

# Behind the spotlight: Using EMA and passive sensing to depict situational context in a clinical sample

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## Background

### What is "context"?

- "sum of environmental conditions or situational circumstances under which behaviour occurs, distinct from person-characteristics or inner states"<sup>1</sup>
- Ambulatory assessments = perfect for assessing context in situ!
  - **Active (EMA):** i.e. Social context, Situation Evaluation (DIAMONDS)
  - **Passive:** Location and Movement, Weather, Surrounding
- Incorporating context leads to improved prediction of proximal (i.e. mood) and distal (i.e. long-term mental health) outcomes!

### Implementation in psychotherapy research

- understand and address conditions and behaviors driving patients' symptoms
- automatically detect critical contexts and trigger an appropriate intervention on the patients' smartphone (JITAI)
- Can we predict situational context using passive data?
- Can we predict mood using active and passive context data?

## Study Setup

### Data collection

- Participants are provided with the Withings Scanwatch and the TIKI-app
- Collect data for 14 days pre-therapy; max. 8 EMA beeps per day
- Active data: situational context (new measure), affect (PANAS)

### Sample

- 173 participants remain after quality control, 58% female, mean age =33.7
- 11055 EMA-beeps in total, mean= 63 ± 22

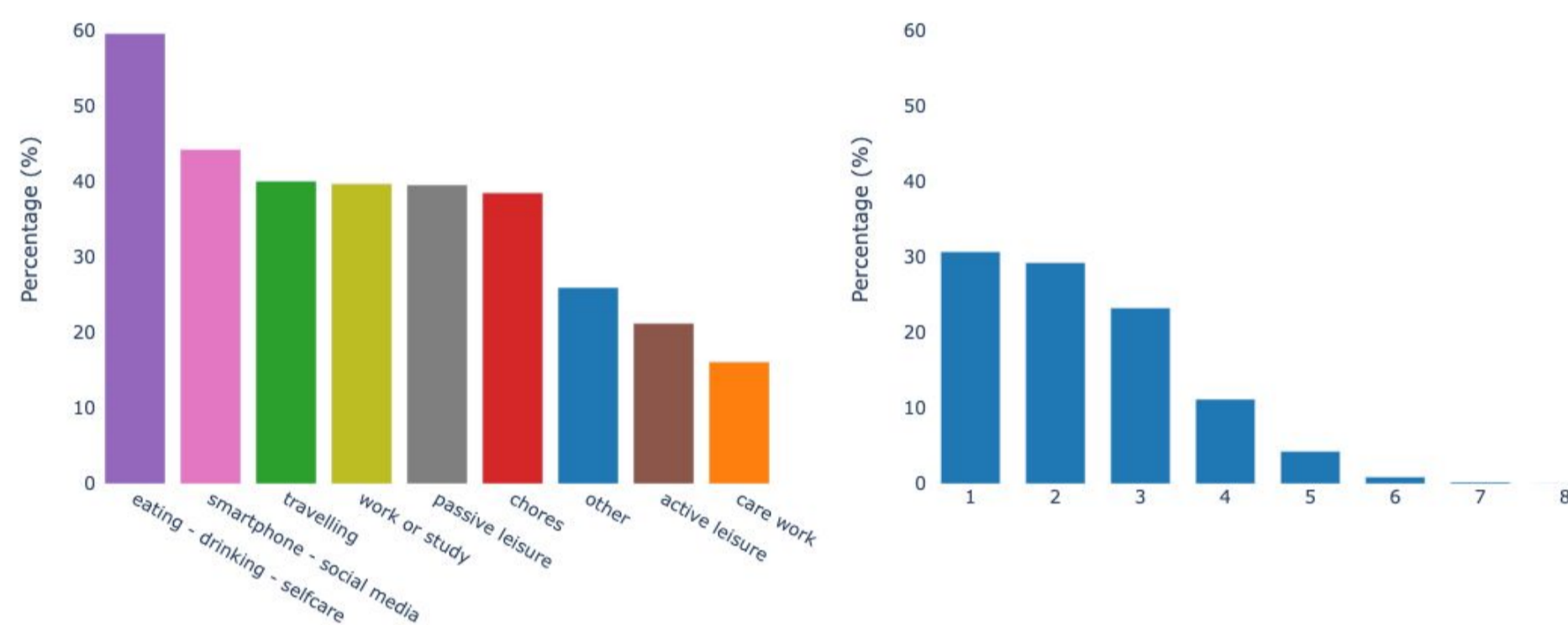
### Features

- 2h before each assessment
- GPS: total distance travelled (km), minutes in transition, minutes at home, n GPS
- Time-based: Season, time of day, weekday, weekend, hour
- Activity: step count

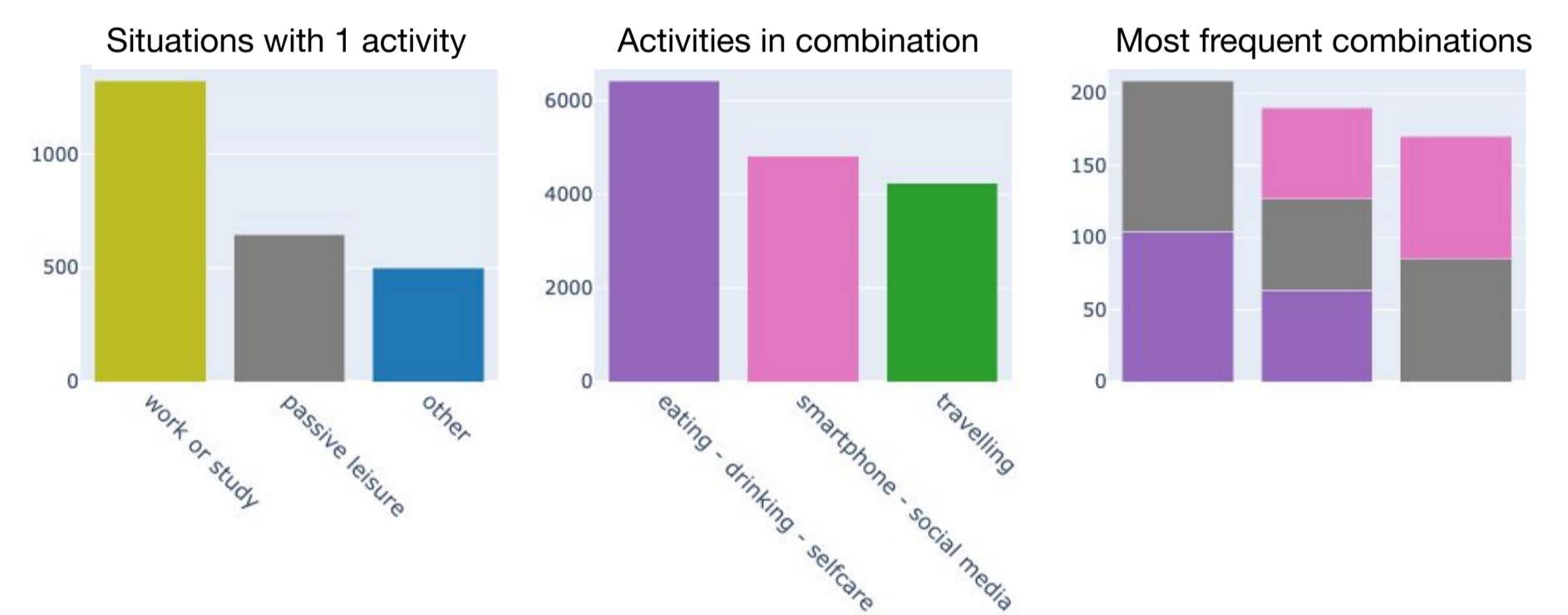
### Model

- Multilabel prediction of situation composition
- Ensemble of 10 Classifier Chains using Random Forests

## Situation distribution



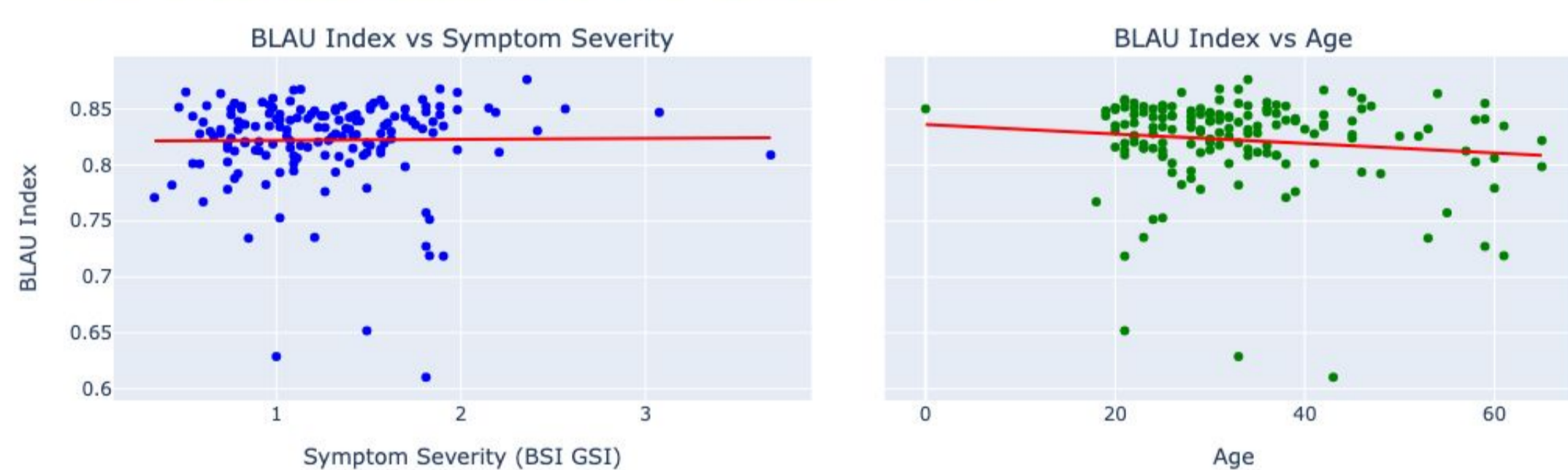
## Situation composition



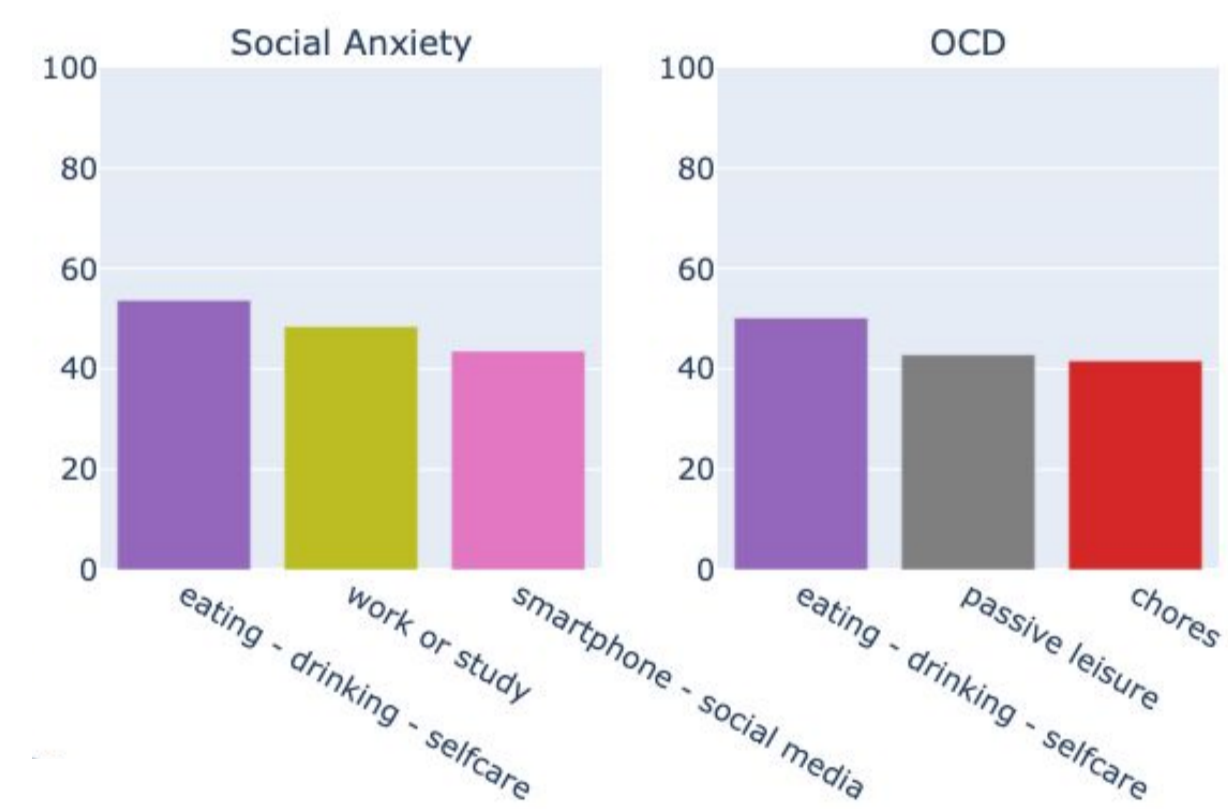
## Situation distribution

BLAU-Index = measure of within person situation diversity (0-1)

→ mean BLAU-Index: **0.83 ± .22**



## Situation Frequencies across diagnoses

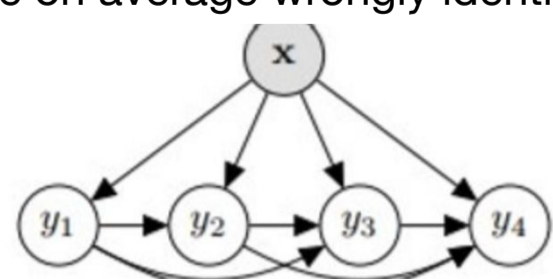


## Passive context prediction

How good can we depict situational context using passive data?

- Accuracy: **14%**
- Hamming-Loss: **25%**

→ only 14% of situation compositions were correctly predicted  
→ ¼ of the labels were on average wrongly identified



## Discussion

- High within-person diversity in situational context; however, patients are **homogeneous** in situational diversity → no adequate measure to distinguish individuals
- Differences in situational contexts between diagnoses, i.e. OCD
- Passive data descriptively match with situational contexts; data used in these analyses **do not suffice** to cover relevant aspects of situational contexts
  - add further available variables like heart rate, weather, physical activity
  - train **idiographic, i.e. individual** models (complexity)
  - outlook: predict above-average negative affect based on active and passive context features (JITAI)

## Literature

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- Zhang, Y., Folarin, A. A., Sun, S., Cummins, N., Vairavan, S., Bendayan, R., ... & RADAR-CNS consortium. (2022). Longitudinal relationships between depressive symptom severity and phone-measured mobility: dynamic structural equation modeling study. *JMIR mental health*, 9(3), e34898.