Monitoring Health Behaviors with Sensor Mobile Technology

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SMART
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STATISTICAL METHODS AND APPLICATIONS FOR RESEARCH IN TECHNOLOGY

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STATISTICAL METHODS AND APPLICATIONS FOR RESEARCH IN TECHNOLOGY

Wearable and Implantable Technologies (WIT)





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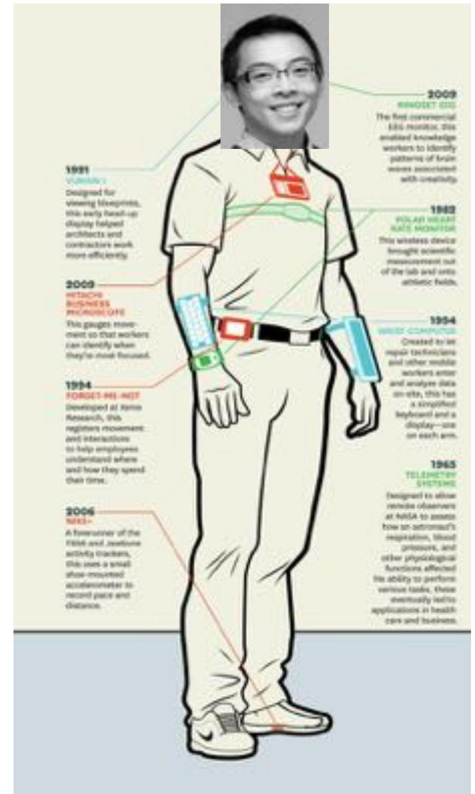
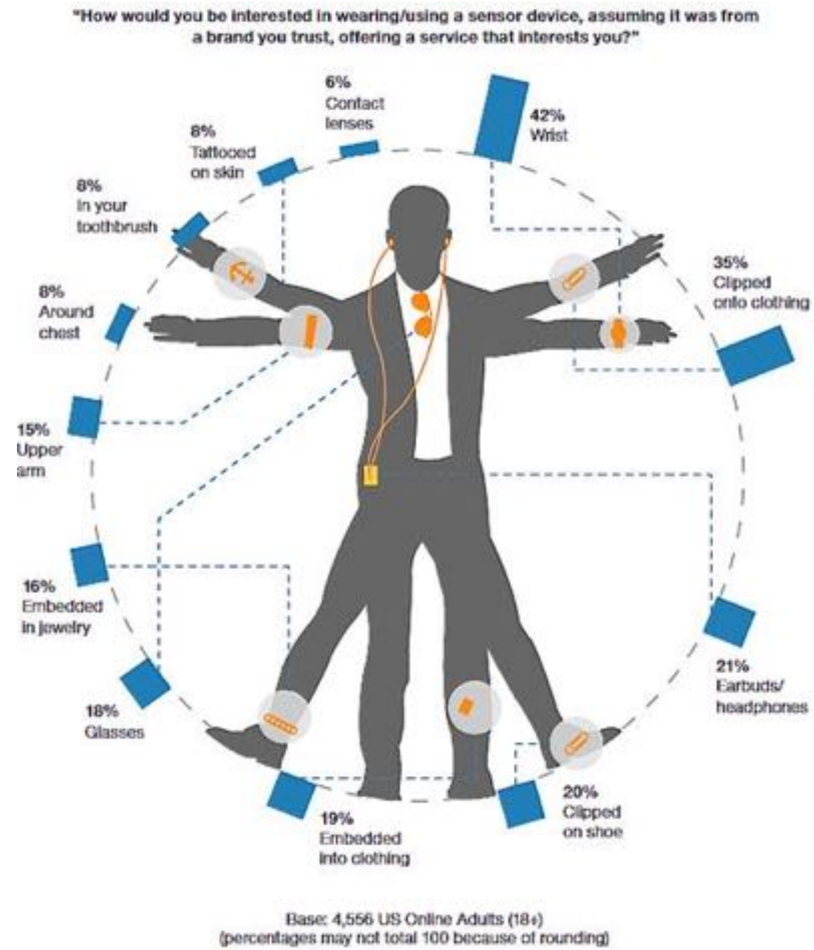


Wearables



Source: North American Consumer Technographics Consumer Technology Survey, 2014

Wearables

Research

Consumer

What do wearables offer?

- Physical Activity, Sleep, Circadian Rhythmicity
- Electronic Diary (EMA):
  - Mood, energy, routines
- Heart Rate (ECG, bpm)
- Blood Glucose
- Ambient light, temperature (circardian markers)
- Voice

Scientific questions

- Physical activity and health
- Circadian rhythms
- Sleep quality
- Response to treatment
- Epidemiology of aging
- Compliance
- Individualized therapy

nhanes
National Health and Nutrition Examination Survey

WOMEN'S HEALTH INITIATIVE

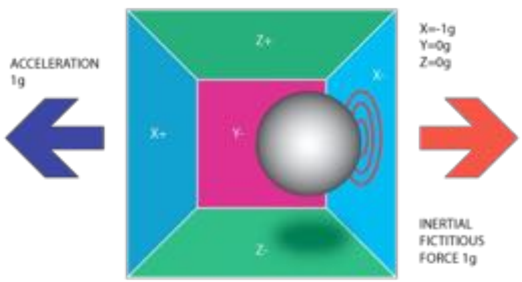
BLSA BALTIMORE LONGITUDINAL STUDY OF AGING

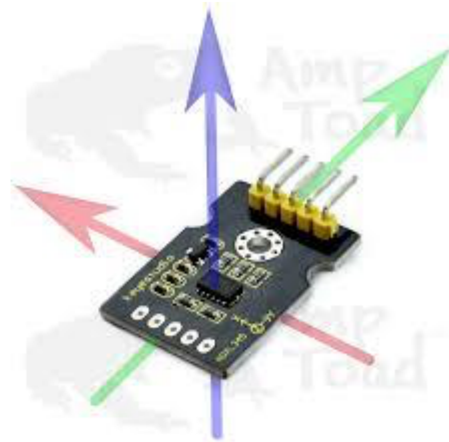
CKiD Chronic Kidney Disease in Children

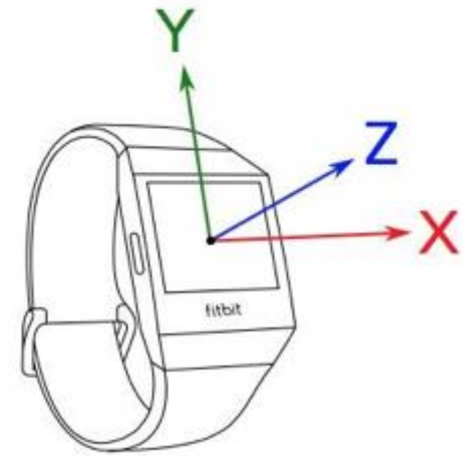
DECOS
Developmental Epidemiologic Cohort Study

HYPNOS
Blood Glucose Monitoring

Accelerometers





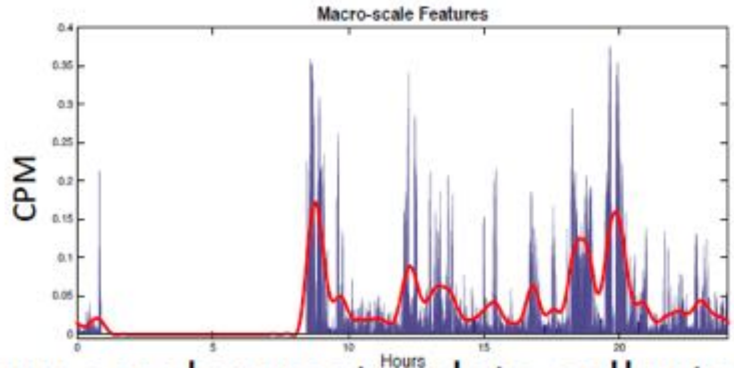


- Detects acceleration in three orthogonal planes

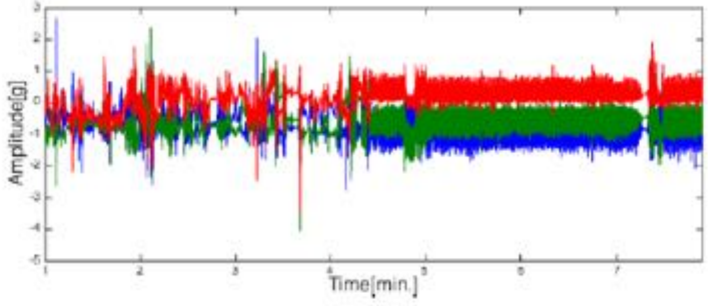
- https://www.youtube.com/watch?v=irjG9Y4NGnE

Macro- and Micro-scale

- **Macro-scale** – summarized data (1 minute intervals)

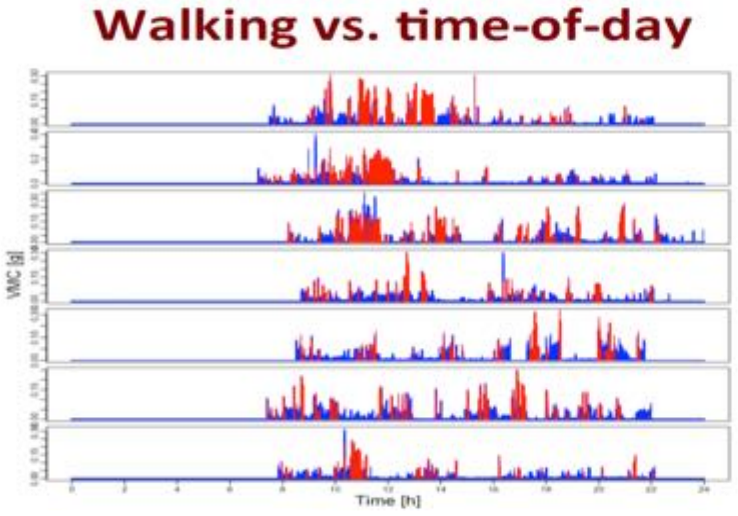


- **Micro-scale** – raw accelerometry data collected (10Hz+)



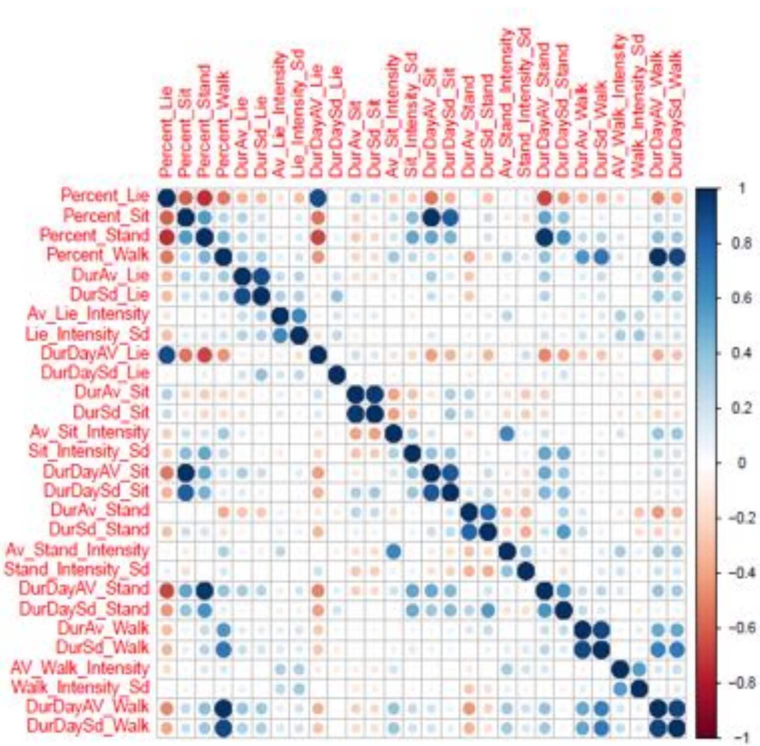
Stage 1: Episode Detection

- Non-wear time
- <u>Posture</u>: sitting, lying, standing, driving, stairs climbing, …
- <u>Activity</u>: walking, running, driving, …
- <u>Sleep</u>: rest/wake, in/out of bed, …



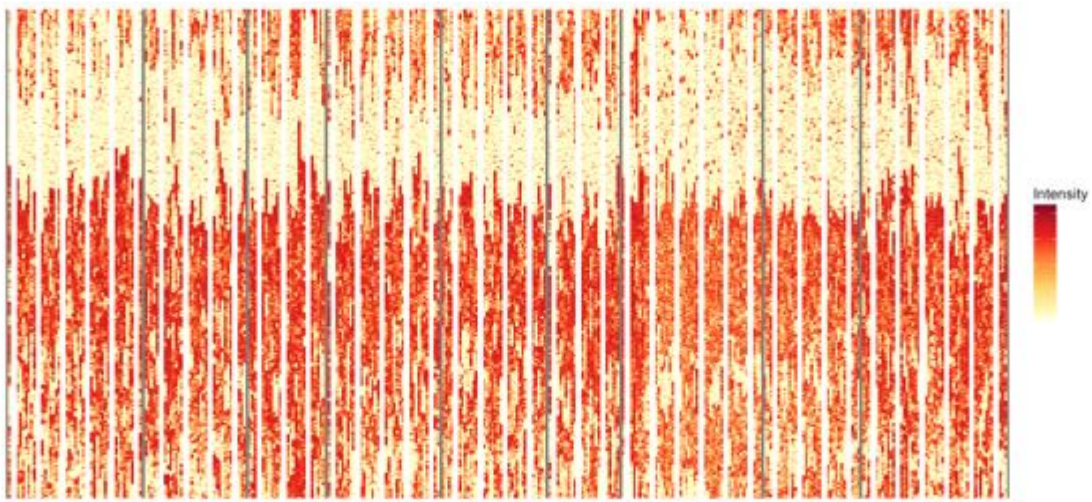
Stage 2: Feature extraction

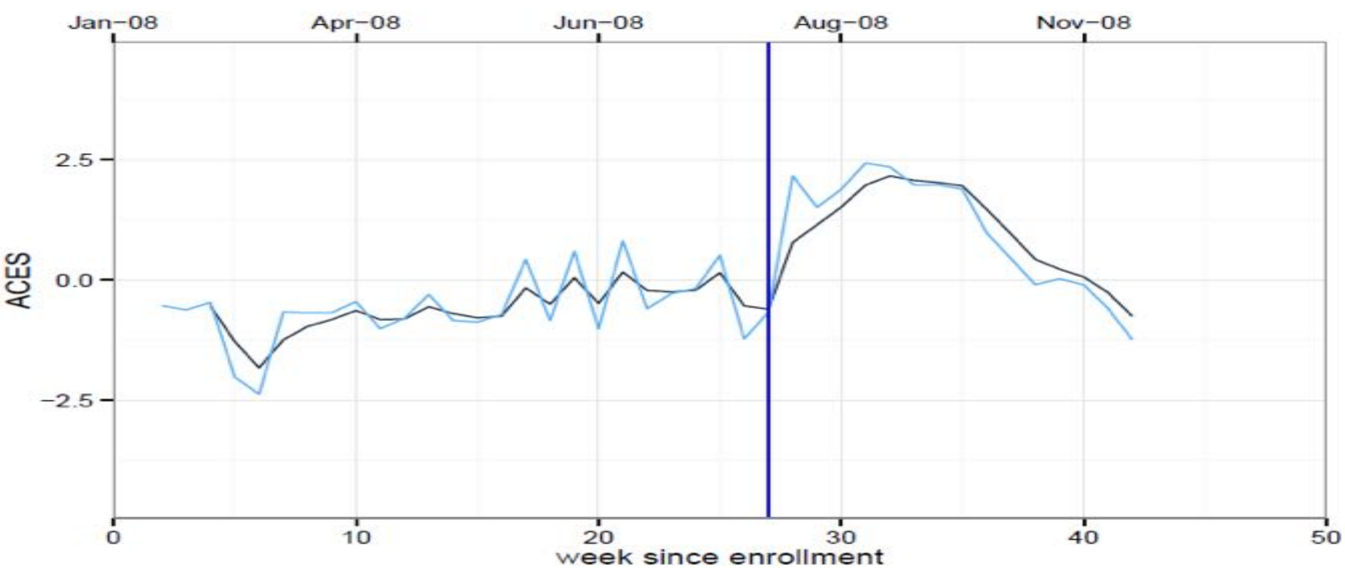
- <u>Walking</u>: cadence, stride-variability, asymmetry, …
- <u>Sleeping</u>: time in bed, fragmentation, variability, …



Stage 3: Feature Fusion

- Example: a subject with a CHF-related hospitalization





Challenges

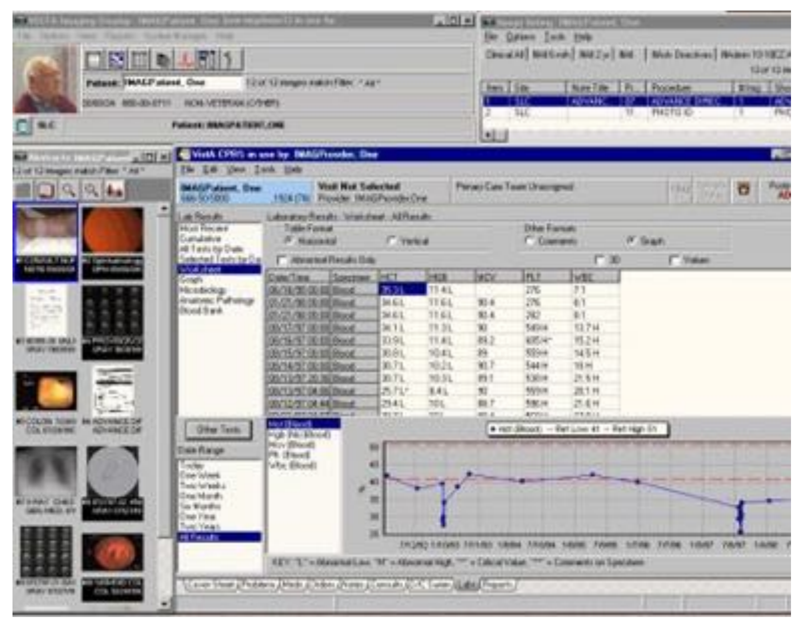
- Need **new** methods that can be applied to:
  - thousands of subjects
  - very large data sets (10 Tb+)
  - free-living environment
  - no visual labeling(camera or person);
  - large between- and within- person variability

Sensor fusion

ENAR & JSM 2019:
Monitoring health behaviors with multi-sensor mobile technology

Personal health data banks

- Personal small data (from wearables)
- Big data from health providers
- Link both in personal health account



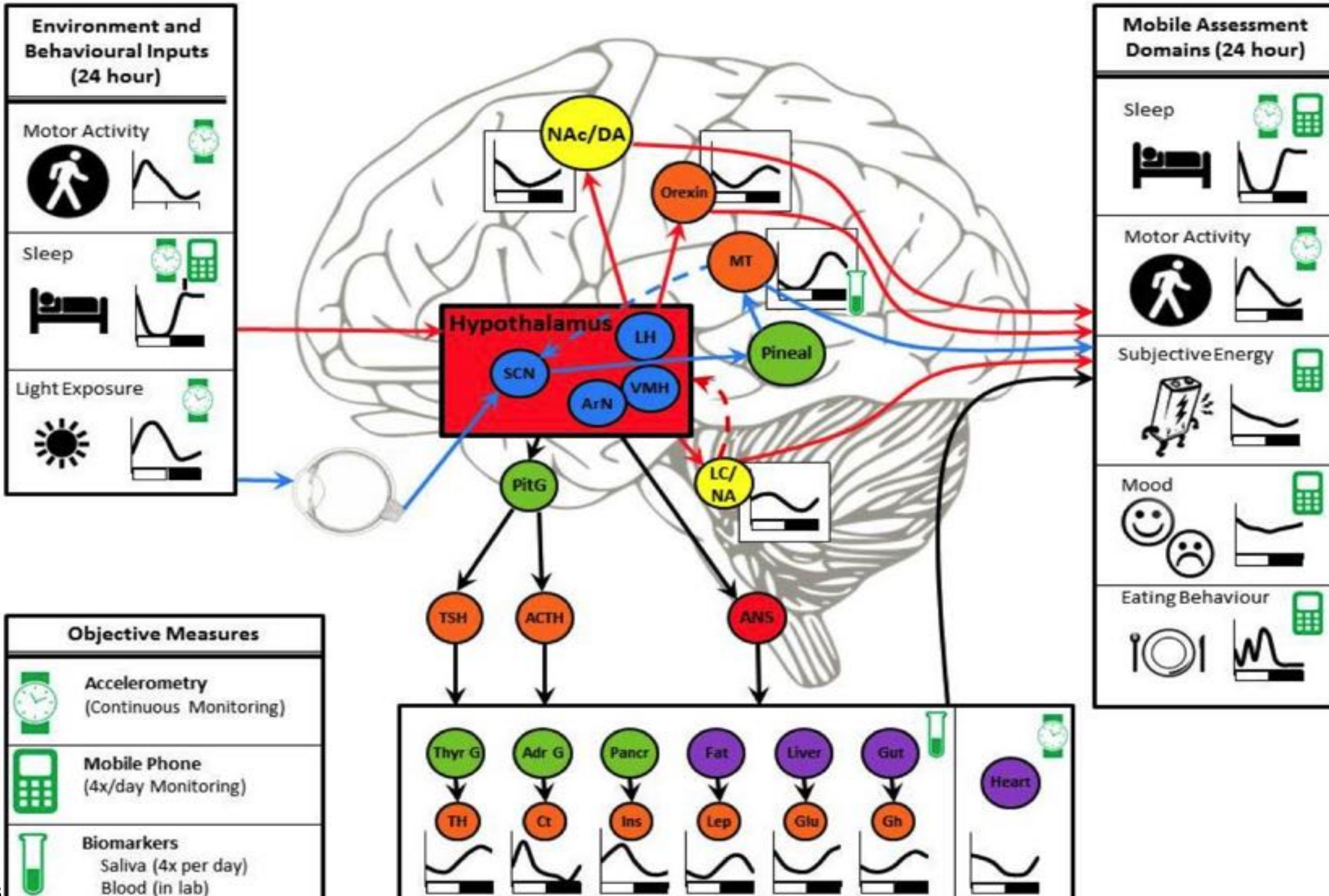
Two snapshots

- Motor Activity Research Consortium for Health *(mMARCH)*
- Monitoring individuals with Congestive Heart Failure

Motor Activity Research Consortium for Health

(mMARCH)

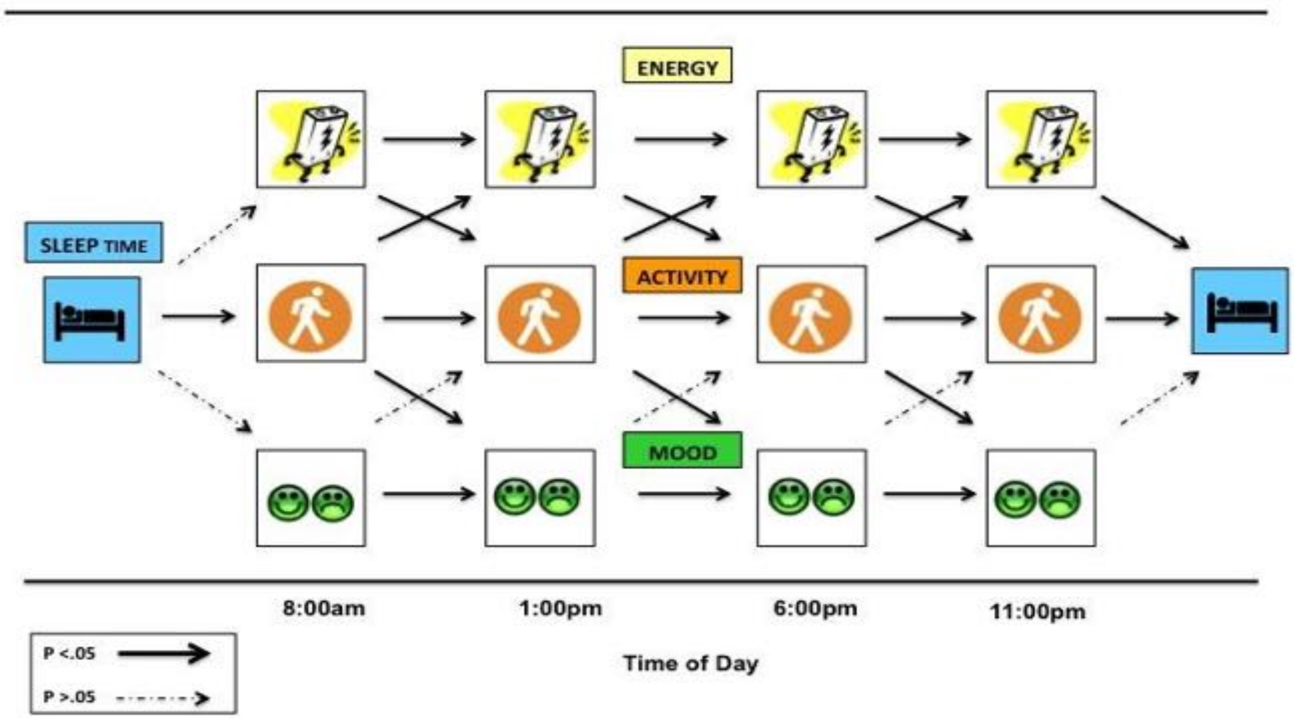
Biological processes associated with regulation of homeostatic domains assessed by mobile tracking



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

Actigraphy and EMA

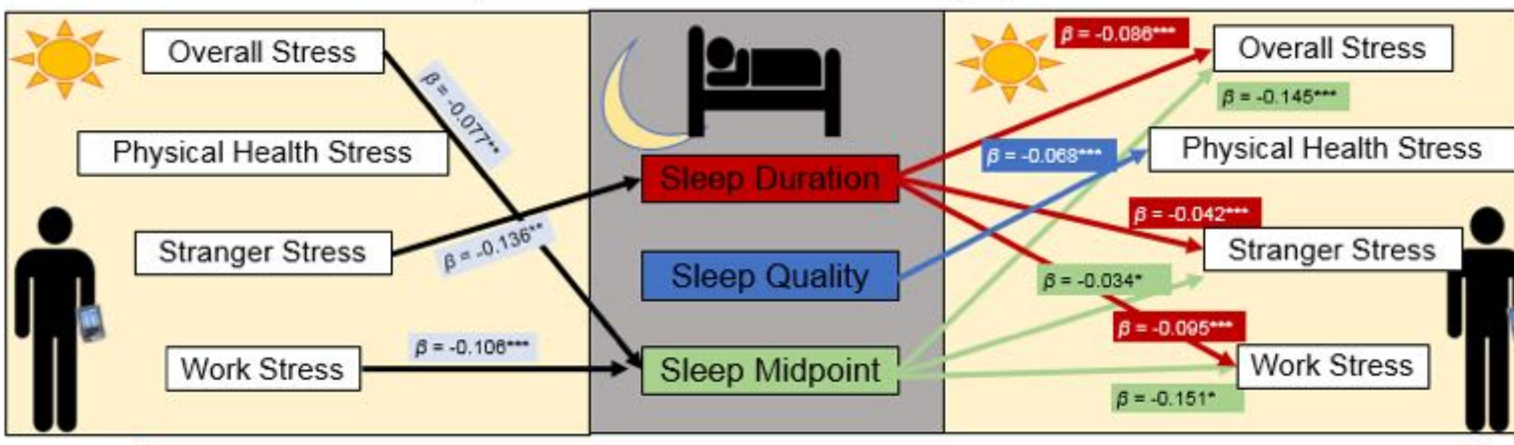


Tracking Inter-relationships of Motor Activity, Sleep, Mood, and Energy via Mobile Technologies: Evidence for Cross-Domain Dysregulation in Bipolar I Disorder; JAMA: Psychiatry (in press)

Merikangas, K., Swendsen, J., Hickie, I., Cui, L., Shou, H., Merikangas, A., Zhang, J., Lamers, F., Crainiceanu, C., Volkow, N., Zipunnikov, V.

Actigraphy and EMA

Bidirectional Day Level Effects between Sleep Measures and Stress Ratings



CHF

- **Heart failure** (HF) is a leading chronic disease in the elderly
- Lifetime risk is 20% for those over age 40 in the US
- HF burden exceeds $30 billion (> 50% on hospitalization costs)
- Identifying subjects with increased risk of hospitalization is important

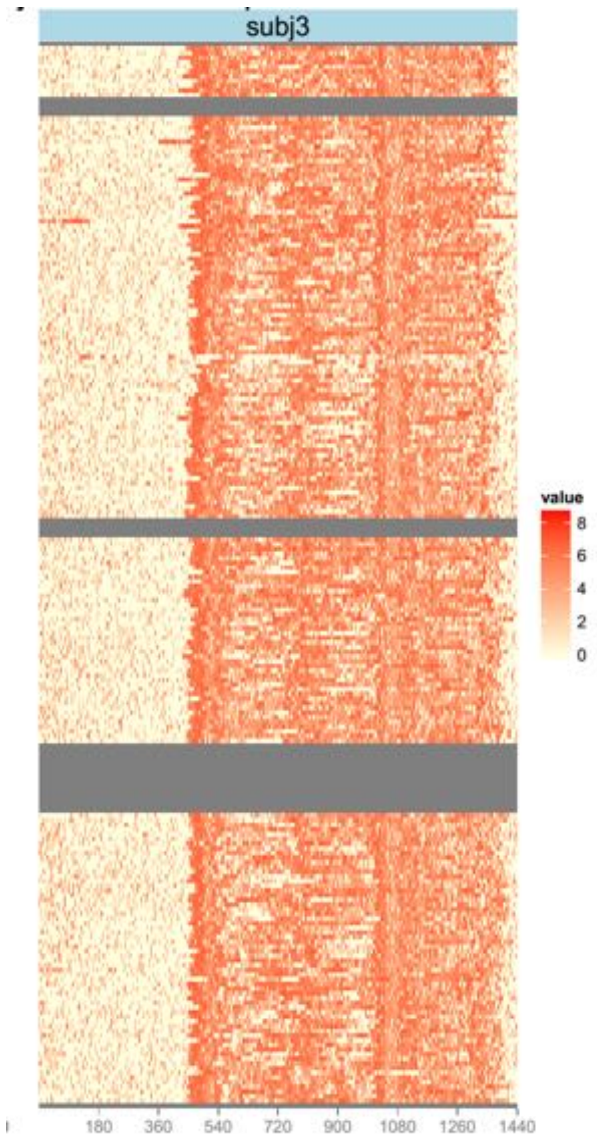
CHF

- **Static risk models** include demographics, comorbidities (AFib, hypertension, diabetes mellitus), income, etc.
- **Dynamic risk models** may be more accurate by including real-time data from wearables
- Cardiac Care Center of Columbia University Medical Center
- 59 individuals with congestive heart failure (CHF)
- 3-9 months of follow up

CHF

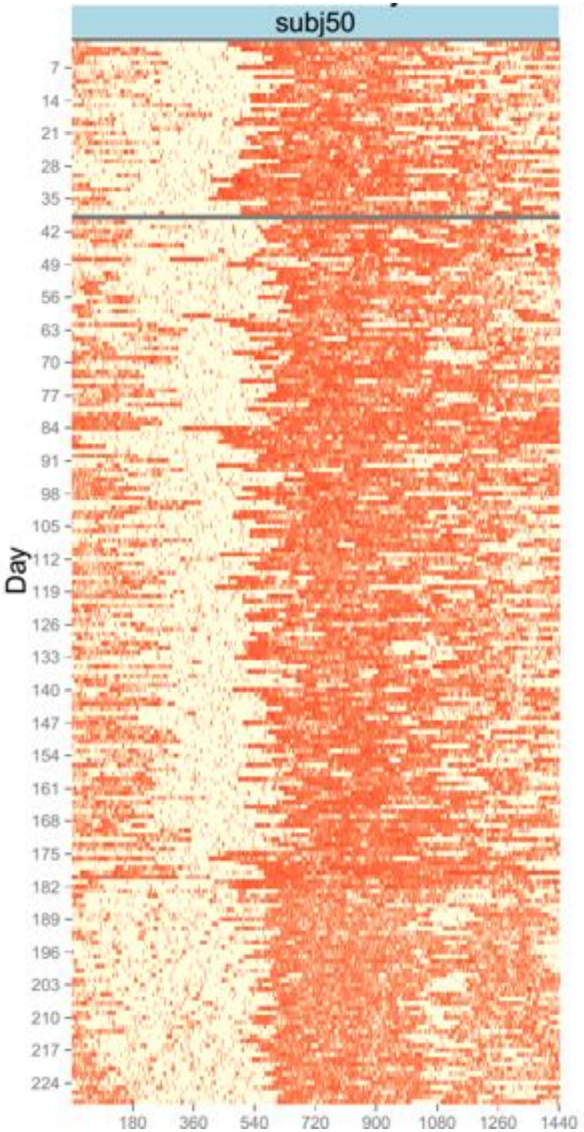
- 24 individuals had adverse clinical events
  - 14 hospitalizations
  - 10 emergency room visits
- **Goal:** model within-subject pre/post event change in patients status
- **Method:** track multi-feature representation in three domains
  - sleep
  - physical activity
  - diurnal/circadian patterns

No-event group subject



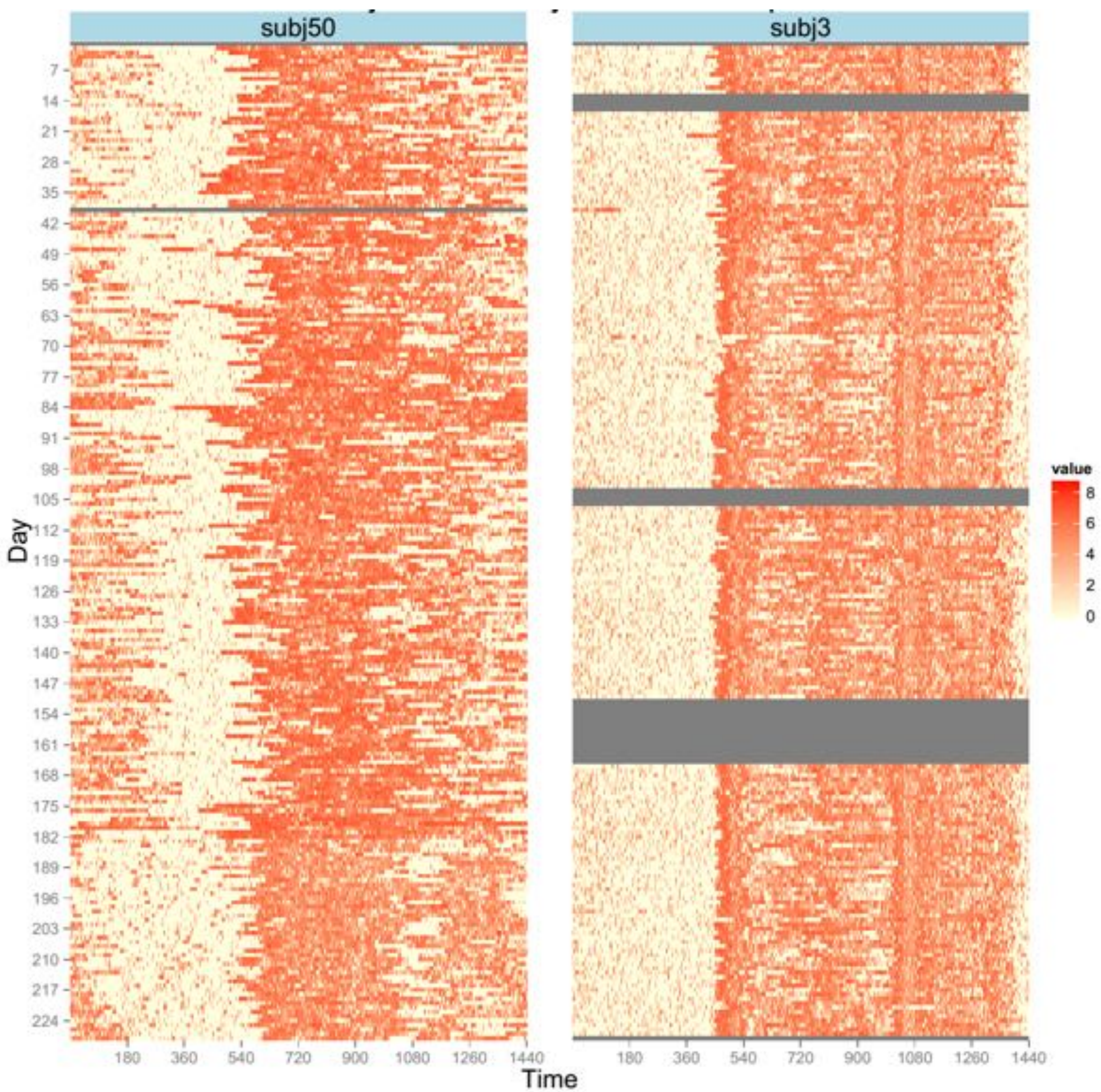
- 8 months of monitoring
- Low week-to-week variability
- **Had no hospitalizations**

Event-group subject



- 8 months of monitoring
- High week-to-week variability
- **Had a hospitalization**

CHF



subj50
subj3
Day
Time
value
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4
2
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28
35
42
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70
77
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105
112
119
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133
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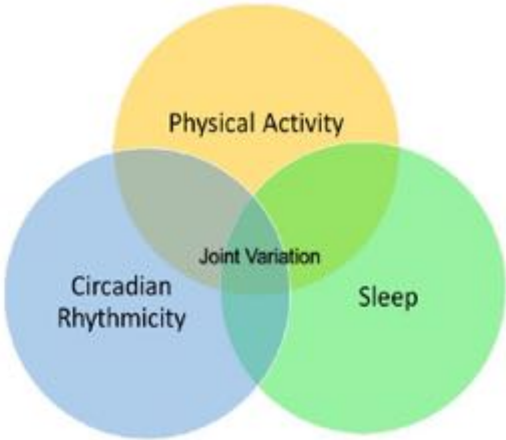
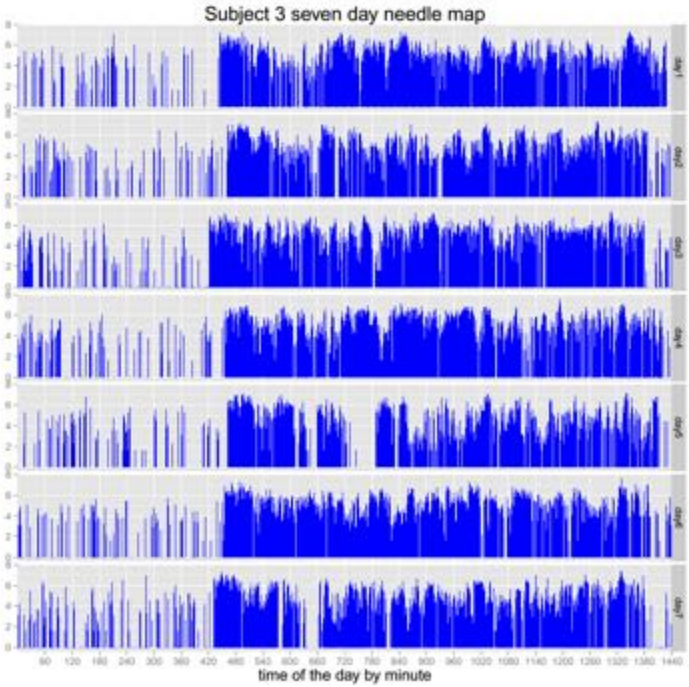
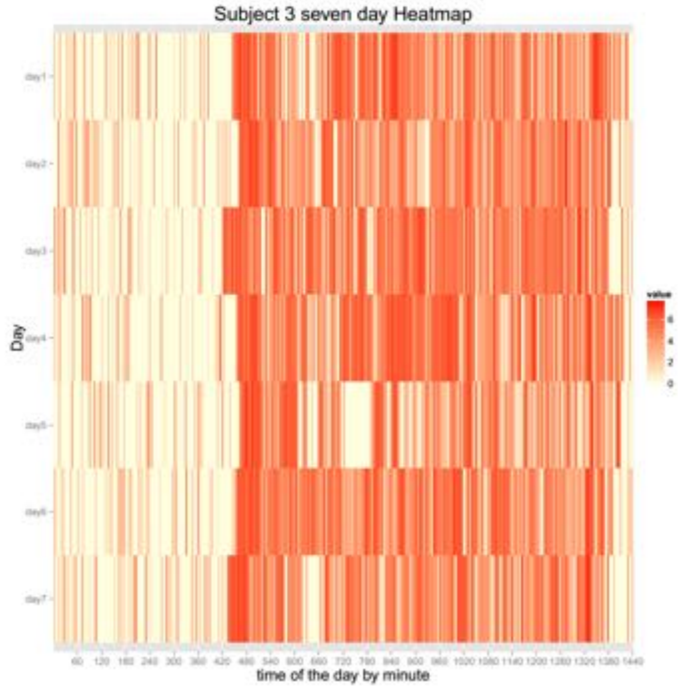
147
154
161
168
175
182
189
196
203
210
217
224
180
360
540
720
900
1080
1260
1440

Multi-domain approach

- Track three domains
  - sleep (11:30pm-07:00am)
  - physical activity (07:00am-11:30pm)
  - diurnal/circadian patterns (12:00am-12:00am)



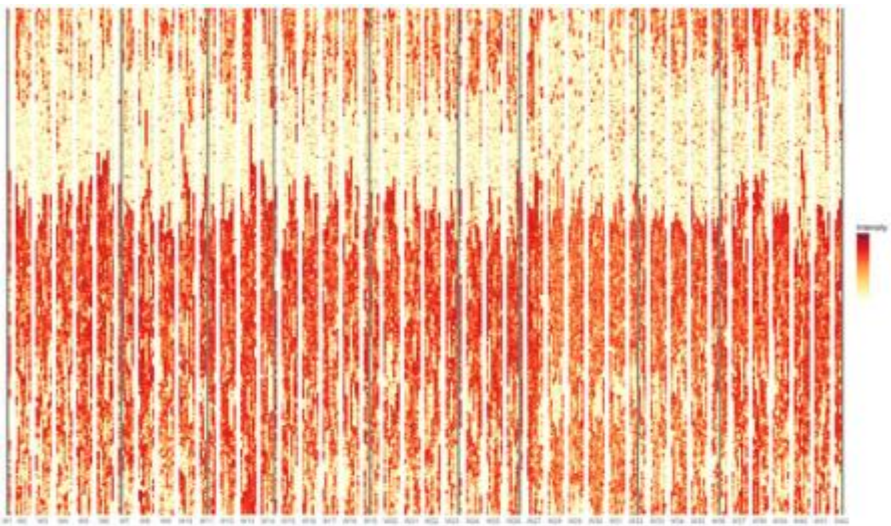


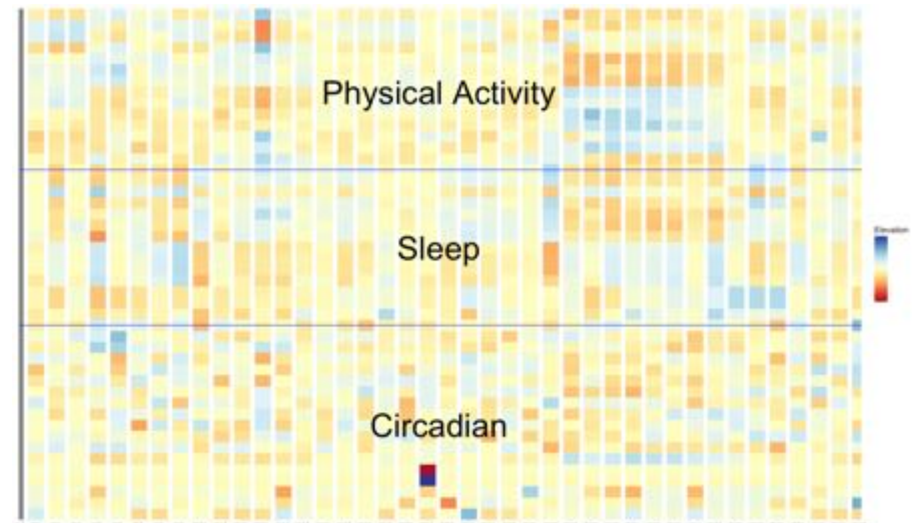


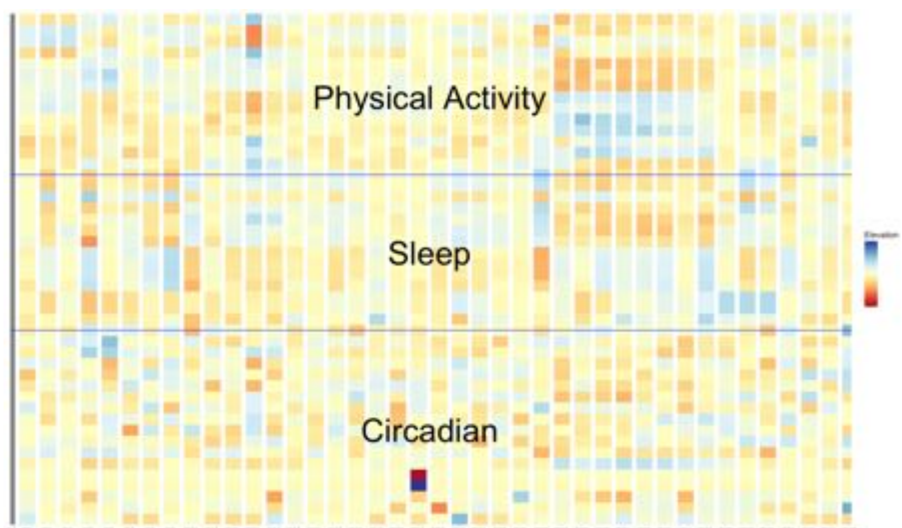
Multi-domain approach

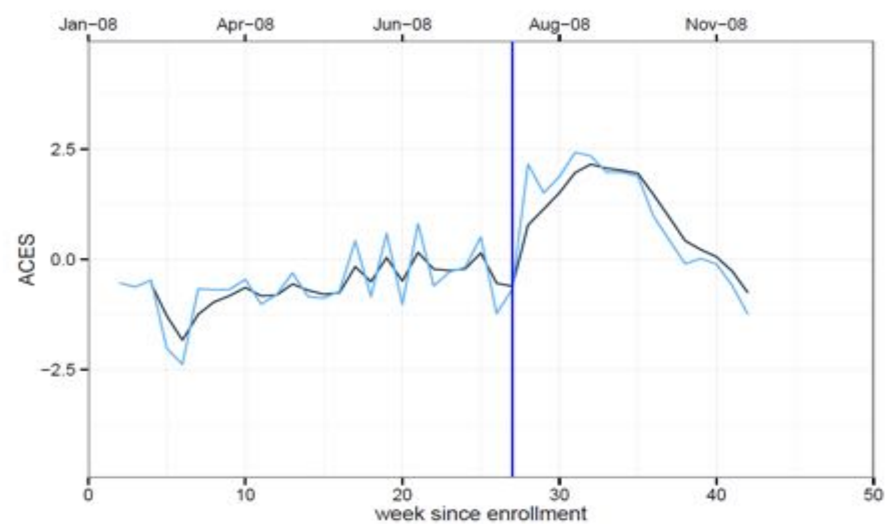
- Physical Activity (PA)
  - Intensity (SePA, LiPA, MVPA), duration (bouted, fragmented), frequency (30-60 mins per day);
  - Steps, Energy Expenditure, Heart Rate Reserve
- Sleep (SL)
  - Stages (REM, NR1-3), transitions/duration, sleep efficiency, fragmentation, sleep onset
- Circadian Rhythmicity (CR)
  - parametric, non-parametric models, strength, stability, variability

ACES

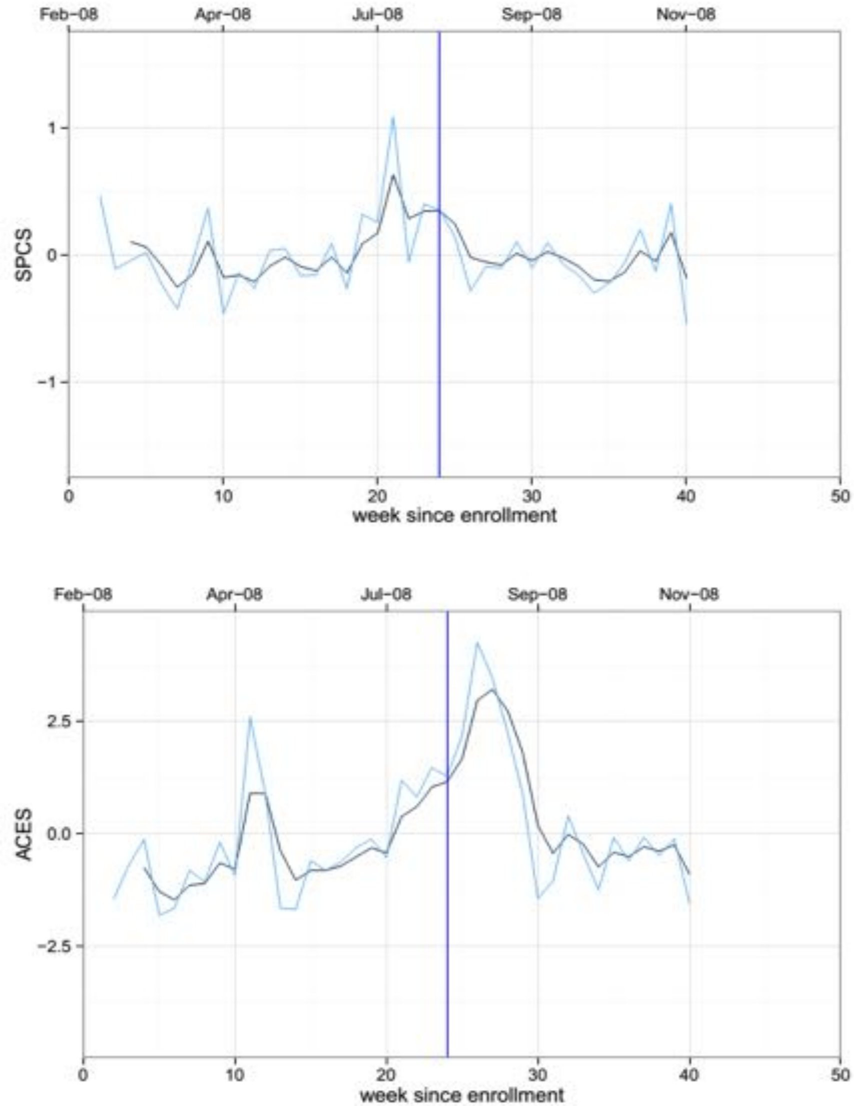



Physical Activity
Sleep
Circadian


Physical Activity
Sleep
Circadian


Jan–08
Apr–08
Jun–08
Aug–08
Nov–08
2.5
0.0
-2.5
ACES
0
10
20
30
40
50
week since enrollment

Event group



Feb−08
Apr−08
Jul−08
Sep−08
Nov−08
SPCS
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0
−1
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10
20
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50
week since enrollment
Feb−08
Apr−08
Jul−08
Sep−08
Nov−08
ACES
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0.0
-2.5
0
10
20
30
40
50
week since enrollment

Conclusion

- ACES may be useful for
  - in pre-event dynamic assignment of risk
  - post-event monitoring of patient status
  - potentially for pre-event intervention

- What is the meaning of pre-clinical (silent) events
- Pre-clinical episodes: not all high-risks periods ends with an event (in both groups)
- <u>Future</u>
  - External validation: on-going multi-site pilot

Joint work with

- Junrui Di, Johns Hopkins University
- Lei Huang, Johns Hopkins University
- Daisy Zhu, Johns Hopkins University
- Yu Du, Johns Hopkins University
- Ximin Li, Johns Hopkins University
- Jiawei Bai, Johns Hopkins University
- Andrada Ivanescu, Montclair State University
- Tamara Harris, NIA
- Mathew Maurer, Columbia University
- Phillip Green, Columbia University

Thank you!