Item Validation in the WARN-D Study

Assessing EMA items to build an early warning system for depression

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WARN-D

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Goal: Develop a personalized early warning system for depression

How?

Follow 2,000 students over 2 years

Integrate multiple modern assessment types

This talk:

How can we learn more about all the EMA items used in the study?

Sample

Data Collection

Recruitment
- Four Cohorts
- 500 students each

Population
- Students of higher education in The Netherlands > 18 years

This Talk
- Cohort 1 + 2
- (C1: Nov 2021; C2: May 2022)
- *N* = 865

Measurement

Baseline

3 Months EMA-Phase
- 4x /day (18-21 items)
- Additional sunday survey (46 items)
- Many items: 1-7 Likert
- Smartwatch

Multiple Follow-Ups

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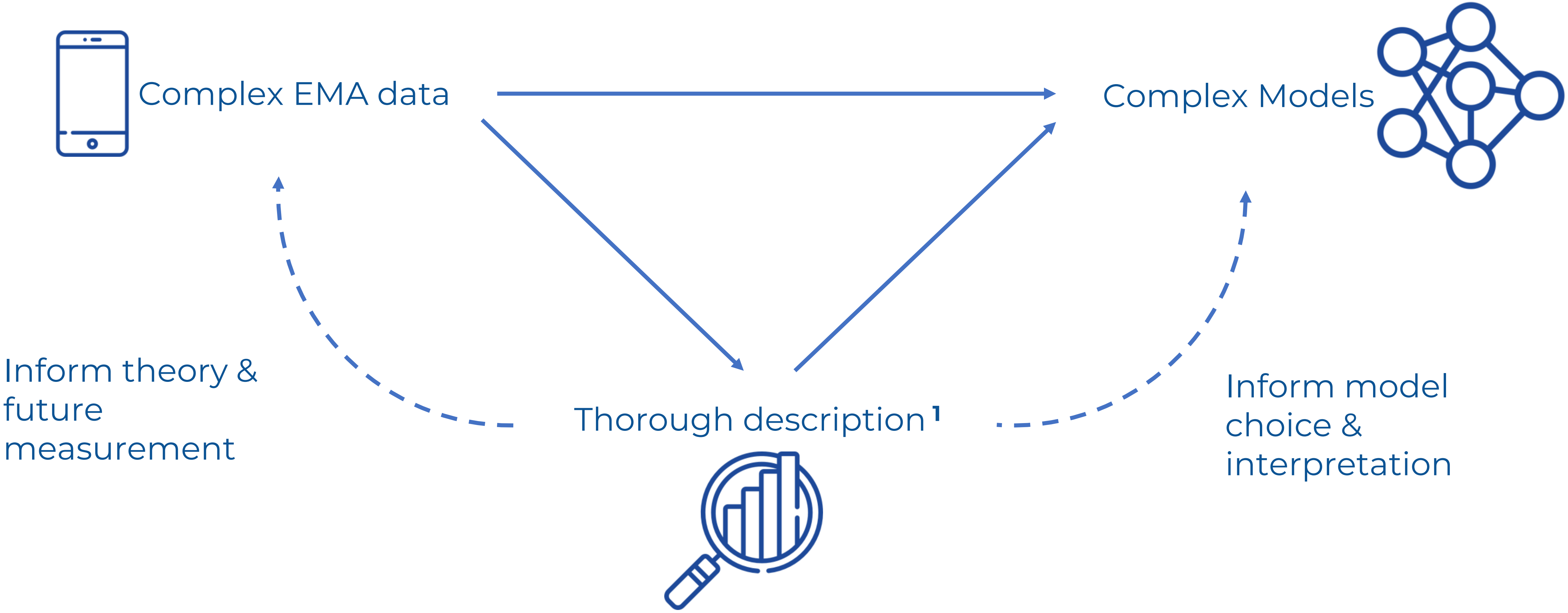
Theoretical Relevance

Complex EMA data → Complex Models

Theoretical Relevance



1 | e.g. Anscombe (1973), Tukey (1977), Haig (2013)

Validation Workflow

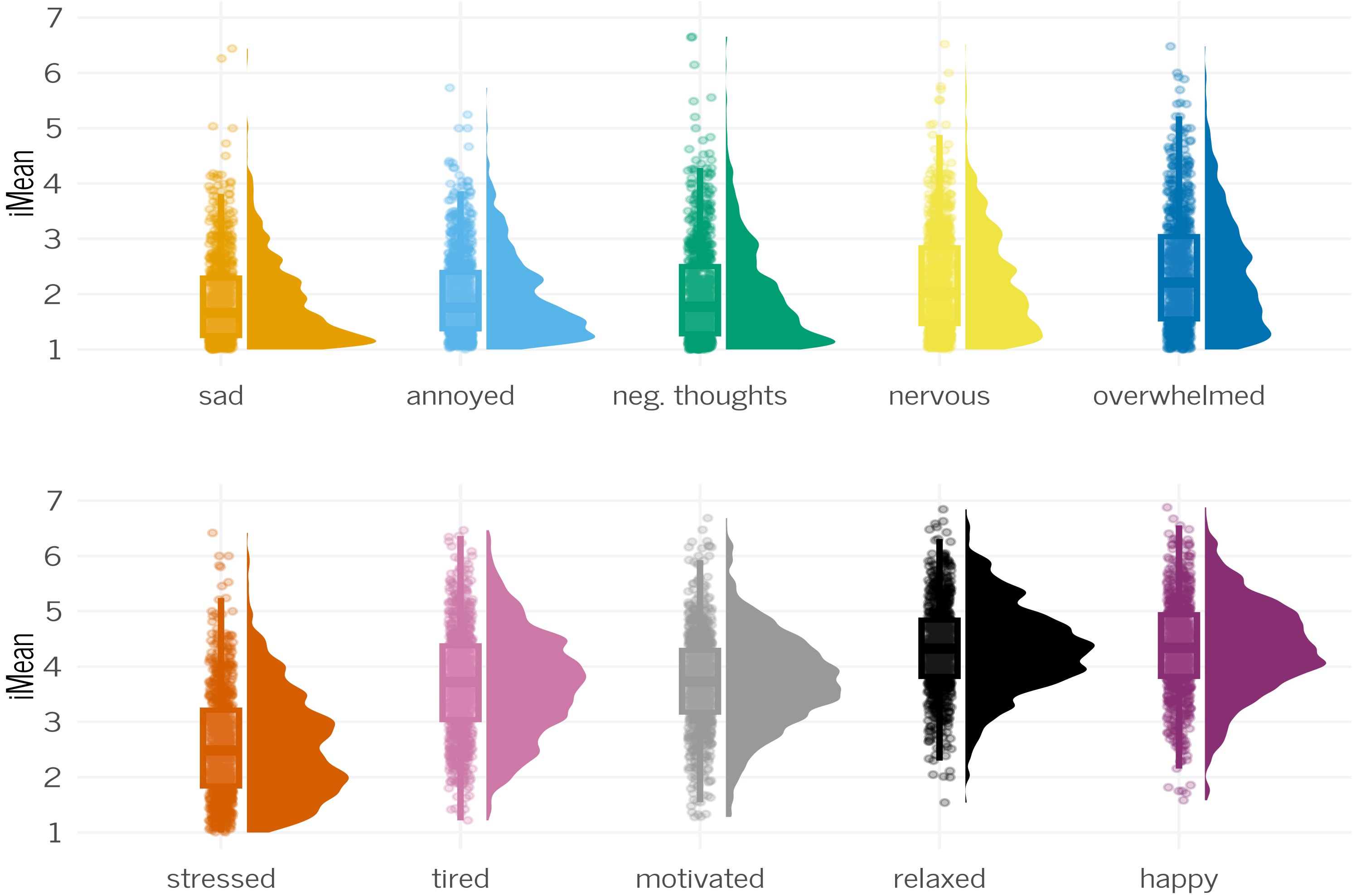
Visualization & Description

1. Distributions
2. Context
3. Time

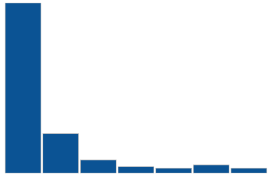
Other parts

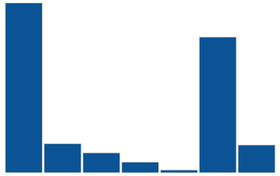
More on this later…

Distributions



Distributions





Floor Effects:

multiple items with ~30% of individuals answering 1 (“*not at all*”) >80% of the time

Multimodality:

multiple negative affect items with ~20% of individuals showing multimodality [1]

Theoretically: Conceptualization of responses [2]

Statistically: Important to account for [3]

1 | Haslbeck et al. (2021) **2** | Ryan et al. (2021) **3** | von Klipstein et al. (2021)

Context

- One of the main pillars of EMA

- In WARN-D:
  - Current activity
  - Online & offline social contacts
  - Location

enjoyment thereof

How similar are responses across different contexts?

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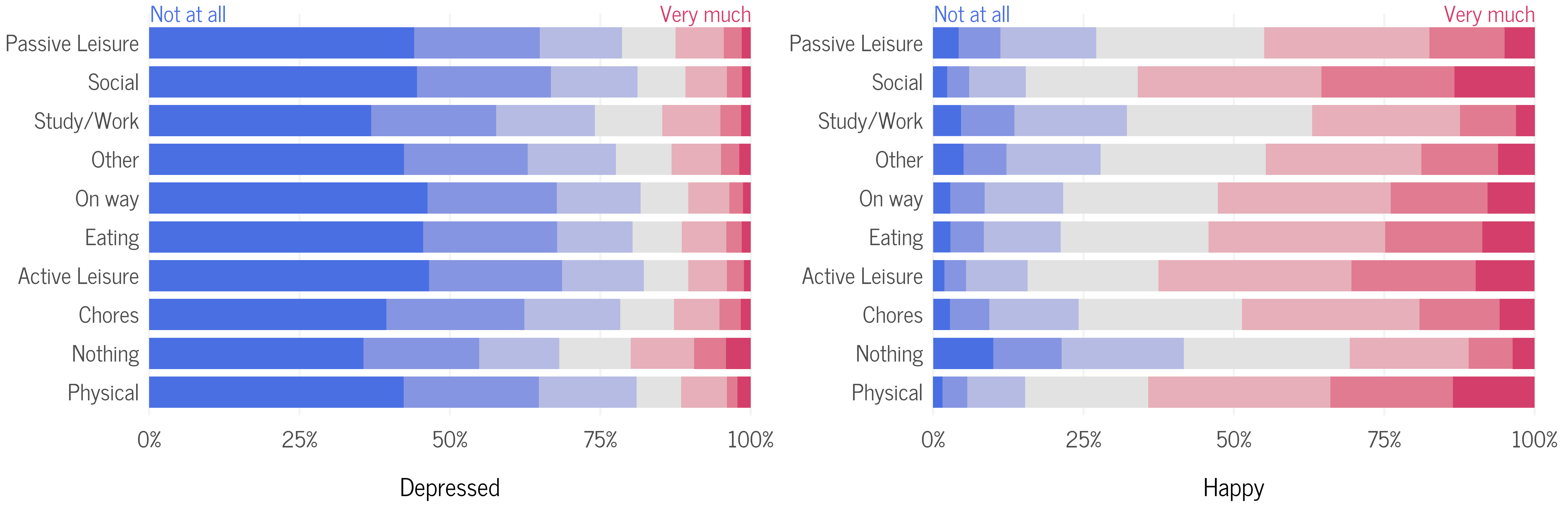
Context



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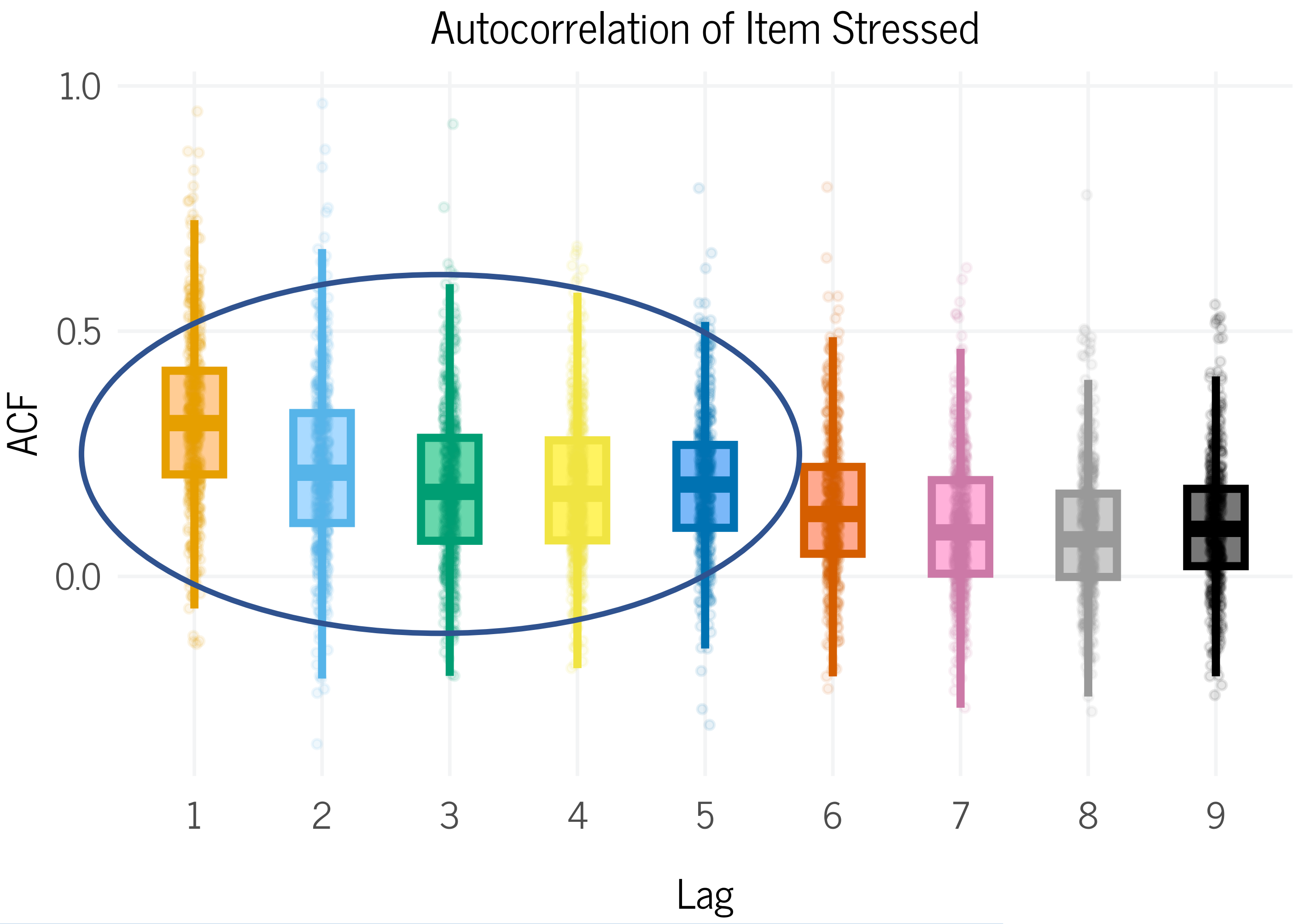
Time


Autocorrelation of Item Stressed
1.0
0.5
0.0
ACF
1
2
3
4
5
6
7
8
9
Lag

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Validation Workflow

Visualization & Description

Other parts

1. Distributions
2. Context
3. Time

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Validation Workflow

Other parts

1. Validating EMA with sensor data
2. Self-reported change vs. inferred change from EMA
3. Prognostic validity
4. Concurrent validity
5. Measurement models

1. Overlap between EMA stress and sensor stress
2. Asking people if they changed vs. calculating change gives different answers
3. Predicting follow-up with EMA
4. Overlap daily vs. weekly depression items
5. Work-in-Progress

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Summary

Implications for WARN-D	General
• Improved understanding of items and their characteristics • Structured workflow • Internal package, external extensive codebook	• Importance of descriptive work • Flexible modeling • More quantitative and qualitative work on item responses, response processes • Broad conception of validity and item quality

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Thank you

The WARN-D team

ERC Starting Grant 2020, agreement No. 949059

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Keeping up

Slides &
My Homepage

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Other WARN-D talks today:

Today, 1pm:
Introducing Fred, Open Software to Create Personalized Reports Utilizing Time-Series Data and Network Science
(Eiko I. Fried)

Today, 4 pm:
Augmenting Self-Reports with Passive Sensor Data to Understand Changes in Mental Health Presenter
(Carlotta L. Rieble)

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Image Sources

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