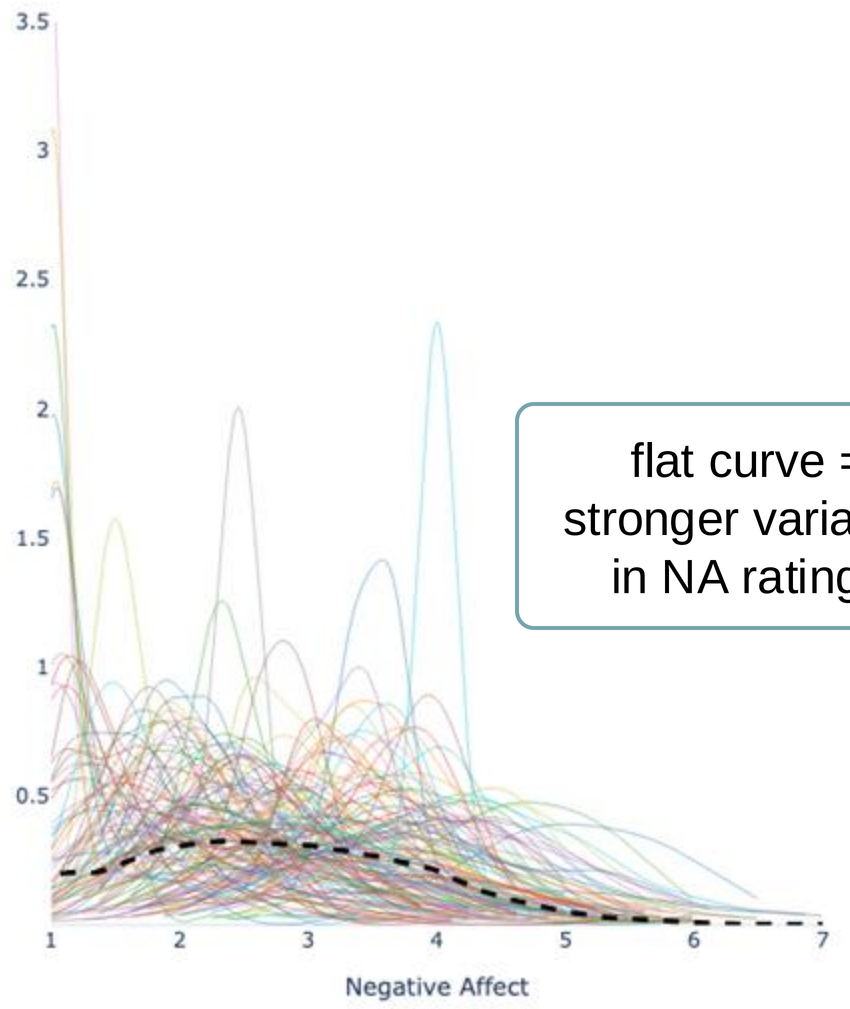
personalized ML

predict short-term
negative affect

Short-term prediction of negative affect

Can we predict **short-term** fluctuations in negative affect with **entirely passive data**?

→high variation in EMA-derived negative affect ratings within and between participants



flat curve = stronger variance in NA ratings

Short-term prediction of negative affect

Can we predict **short-term** fluctuations in negative affect with **entirely passive data**?

→high variation in EMA-derived negative affect ratings within and between participants

→ **personalized ML** models perform best; however, best models achieve similar errors as the average NA per person.

→ passive data alone do not contain enough signal!

Model	MAE [a]	R^2 [b]	RMSE [c]
Global Intercept	.878	-.007	1.053
Per Person Intercept	.631	.522	.818
LR	..964	.010	1.177
RF	.959	.015	1.174
FFNN	.984	-.015	1.192
LR + PS	.944	.051	1.153
RF + PS	.912	.108	1.117
FFNN + PS	.968	.011	1.177
MERF	**.609**	**.525**	**.816**
MERF + PS	.614	.522	.818
FFNN + Embedding	**.608**	**.532**	**.809**

Thank you!

Leona Hammelrath

Freie Universität Berlin, AB Klinisch-Psychologische Intervention

leona.hammelrath@fu-berlin.de

Study Protocol SP6 **Preregistration**

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Literature

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