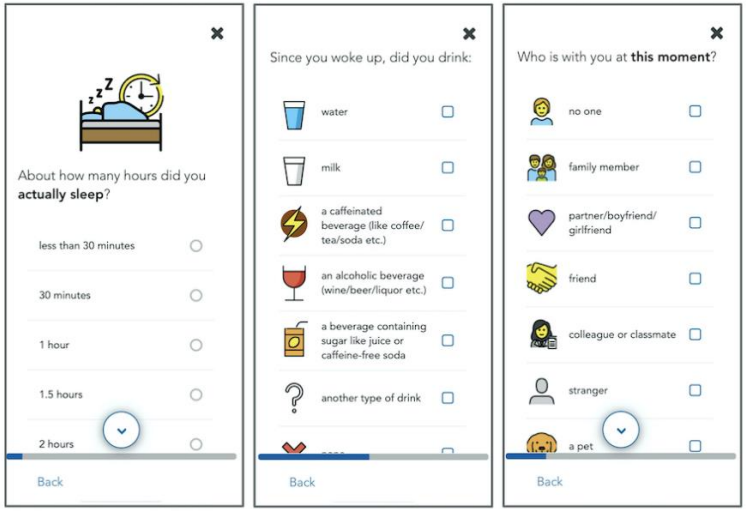
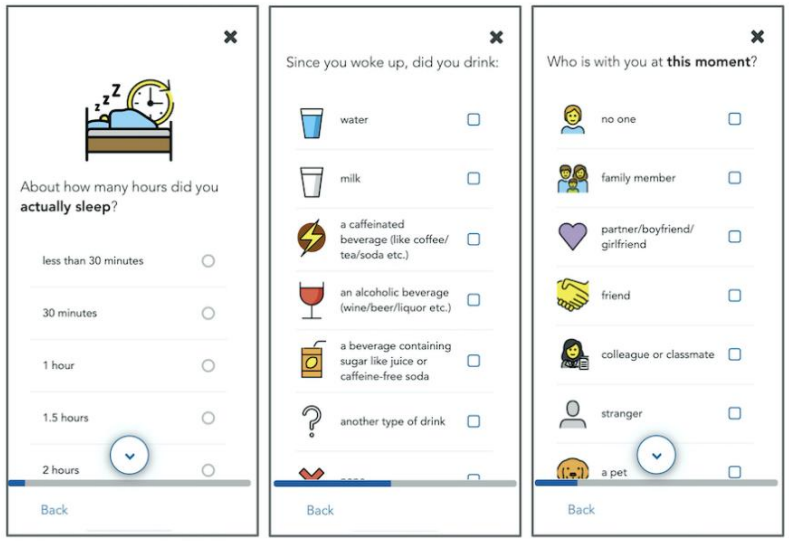
Intensive Longitudinal Data (ILD)

- Ecological Momentary Assessment (EMA)
  - Intensive longitudinal data (ILD)
  - Experience sampling method (ESM)
  - Daily electronic diaries
  - Ambulatory assessment
  - Real-time cognitive assessment
  - Burst (trigger-based) measurements
  - Adaptive (Just-in-Time) intervention studies
    - quit smoking/drinking/drugs
    - staying on a diet
    - becoming more physically active



Intensive Longitudinal Data (ILD)

- Multiple observations per day, one or more weeks of data
- (almost) Real-time recall
- No measurement tools except report: pain, sleep quality, mood, …
- Capture dynamical nature of phenomena
- Higher frequency (more reliable)
- Natural environment (home, work, etc)



Examples

- Context (current location, situation, immediate experiences)
- Health Behaviors (sleep, pain, mood)
- Real-time cognitive assessment
- Dietary assessment
- Reactivity

Examples: Context

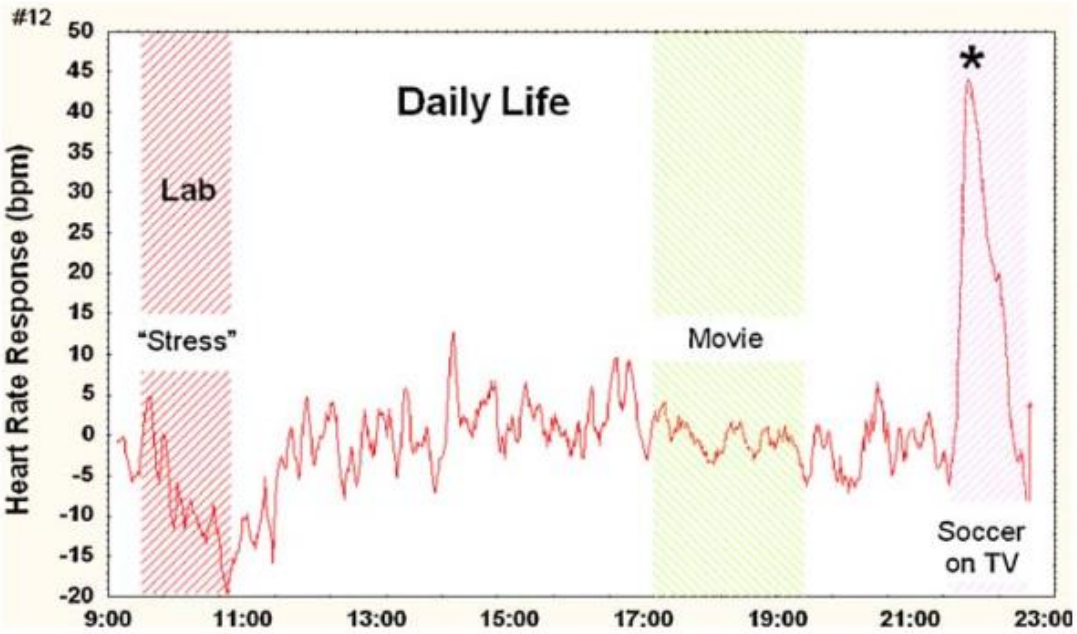


Fig. 1. Heart rate responses (1-min averages) of a study participant (subject 12) monitored with the LifeShirt during and after a laboratory stress protocol consisting of five resting baselines and mild-to-moderate mental stressors ("Lab"). Laboratory stress responses and responses to the movie were small compared to responses to a soccer game the participant watched at home. Note: heart rate was adjusted for ongoing physical activity.

Biological Psychology 84 (2010) 552–569

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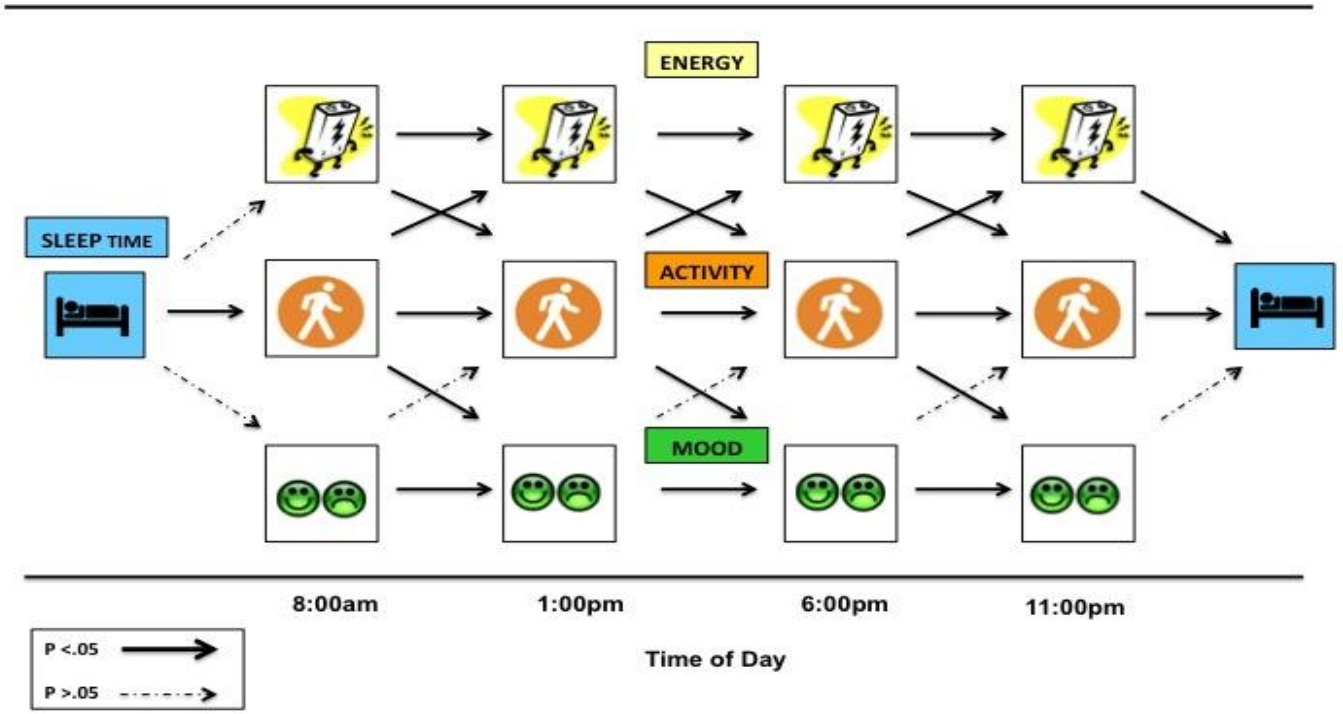
Emotions beyond the laboratory: Theoretical fundaments, study design, and analytic strategies for advanced ambulatory assessment

Frank H. Wilhelm [a,*], Paul Grossman [b]

[a] University of Basel, Institute for Psychology, Department of Clinical Psychology and Psychotherapy, Missionsstrasse 60/62, CH-4055 Basel, Switzerland
[b] University of Basel Hospital, Division of Internal Medicine, Department of Psychosomatic Medicine, CH-4055 Basel, Switzerland

Examples: Within-day interplay of Energy, Mood, Physical Activity



Original Investigation

FREE

December 12, 2018

Real-time Mobile Monitoring of the Dynamic Associations Among Motor Activity, Energy, Mood, and Sleep in Adults With Bipolar Disorder

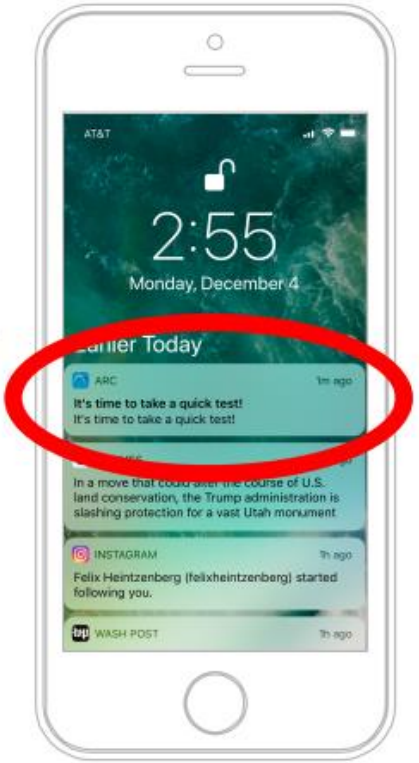
Kathleen Ries Merikangas, PhD[1]; Joel Swendsen, PhD[2,3]; Ian B. Hickie, MBBS[4]; et al

» Author Affiliations | Article Information

JAMA Psychiatry. 2019;76(2):190-198. doi:10.1001/jamapsychiatry.2018.3546

Examples: Real-time cognitive assessment

Get a notification that it is "Time to take a quick test", tap on the notification and begin the test.



higher frequency;
natural environment

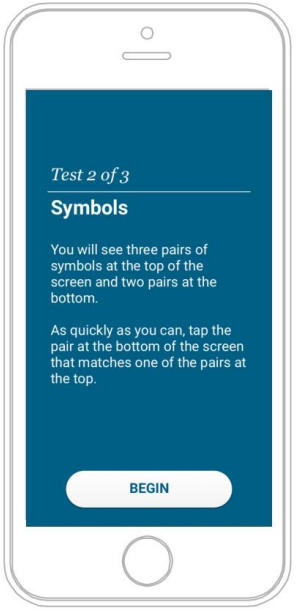
High Frequency Cognitive Assessments in Alzheimer's Disease

Jason Hasse(N)s-τ-Aβ, PhD
Associate Professor
Neurology and Psychological & Brain Sciences
Director, Cognitive Technology Research Laboratory
Washington University in St. Louis

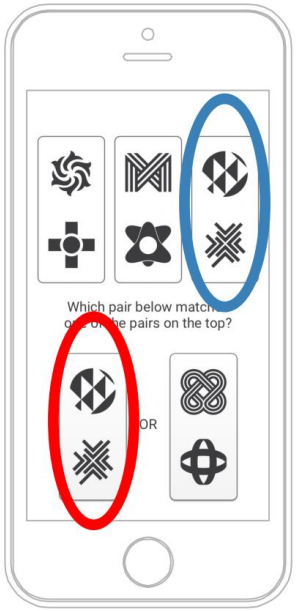
Applications: Real-time cognitive assessment

SYMBOLS Test (20-30 seconds)
Processing Speed

SYMBOLS Test
Participants are asked Which pair below matches one of the pairs on top?



SYMBOLS Test
Participants complete 12 items as quickly as possible. Primary outcome: Number correct and response time.



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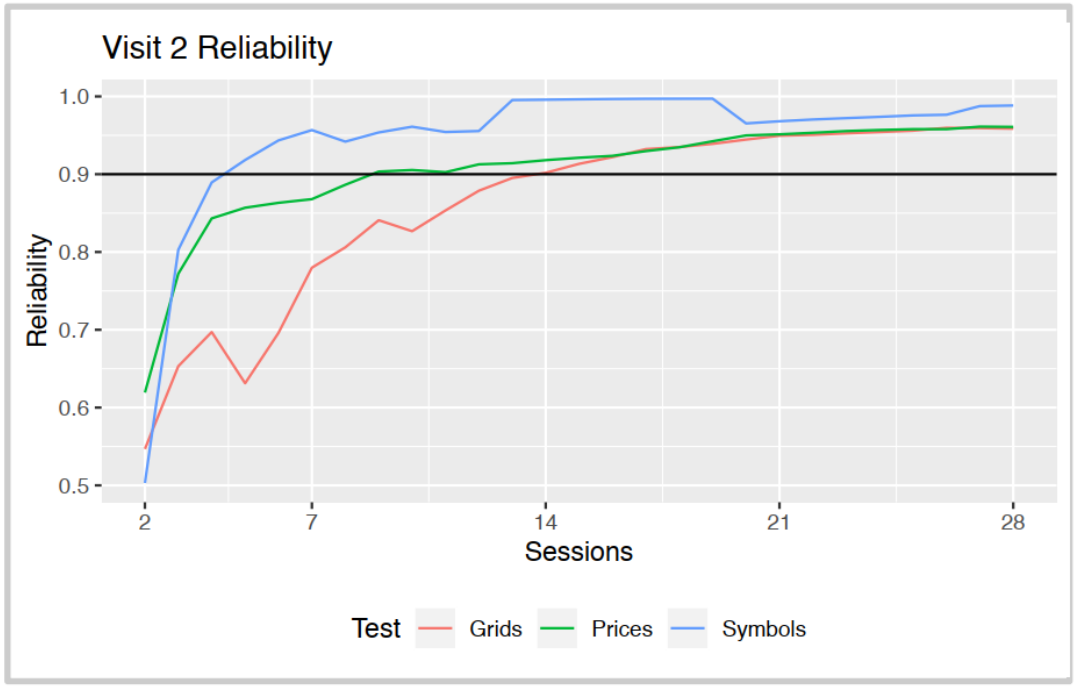

High Frequency Cognitive Assessments in Alzheimer's Disease

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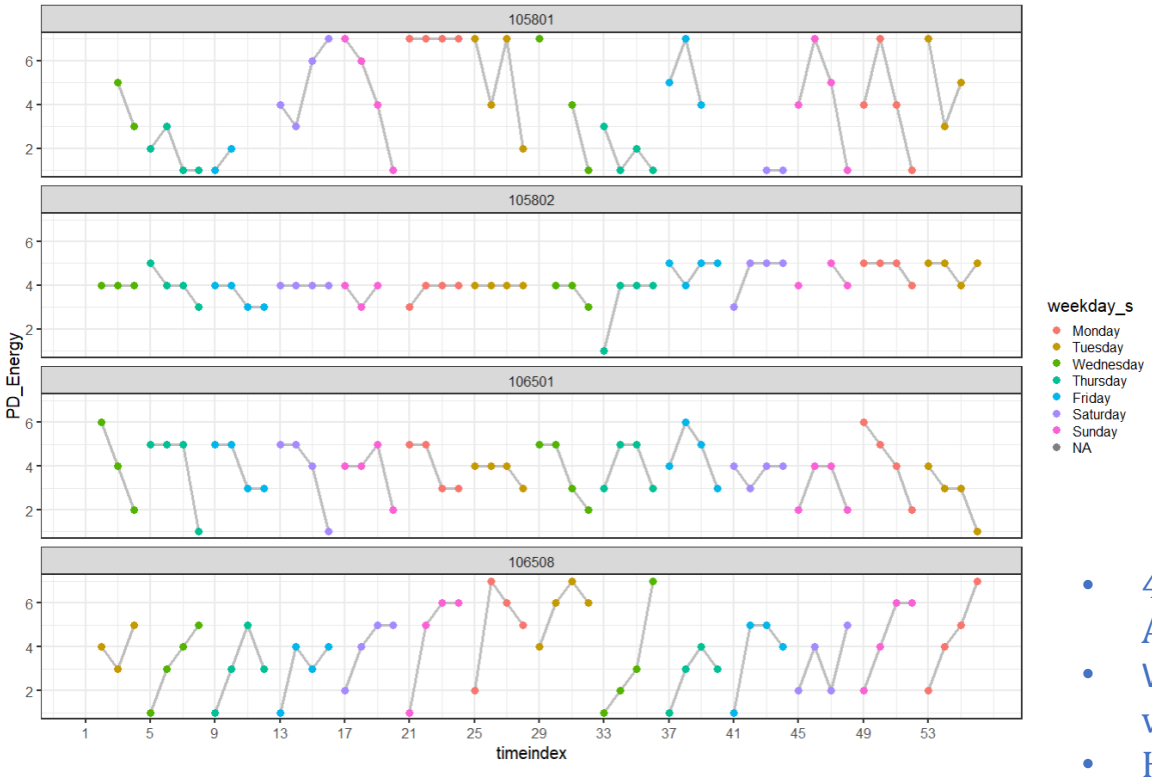
Example: How/what to model?



- 4 assessments per day (Morning, Noon, Afternoon, Evening), two weeks
- What to model? Subject-specific mean, variance, autocorrelation?
- How to take into account diurnal and weekly trends?
- Is there a structural change? In mean, variance, autocorrelation?

ILD Data

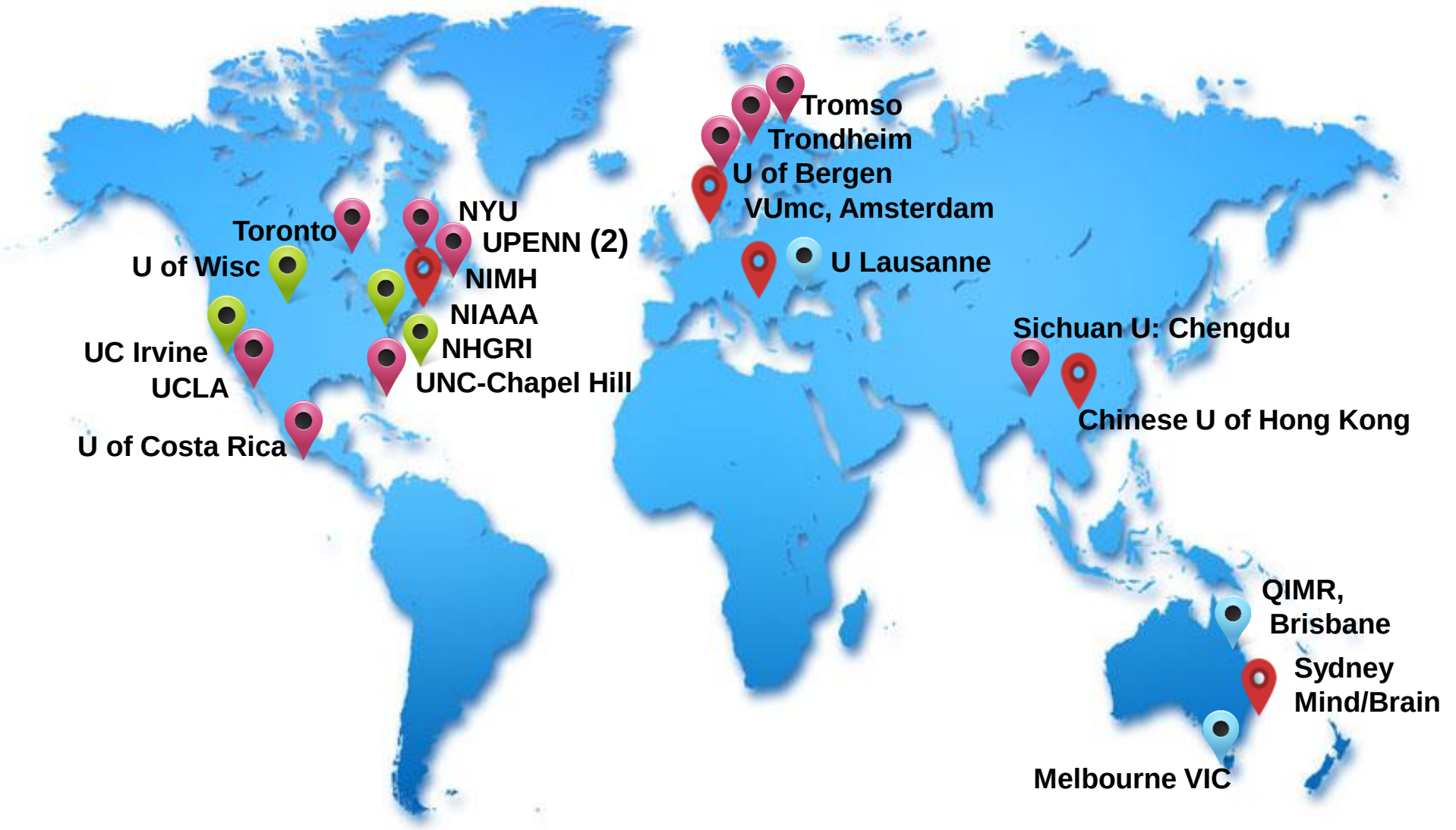
Challenges:

- Clustering (over time, within assessment)
- Temporal dynamics
- Multivariate mixed data types
  - Binary (had meal, smoking urge)
  - Categorical (type of foods, current location)
  - Ordinal (sadness, anxiety)
  - Truncated (pain level)
- Trends: Diurnal (within-day), Weekly, Seasonal
- Subject-specific vs population-level modeling
  - Within-subject clustering, between/within subject variability
  - Normalization of subject-specific interpretation of the scales (1-7, 1-10)
  - Bringing context: workdays vs workfree days, weekdays vs weekends
- Missing data

Models

- Clustering
  - Multi-level modelling (between/within subject variability)
  - Marginal modelling (GEE)
  - Item Response Theory modelling
  - Structural Equation Modelling (SEMs)
- Temporal Dynamics
  - Time-varying (TVEM) modelling
  - Functional data modelling
  - Single-subject temporal analysis: N of 1, within-person study
    - Time-series (AR, ARMA, VAR, etc)
    - Hidden-Markov Models
    - (regime-switching) State-space models
    - Change-point and structural-break models
  - Multiple subjects: multilevel (time-series) modelling
  - Dynamic Structural Equation Models
- Mixed data types
  - Binary, truncated, ordinal, categorical time-series
  - Item Response modelling
  - Bayesian modelling

Motor Activity Research Consortium for Health
(mMARCH)



mMARCH

Kathleen Merikangas, PhD
National Institute of Mental Health

Andrew Leroux, PhD
University of Colorado at Denver

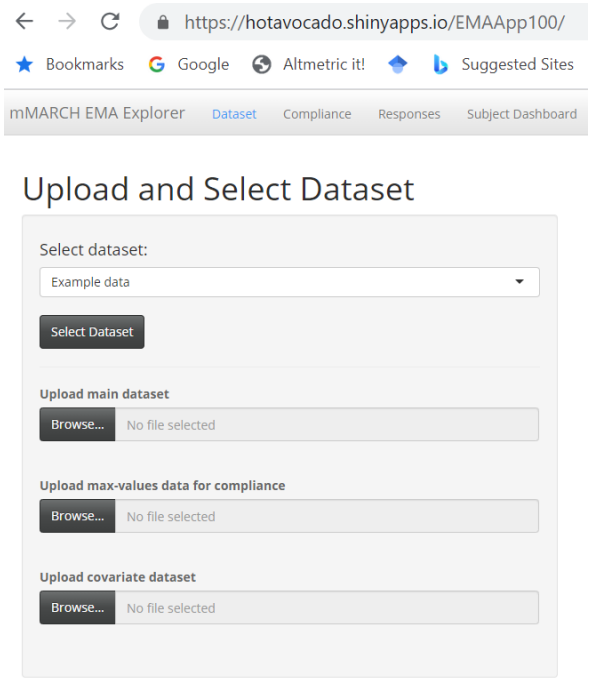
Mike Xiao, BA
Child Mind Institute, NYC

mMARCH

- Leverage mobile technology via
  - standardizing data collection protocols across sites
  - developing and applying novel analytical methods
- The range of scientific questions
  - interrelationship of physical activity, sleep and mood
  - interplay between sleep, stress, and alcohol use

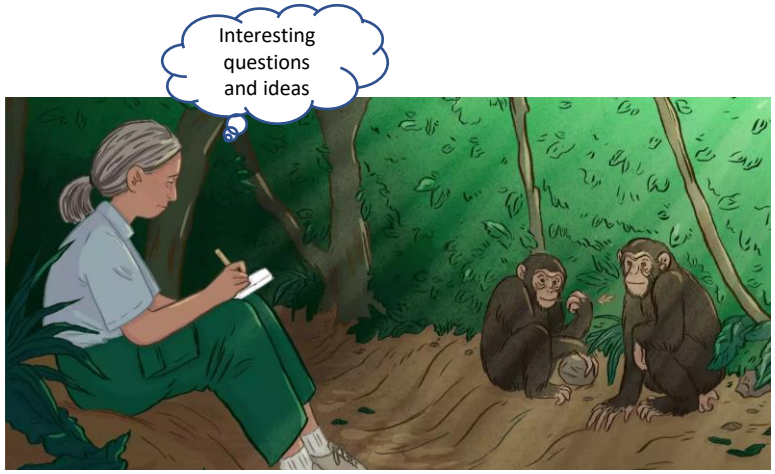
mMARCH EMA Explorer: Shiny App

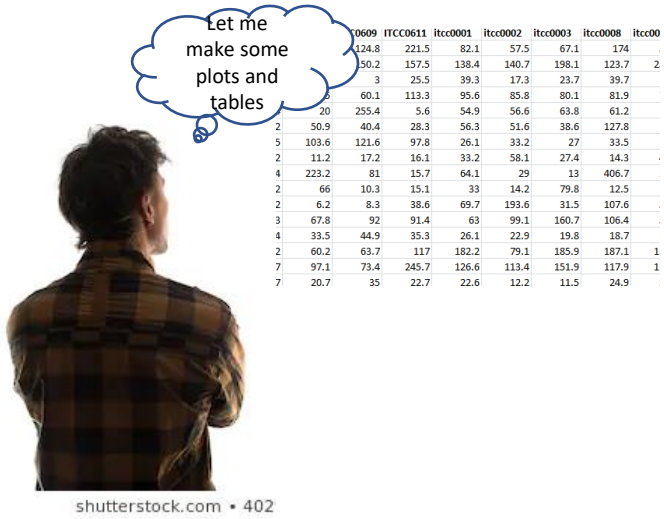
- quickly assesses the patterns of compliance and response
- facilitates exploration and visualization of EMA data
- pays special attention to the time-dependent and multi-level design
- hotavocado.shinyapps.io/EMAApp100/
  - Play with a synthetic dataset
  - Upload your dataset



Observations in the Field

- The field is like a huge dataset, and we can process this information efficiently with our eyes and ears. The shiny app tries your eyes and ears for EMA data. From observing, you can gain insights and begin to ask questions and generate testable hypotheses.





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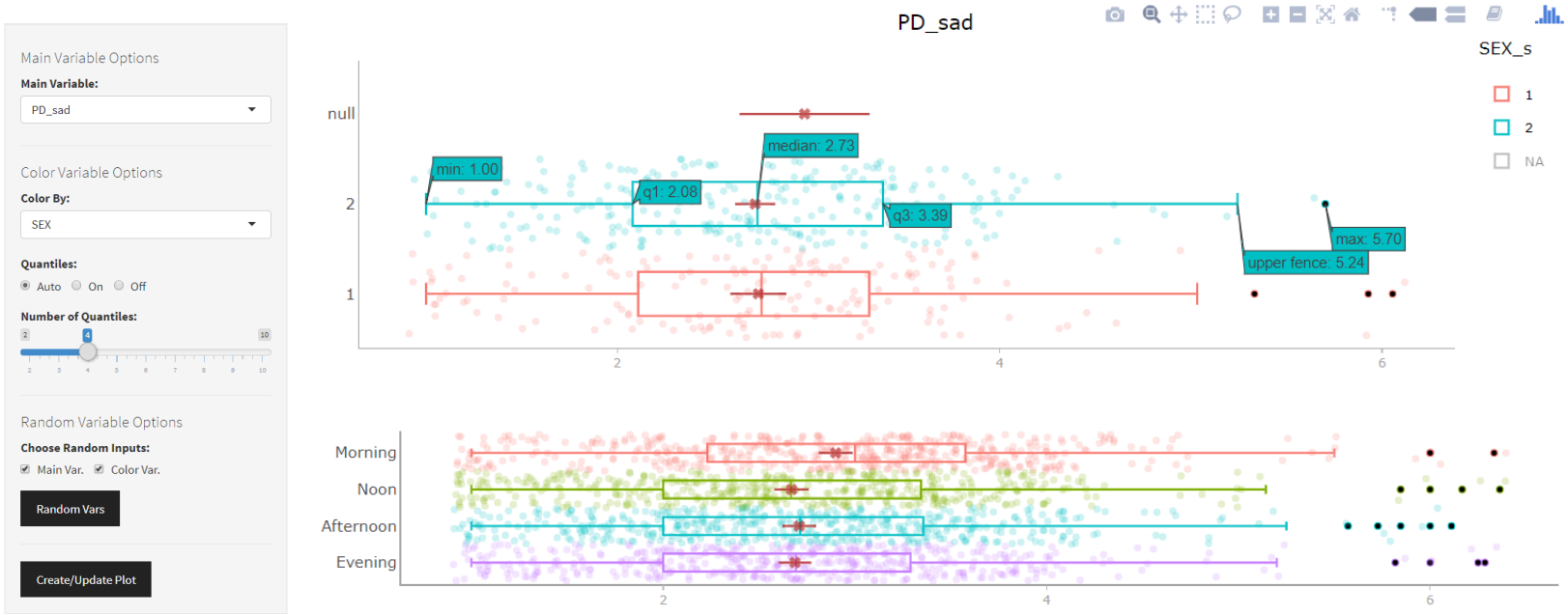
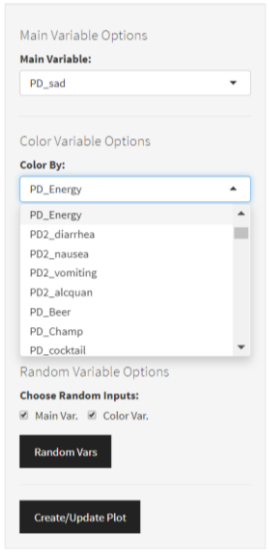
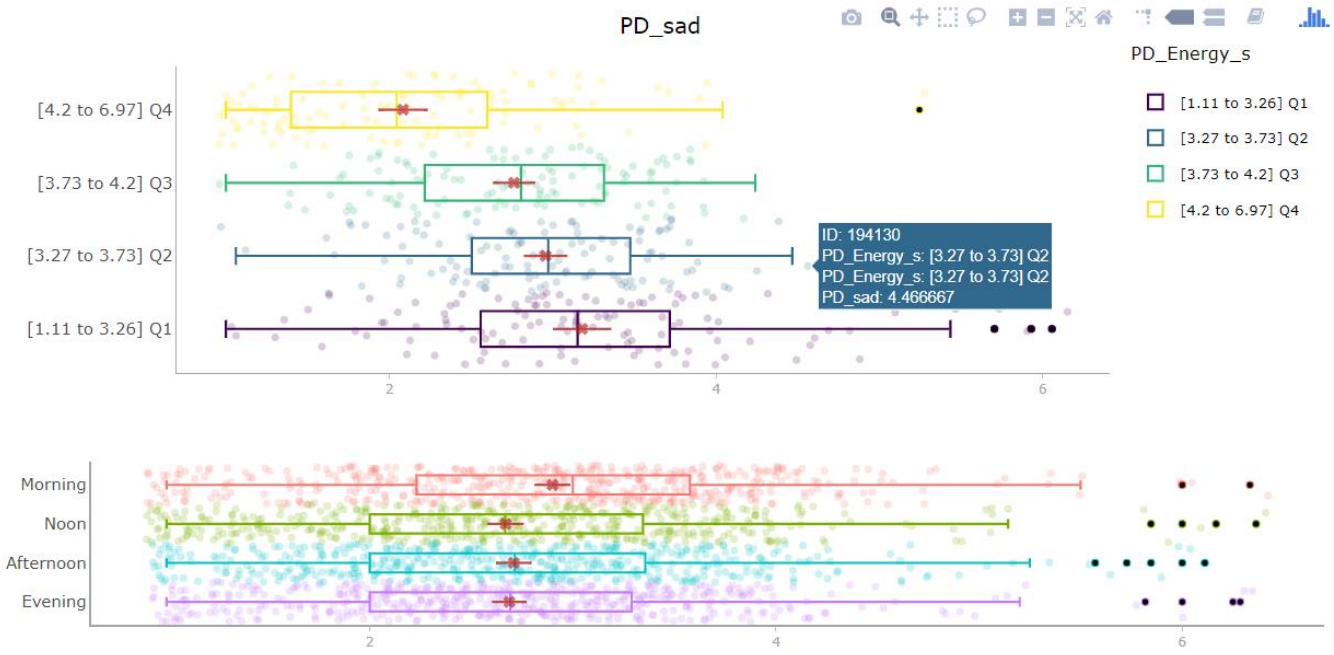
	150.2	157.5	138.4	140.7	198.1	123.7	2
	3	25.5	39.3	17.3	23.7	39.7	
	60.1	113.3	95.6	85.8	80.1	81.9	
20	255.4	5.6	54.9	56.6	63.8	61.2	
50.9	40.4	28.3	56.3	51.6	38.6	127.8	
103.6	121.6	97.8	26.1	33.2	27	33.5	
11.2	17.2	16.1	33.2	58.1	27.4	14.3	
223.2	81	15.7	64.1	29	13	406.7	
66	10.3	15.1	33	14.2	79.8	12.5	
6.2	8.3	38.6	69.7	193.6	31.5	107.6	
67.8	92	91.4	63	99.1	160.7	106.4	
33.5	44.9	35.3	26.1	22.9	19.8	18.7	
60.2	63.7	117	182.2	79.1	185.9	187.1	1
97.1	73.4	245.7	126.6	113.4	151.9	117.9	1
20.7	35	22.7	22.6	12.2	11.5	24.9	

Using the App: Aggregate Level Exploratory Visuals (boxplot)

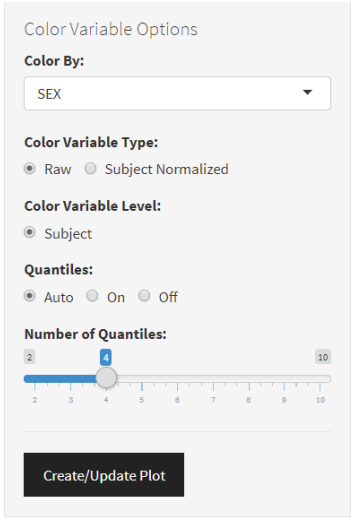


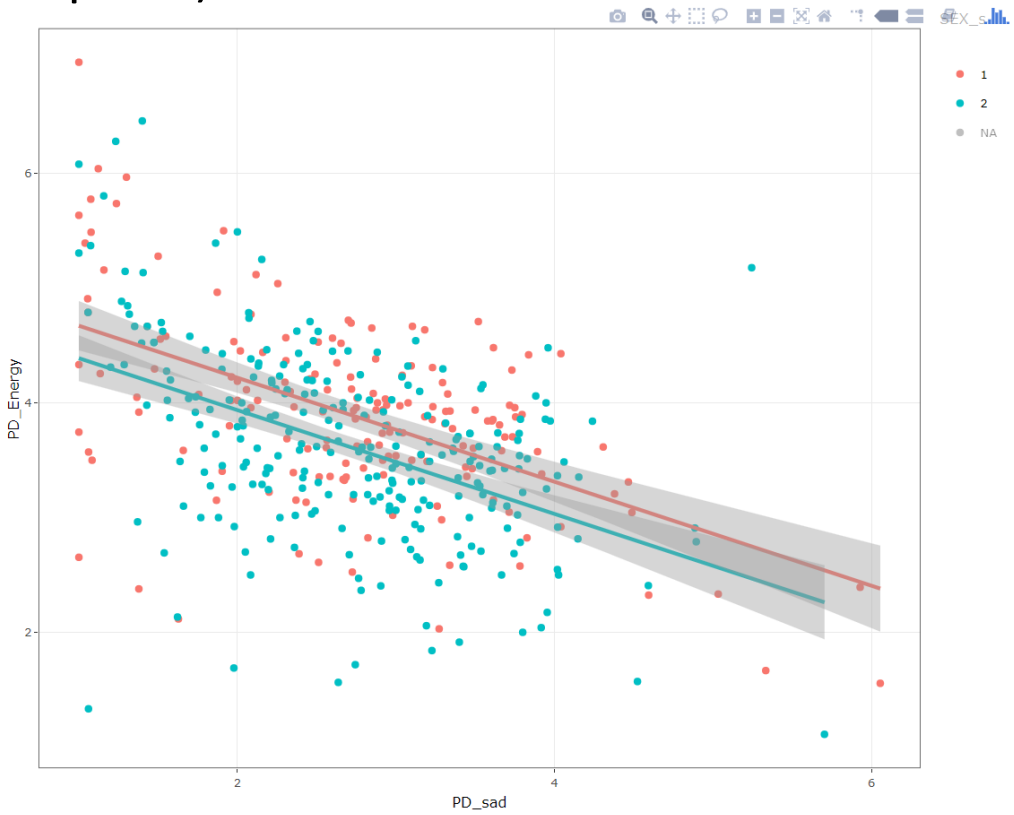
Using the App: Aggregate Level Exploratory Visuals



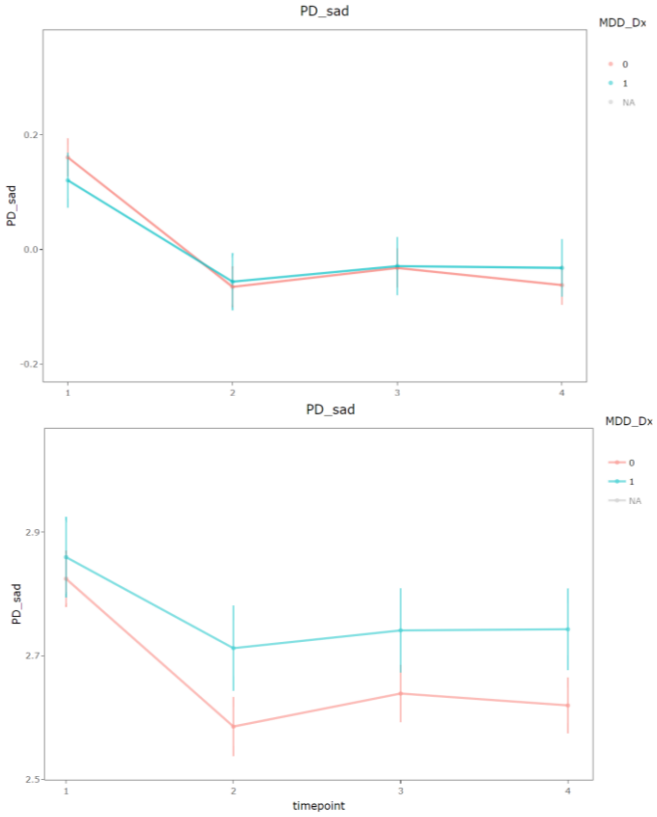


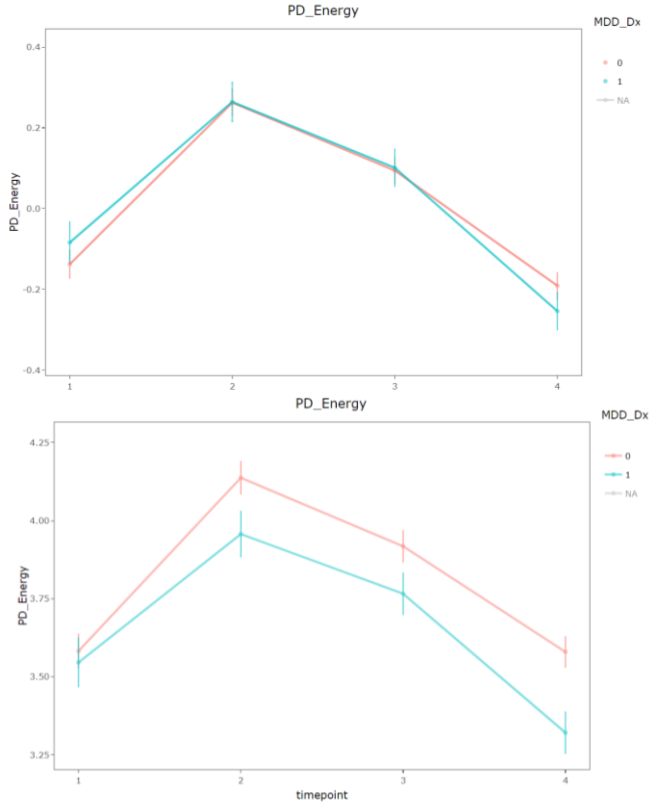
Using the App: Aggregate Level Exploratory Visuals (scatterplot)



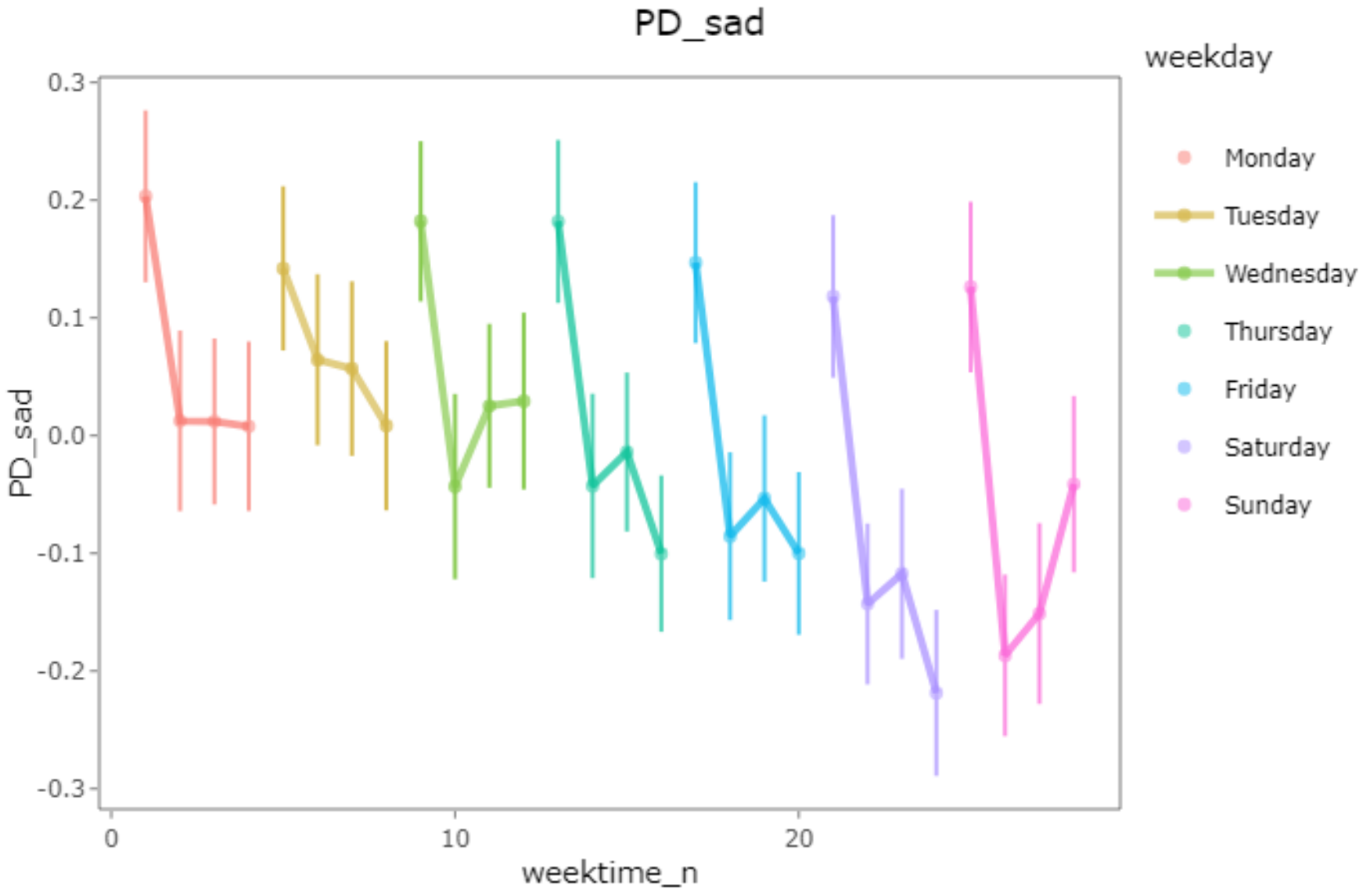


Using the App: Focus on temporal structure (trajectory plot)

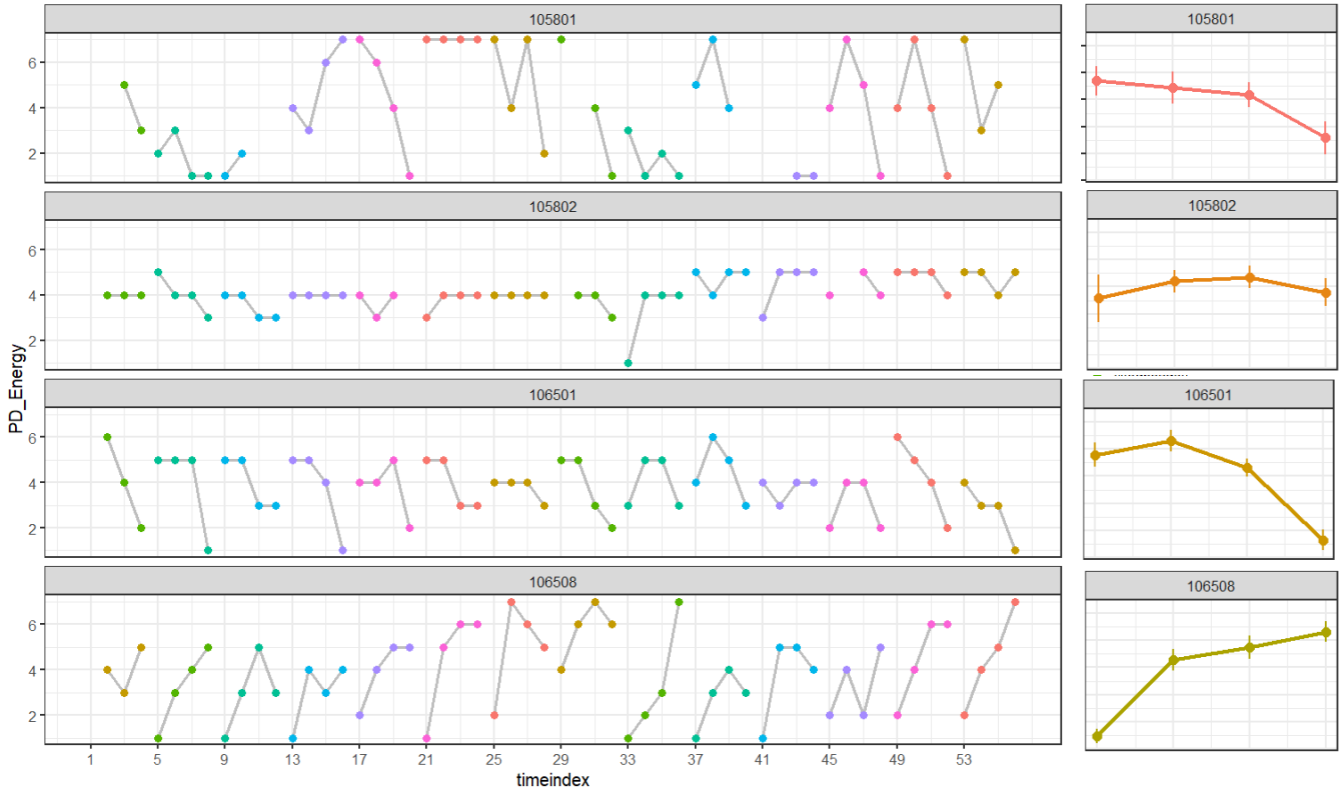




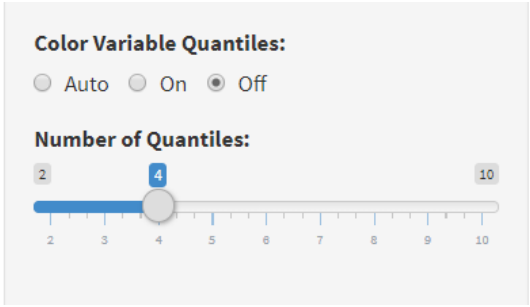
Mood

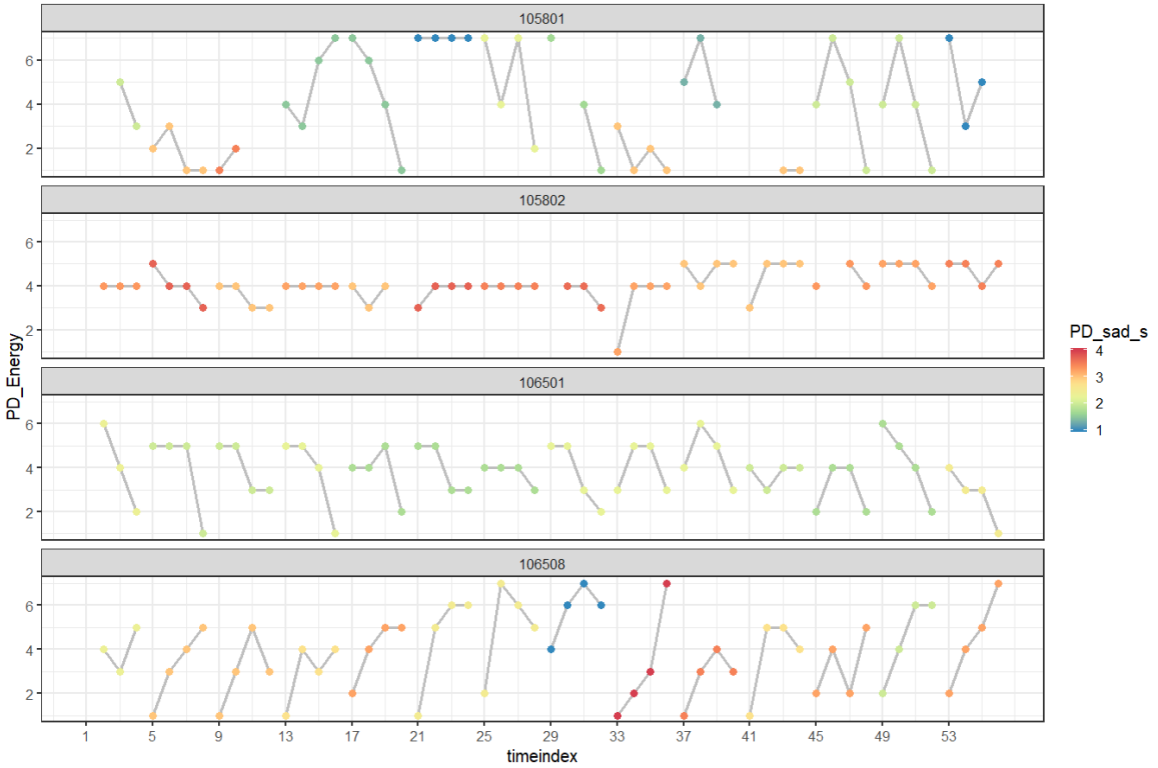

PD_sad
weekday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
PD_sad
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
0
10
20
weektime_n

Using the App: Subject Level Visuals (subject browse)



Using the App: Subject Level Visuals (subject browse)

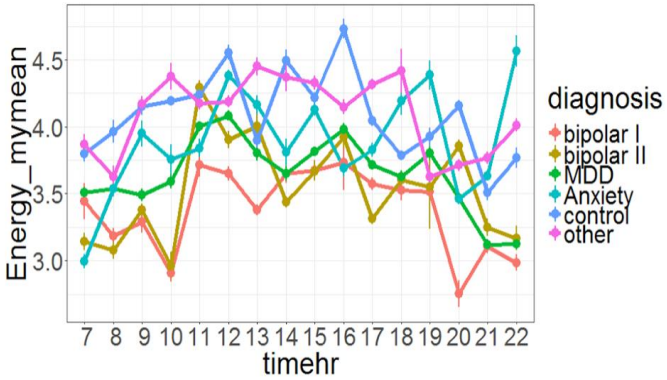




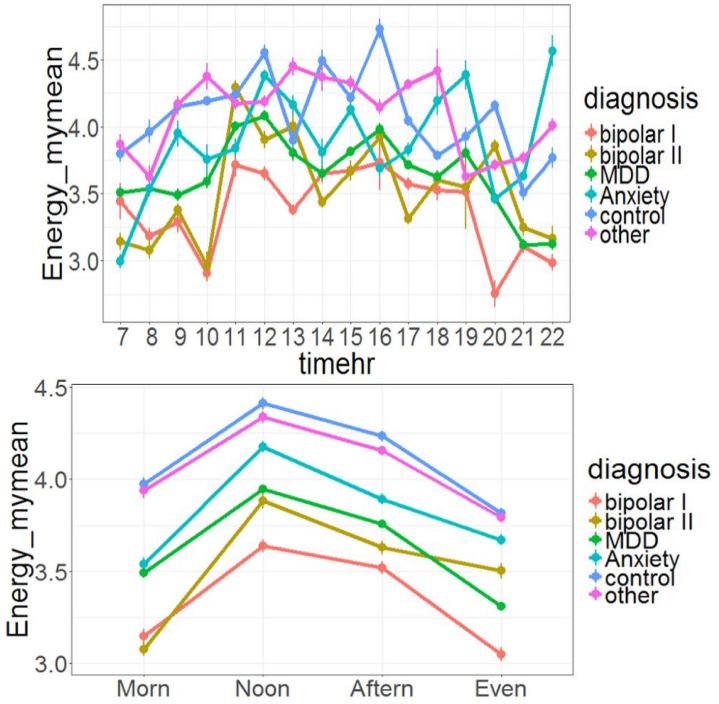
Important considerations

1. Normalization
   - Normalize to the subject-specific internal time
   - Estimate subject-specific diurnal pattern
   - Understand subject-specific weekly pattern
   - Do subject-specific normalization of the measurement (subjective scores)
2. Standardization
   - Using subject-specific standard deviation
   - Using population-level/sample-based references

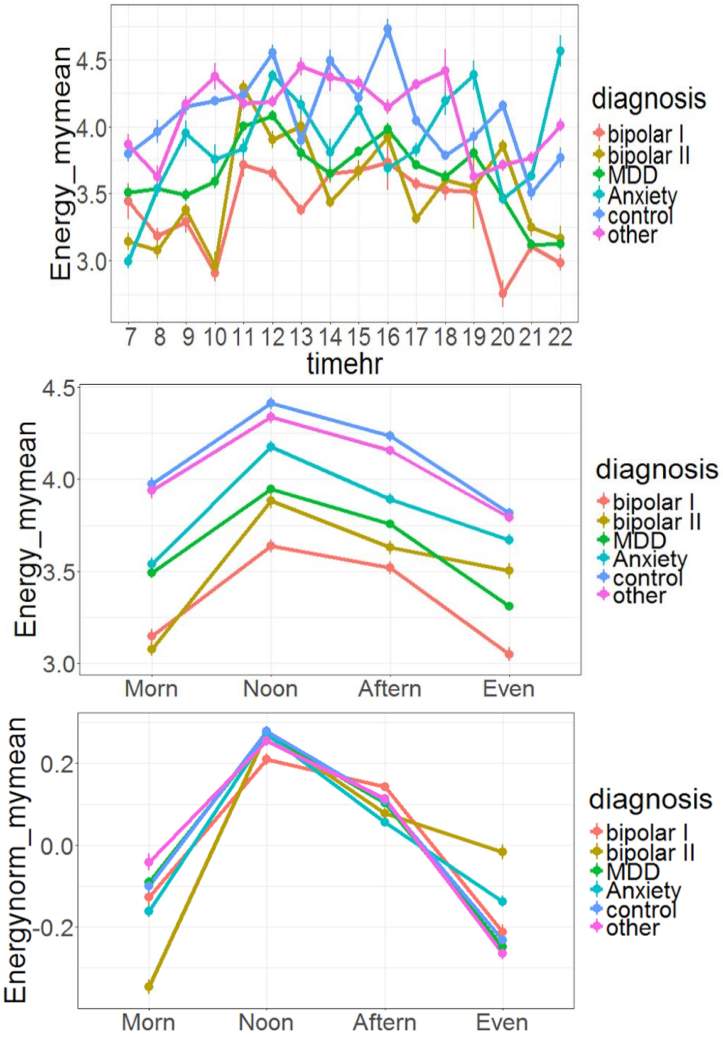
Steps 1 and 2: internal (wake) time and diurnal patterns



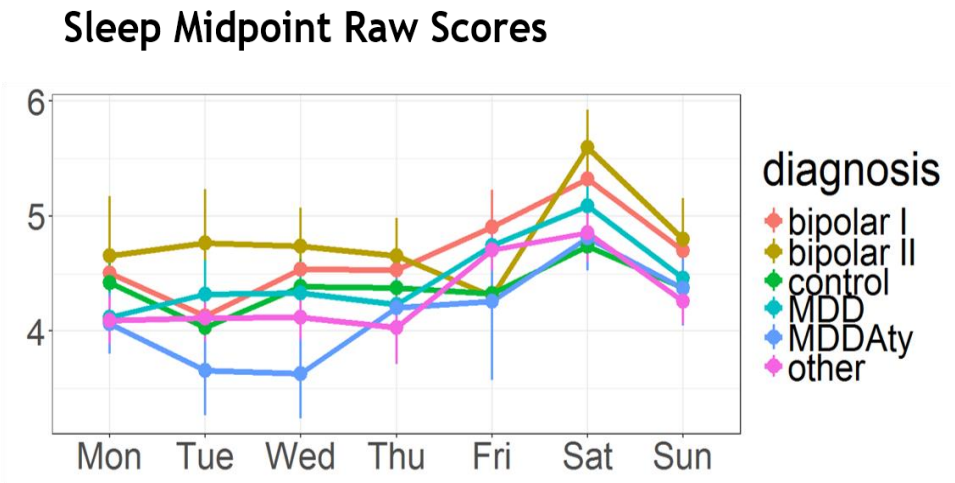
Steps 1 and 2: internal (wake) time and diurnal patterns



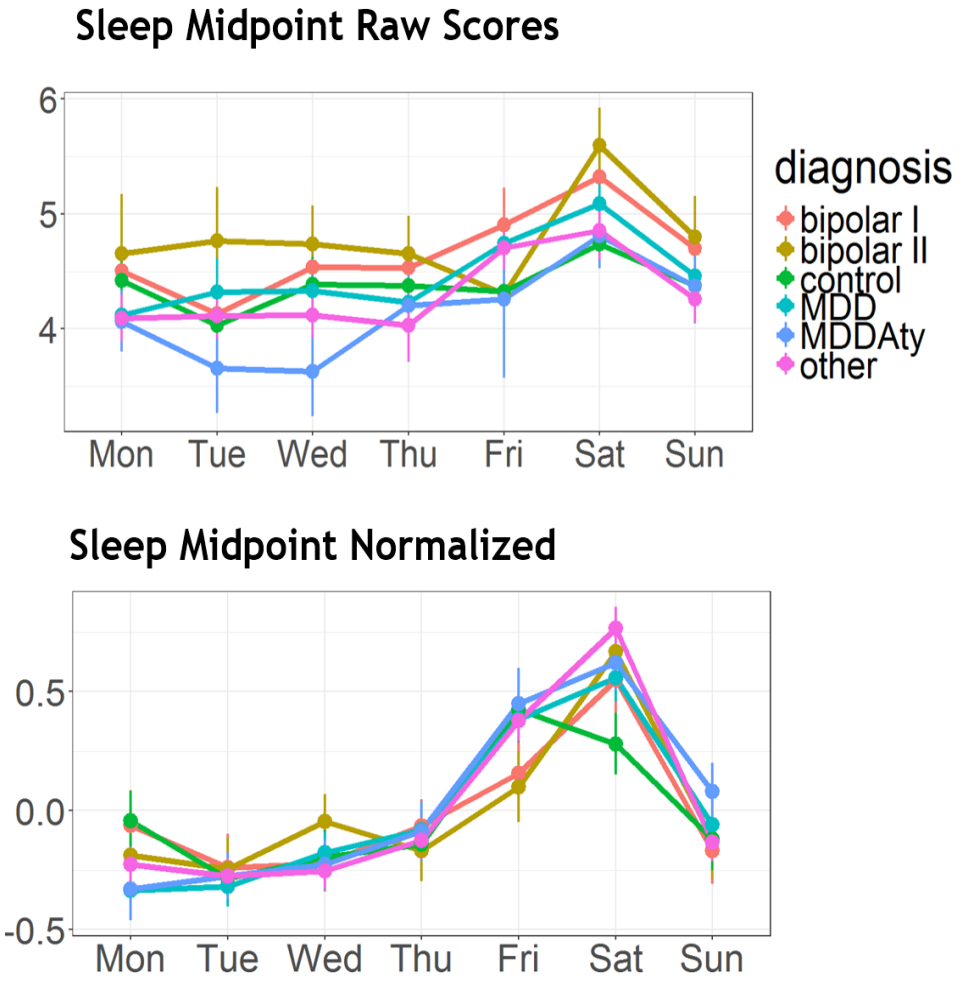
Steps 1 and 2: internal (wake) time and diurnal patterns



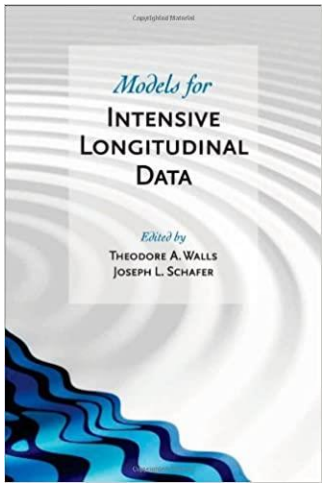
Step 3: Subject-specific weekly patterns

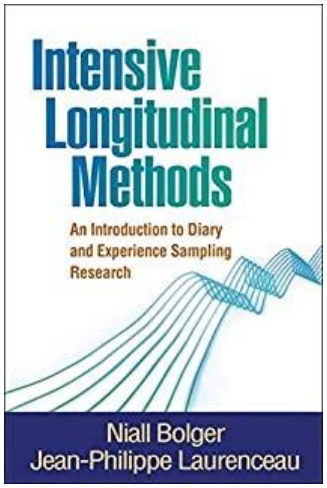


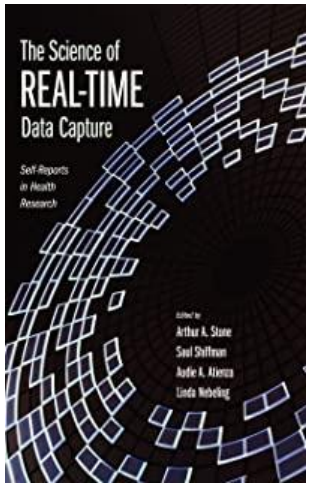
Step 3: Subject-specific weekly patterns

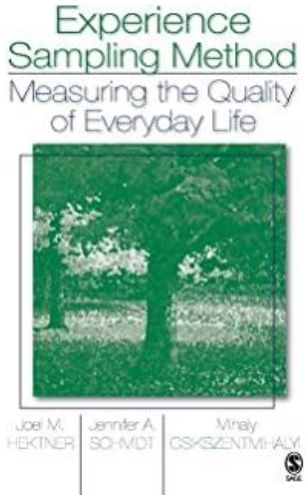


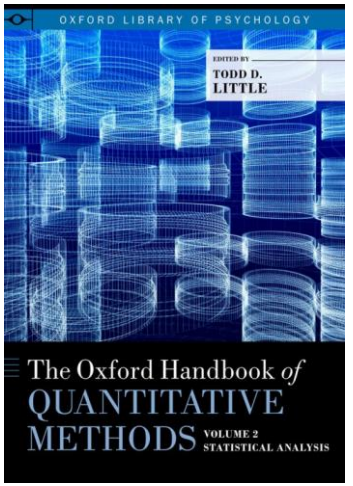
Literature

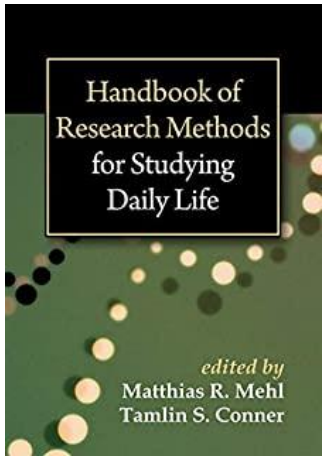


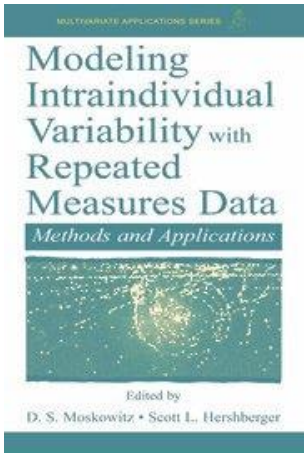












- https://jruwaard.github.io/aph_ema_handbook/
- https://statmodel.com/ (M-plus)
- https://www.methodology.psu.edu/ra/

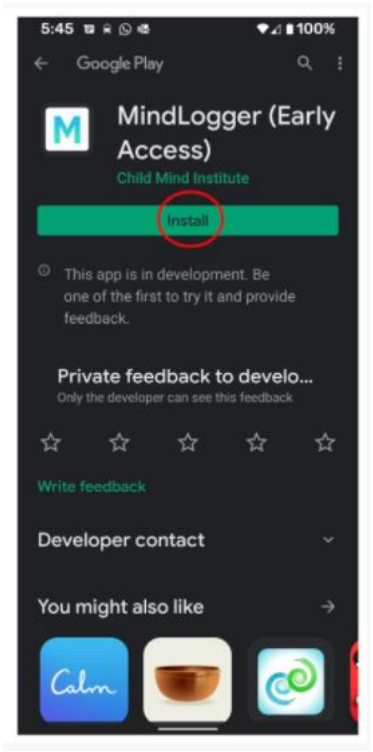
Modelling Software

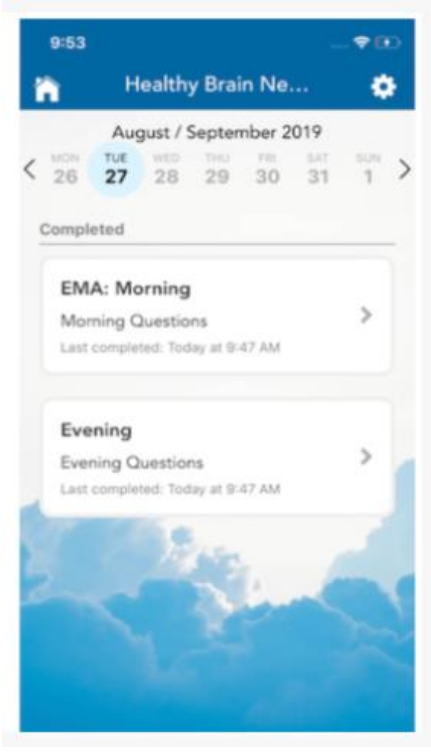
- **lme4** and **nlme**: linear and nonlinear mixed effects models
- **refund**: functional data models
- **qgraph**: network visualization and analysis
- **lavaan:** growth curve models, structural equation models
- **dynr:** discrete and continuous time dynamic models

- **M-Plus:** dynamic structural equation modelling, growth curve models (bayesian)

App developers

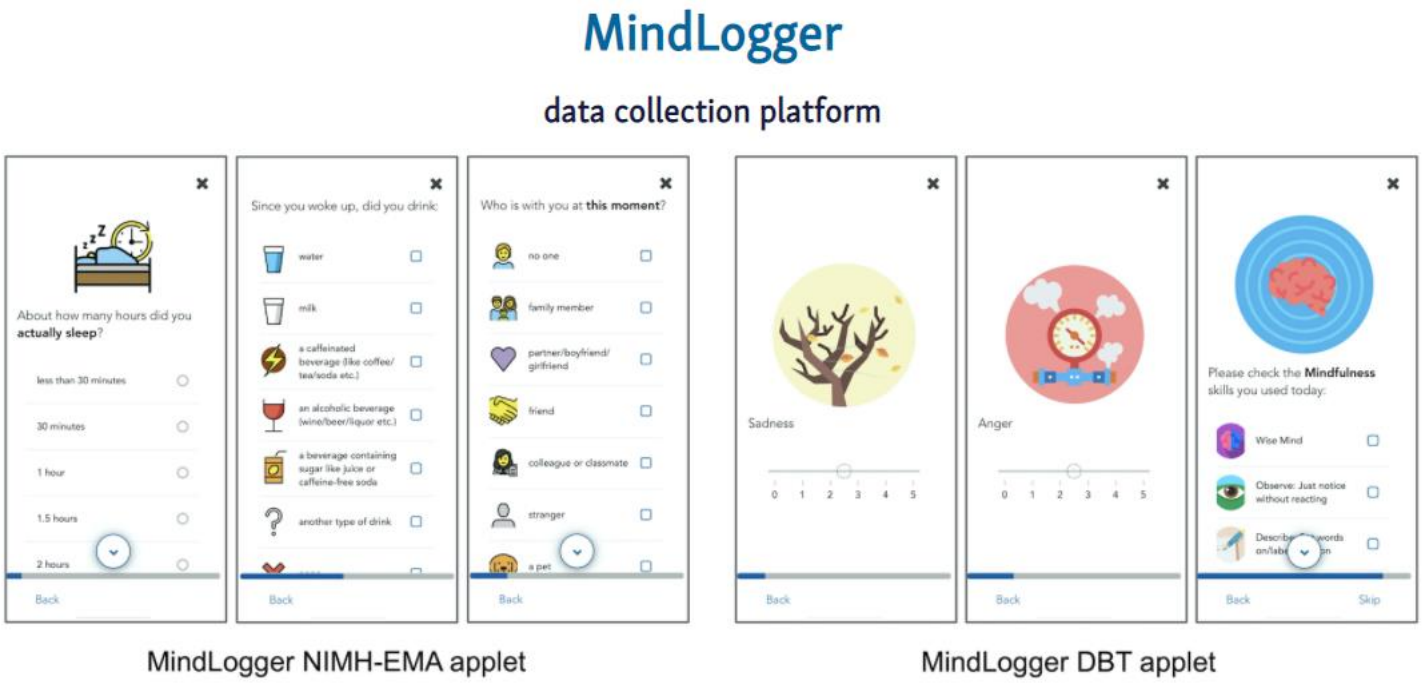
- https://mindlogger.org/ (iOS and Android, free)





App developers

- https://mindlogger.org/ (iOS and Android, free)
- https://jruwaard.github.io/aph_ema_handbook/ema-instruments-catalogue.htm



MindLogger NIMH-EMA applet

MindLogger DBT applet

- **Thank you!**