A Step-by-Step Guide to Using Wearables

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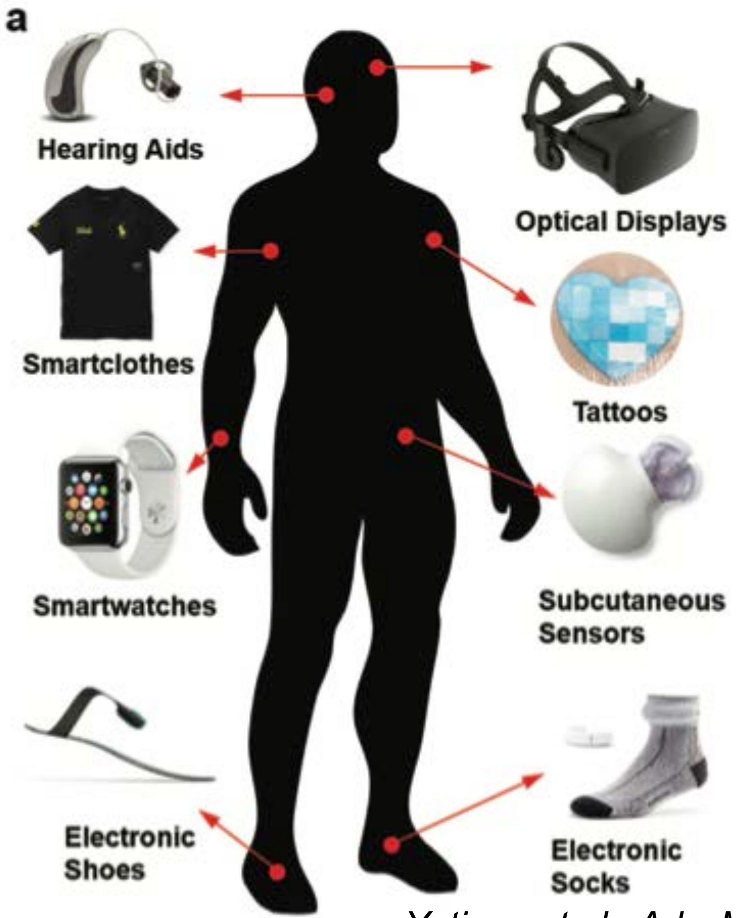
The Wearables Market is Rapidly Expanding

- Wearable: body-worn device that measures some aspect of human behavior and/or physiology
- Wearables are embedded in modern society
- Break free from the laboratory and clinic
  - Clinic: snapshot of someone's capacity
  - Free-living environment: continuous footage of someone's day-to-day reality



Yetisen et al., Adv. Mater., 2018

Objectives

- Understand the factors to consider when selecting an accelerometer to measure physical activity
- Review best practices for data collection to set yourself up for success during data analysis

I want to measure physical activity, what are my options?

Advantages
- Wearability/style
- User interfaces
- Inexpensive

Disadvantages
- Data extraction and analysis
- Difficult to assess accuracy/precision
- Stability of company

Commonly used monitors at CU-AMC

Advantages
- Accuracy and precision
- Easy extraction of data
- Software analysis suites

Disadvantages
- Generally, less cool
- Can be expensive

Factors To Consider During Monitor Selection

- Who is wearing the monitor?
  - Population (barriers with using wearables)
  - Wear location

- How long will monitor be worn for?
  - Duration of wear (battery life)
  - Wearability/user experience

- What do you want to measure?

Specificity of Measurement Outcomes is Essential in Monitor Selection

- *Total steps*
- *Step cadence*
- *Light physical activity*
- *Moderate to vigorous physical activity*
- *Sitting time*

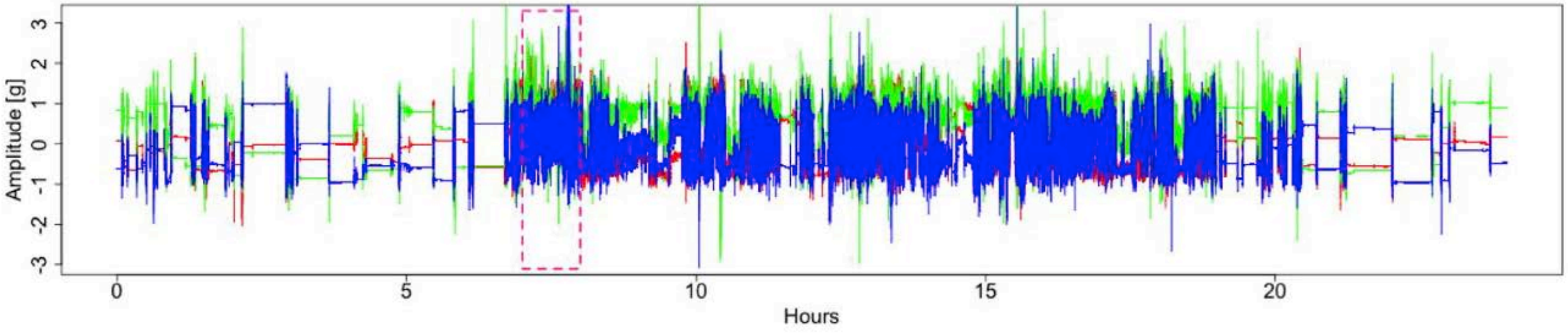
Specificity of Measurement Outcomes is Essential in Monitor Selection

What can my device measure?

- *Sedentary behavior*
- *Breaks in sedentary behavior*
- *Steps and true cadence*

__The bottom line__: make sure your device can actually measures what you want to measure in your specific clinical population

Physical Activity Monitors <u>Measure</u> Acceleration and <u>Estimate</u> Physical Activity/Behavior



Karas et al., 2018

Automated Algorithms
(wear time/sleep detection)

Activity counts/composite metrics

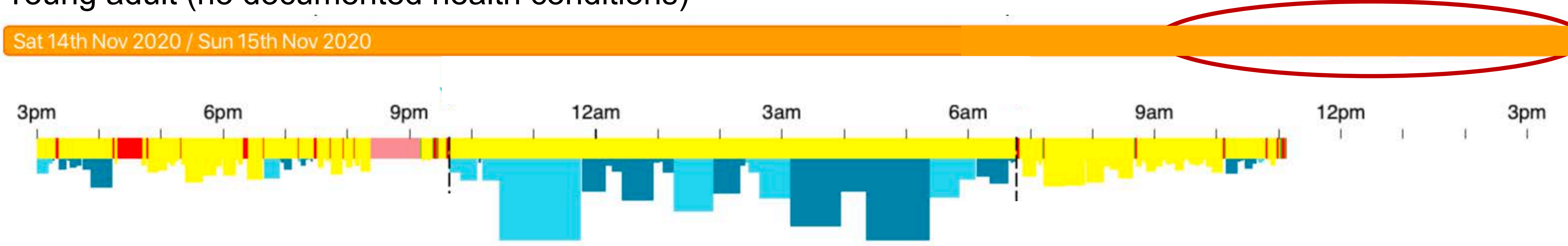
Meaningful metrics (steps, time in MVPA, sleep duration)

Errors and misclassification can happen along this process

Automated Sleep Detection Algorithms

PALanalysis

Young adult (no documented health conditions)

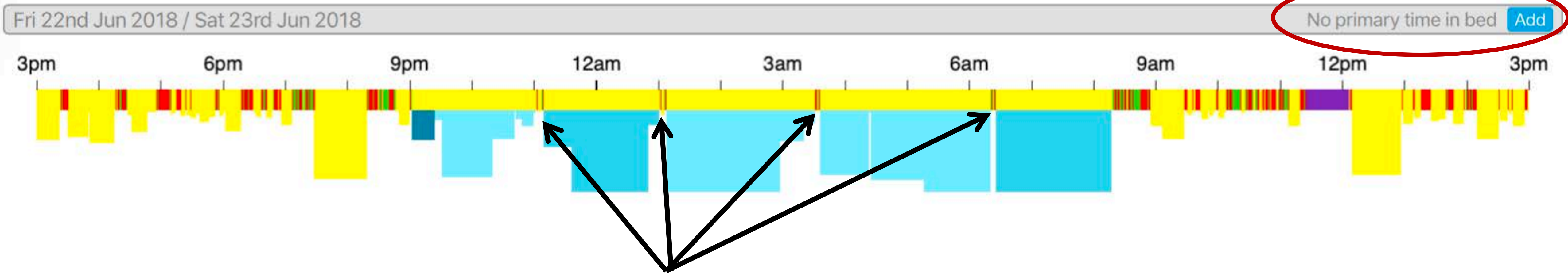


When the Automated Algorithms Breakdown…

PALanalysis

Older adult with heart failure

No detected sleep period



Interruptions in sleep period

Importance of Self-Reported Data

- Self-reported logs can be used to make sense of potentially erroneously classified behaviors

- Can complement objective data and provide context for behavior

- Particularly important for clinical populations

Example log for activity monitoring

Day	Date	Day (Mon.-Sun)	Condition (circle one)	Time out of bed in the morning	Time into bed for the night	List times during the day the monitor was not worn. Include reason not worn	Time of Exercise
1	9/8	T	Normal Activity	__:__ am/pm	11:45 am/pm	Wrist Hip	__:__ am/pm
2	9/9	W	Control Exercise Activity Breaks	7:20 am/pm	11:40 am/pm	Wrist Hip 7:15-7:30 AM Shower	__:__ am/pm
3	9/10	Th	~~Normal Activity~~ Exercise	6:50 am/pm	11:50 am/pm	Wrist 7:15-9:45pm Play rehearsal Hip	8:45 am/pm
4	9/11	F	Control ~~Exercise~~ ~~Activity Breaks~~	6:50 am/pm	11:50 am/pm	Wrist 6:00-6:15 PM Shower 7:15-9:15 performance Hip	__:__ am/pm
5	9/12	S	Activity Breaks ~~Normal Activity~~	7:30 am/pm	11:45 am/pm	Wrist 6-6:15 Shower Hip	__:__ am/pm

Tips to maximize utility of self-reported data

- Review objective data concurrently with logs as soon as possible with participants
  - Handwriting issues
  - Better recall
- Consider sections to include "nap times"

Data Analysis

- Basic steps for analyzing physical activity data
  - Clean data and remove non-wear time
  - Distinguish waking time from sleeping time
  - Convert accelerations/activity counts to meaningful metrics to quantify physical activity during waking wear time

- Many device manufactures have software which integrates published automated algorithms to score physical activity data

Extracting Meaningful Data

- 24-hour summary measures commonly reported
  - Steps per day
  - Time in moderate to vigorous activity
  - Sleep duration

- Wearables provide frequently sampled data over many days at a time

- 24 hour summary measures are only scratching the surface of information wearables can provide
  - Seth: “You are more than the sum of your steps”
  - Julia: “Stepping into the future”

Interested in Learning More?

Physical Activity Methods Journal Club

This journal club is focused on discussing recent advancements in the methodologies used to process and interpret accelerometer data. Every month, one individual will lead a discussion on a recently published paper, a manuscript they are currently working on, or data they have recently collected. Content is distributed through a private google group. If you are interested in participating and joining the discussion (virtually over Zoom).

Organizer: Jen Blankenship (jennifer.blankenship@cuanschutz.edu)

Meetings: the 1st Monday of the month at 10 am during the academic year (September – May)

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COLORADO NORC Nutrition Obesity Research Center

NIH National Heart, Lung, and Blood Institute

NIH National Institute of Diabetes and Digestive and Kidney Diseases

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F32 DK121403

You are <u>More</u> than the Sum of Your Steps

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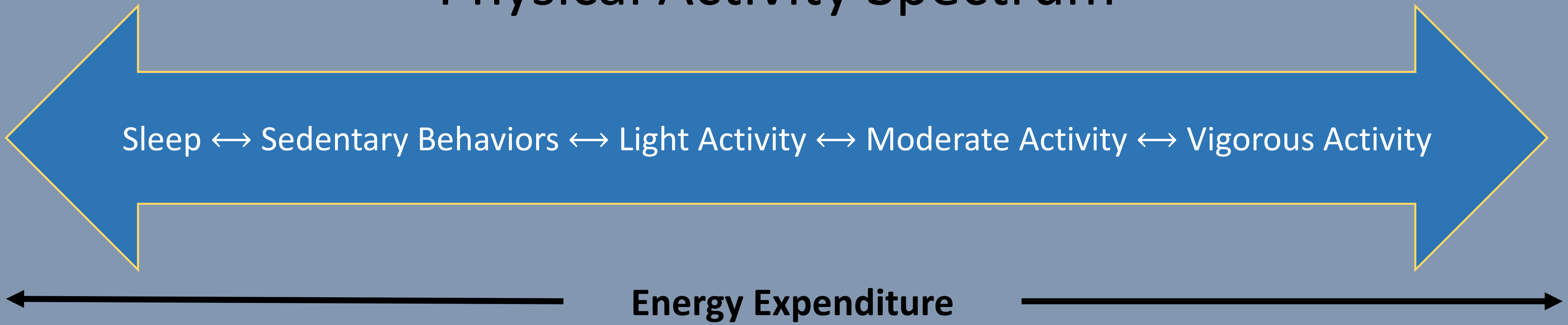
What are we measuring?

Physical Activity Spectrum



Measures of Sleep

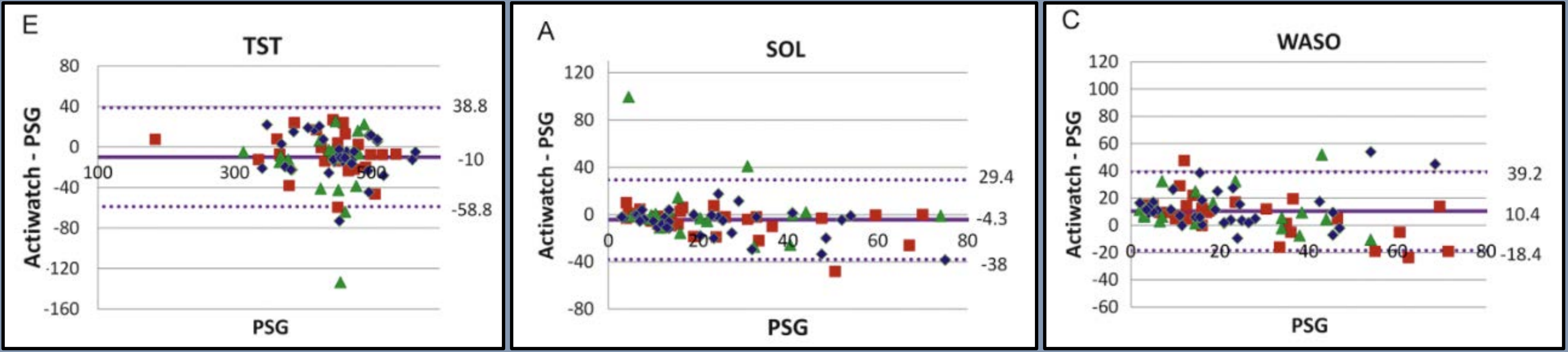
Wearables use movement (accelerometry), light sensors, skin temperature, and heart rate to estimate sleep

- **Sleep Duration** (h/day)
- **Sleep Timing** (Bedtime, Waketime, Mid-point of Sleep)
- **Sleep Consistency/Regularity** (Social Jetlag, SD of Bedtime/Waketime, Sleep Regularity Index)
- **Measures of Sleep Quality** (Sleep Onset Latency, Wake After Sleep Onset, Number of Awakenings, Sleep Efficiency)

Measures of Sleep

Estimated Indices of Sleep from Actiwatch2 at different room temperatures of:

◆ 63°F ▲ 72°F ■ 84°F

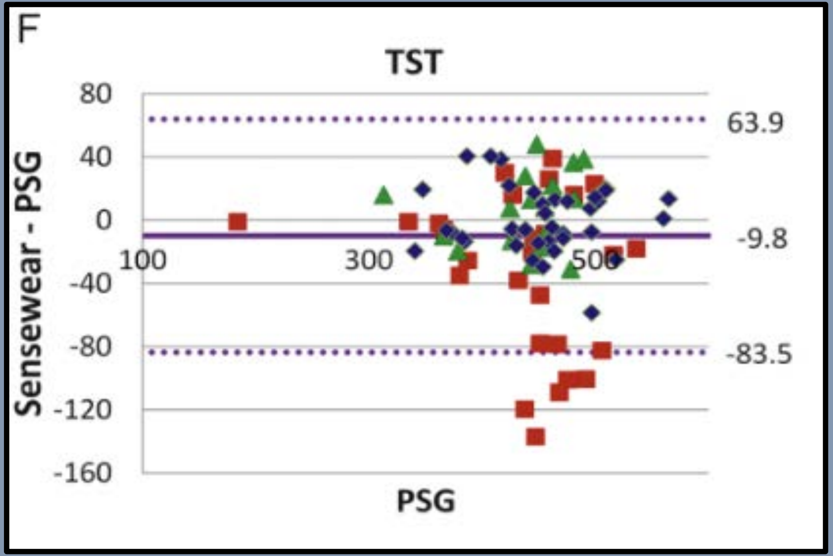


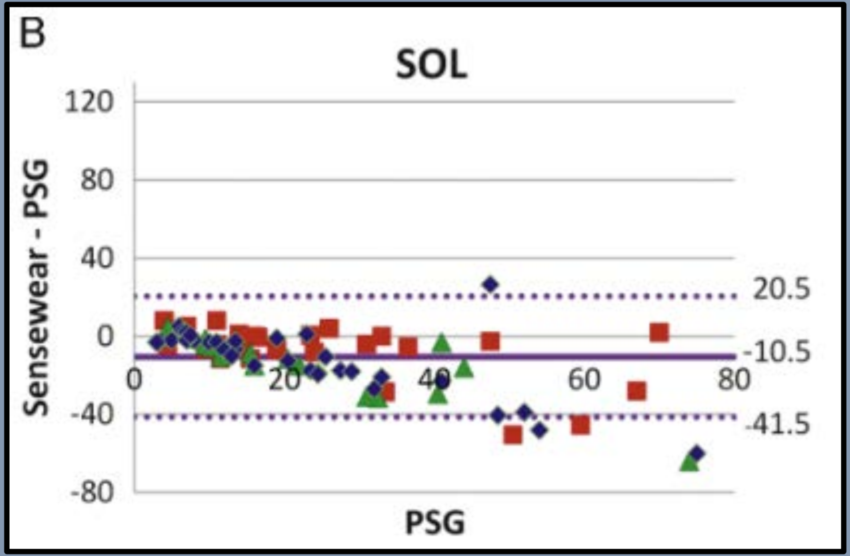
Shin et al. *Sleep Sci*, 2015.

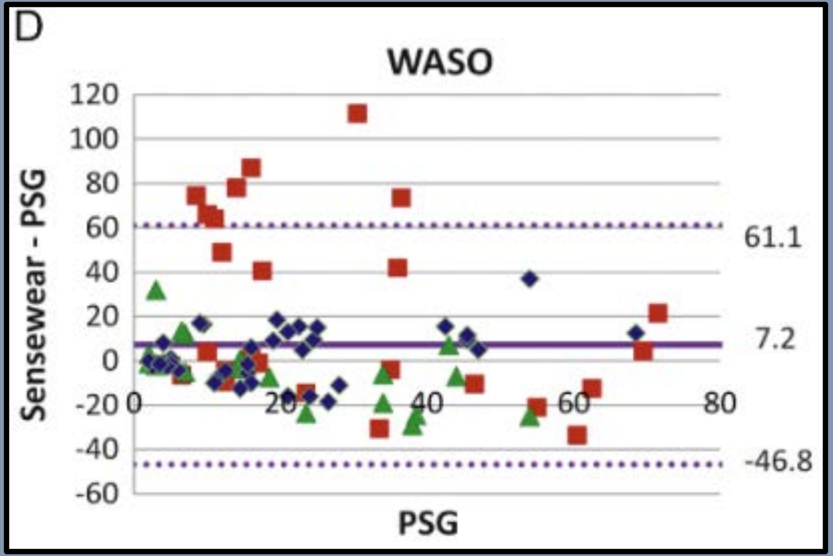
Measures of Sleep

Estimated Indices of Sleep from SW Armband at different room temperatures of:

◆ 63°F ▲ 72°F ■ 84°F







Shin et al. *Sleep Sci*, 2015.

Clinical Implications

CU-Anschutz Shoutout

Laura Grau, MPH and Jaron Arbet, PhD

↑ Sleep Efficiency = ↑ Weight Loss

Later Waketimes and ↑ WASO = ↓ Weight Loss

Later Waketimes and ↑ WASO= ↓ Odds of meeting recommended amounts of MVPA

↓ Sleep Efficiency and ↑ WASO= ↓ Odds of meeting dietary recommendations.

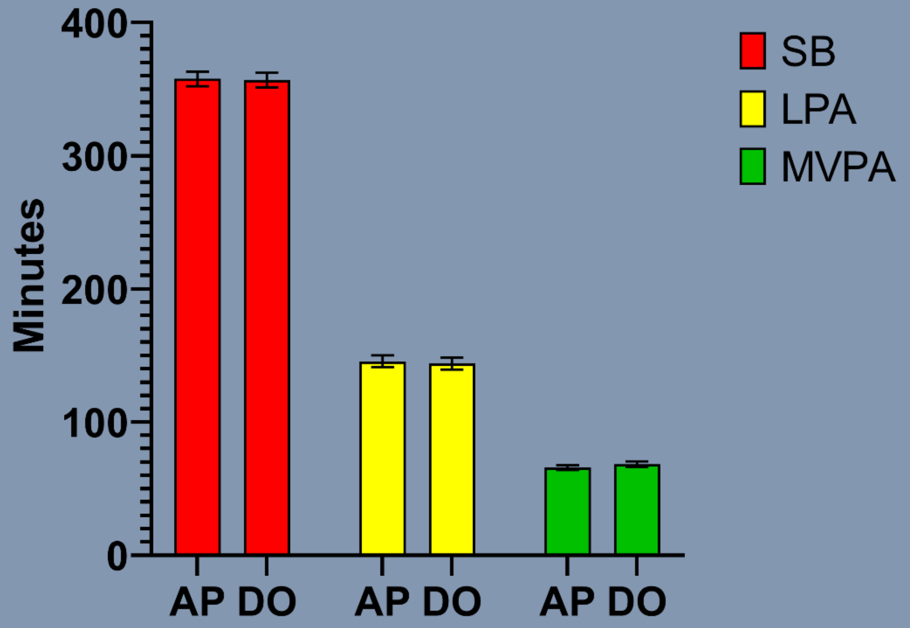
Measures of Sedentary Behavior

Wearables use posture and/or movement estimate sedentary behavior:

- **Sedentary Time** (Total duration, duration in bouts of >30, >60, >120 minutes)
- **Sedentary Events** (Number of sedentary events across the day)
- **Breaks** (Number of times a sedentary event is broken per hour)

Validation Studies of Sedentary Behavior

Typically believed that the activPAL device = better measurement of sedentary behavior due to placement on thigh.



Sedentary behavior can be measured using the Actigraph (hip worn or wrist worn) and other devices using count thresholds or other inputs.

Lyden et al. *MSSE*, 2017.

Clinical Implications

CU-Anschutz Shoutout

Danielle Ostendorf, PhD and Victoria Catenacci, MD

Weight loss maintainers engage in lower amounts of total sedentary time compared to controls with obesity

Weight loss maintainers engage in ~1 fewer bout of sedentary behavior >30 minutes compared to controls with obesity

Weight loss maintainers break up their sedentary time ~6 times every hour which was more than controls with and without obesity.

Weight loss maintainers engage in significantly more MVPA in bouts of 10 min (272 min/wk) compared to controls with (63 min/wk) and without obesity (117 min/wk).

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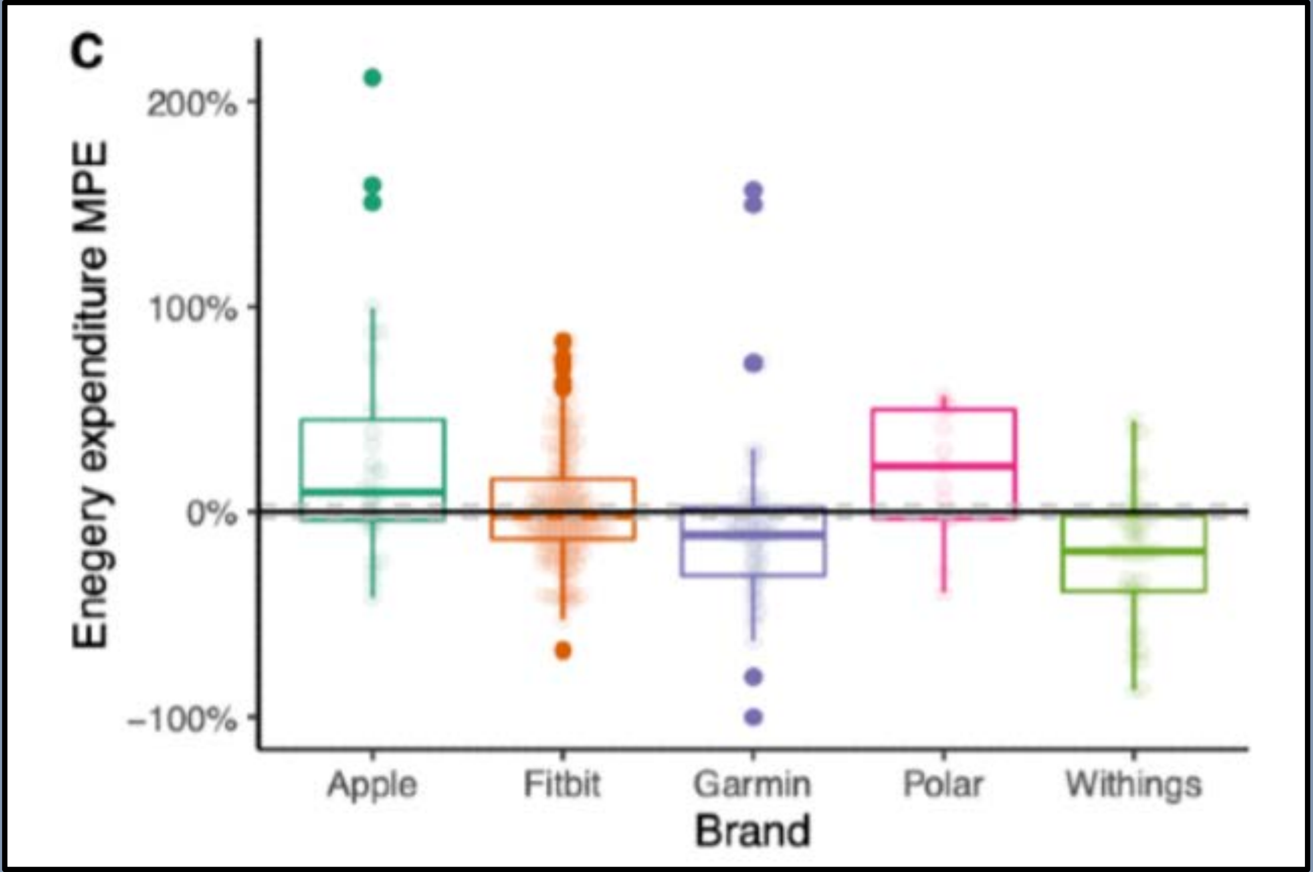
Ostendorf et al. *Obesity*, 2018.

Measures of Physical Activity

Wearables use posture and movement to determine variables related to physical activity (can also include heart rate, skin temperature, age, sex, etc.):

- **Volume** (total counts, total steps, total energy expenditure)
- **Intensity** (time spent in light, moderate, and vigorous intensity physical activity)
- **Timing** (clock time, relative to waking, relative to another event)
- **Duration** (time spent engaging in moderate to vigorous physical activity, time spent in bouts of >10 minutes)

Validation Studies for Physical Activity



Fuller et al. *JMIR*, 2020.

Clinical Implications

CU-Anschutz Shoutout

Eleanor Cotton, MPH and Victoria Catenacci, MD

Subject 2 – 27 lbs. WL (17%)

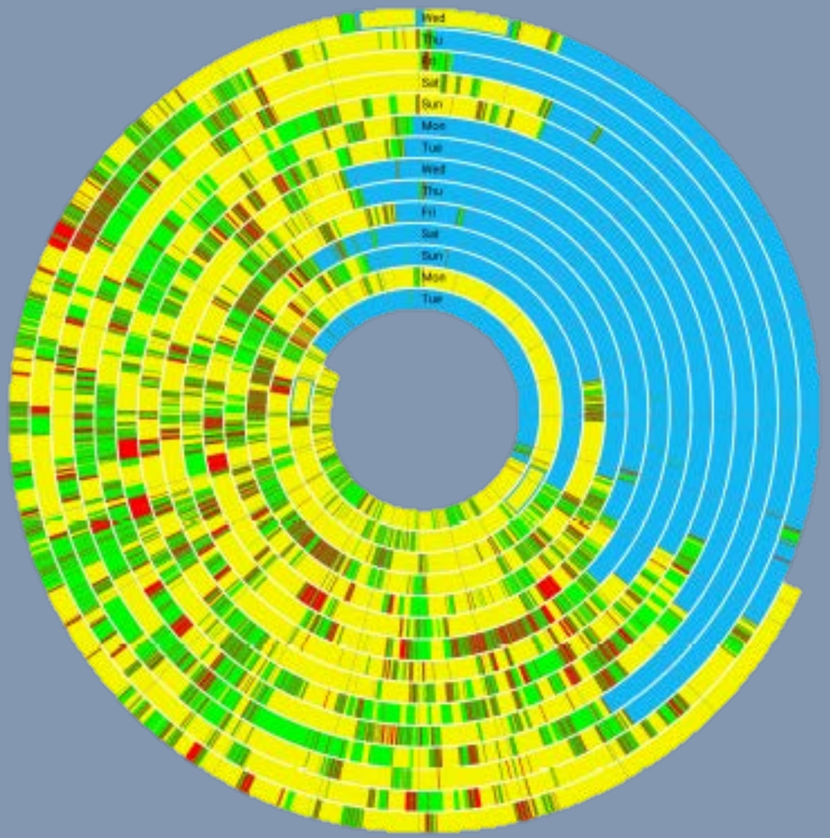
Bed Time: 12-1 AM   Wake Time: 7-9 AM

14 walking bouts >10 min

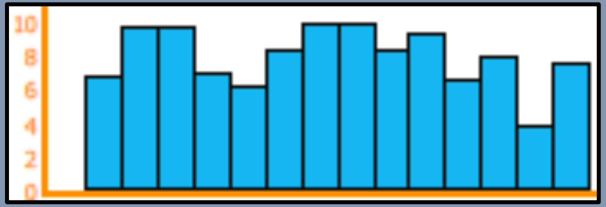
5 walking bouts >30 min

Blue= Sleep   Yellow= Sitting/lying

Green= Standing   Red= Walking

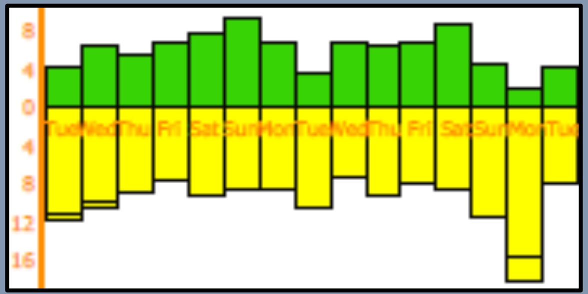


Sleep – 7.8 h/d

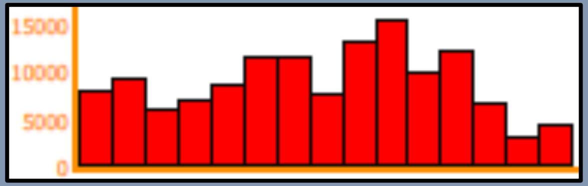


Upright – 6.2 h/d

Sitting – 9.8 h/d



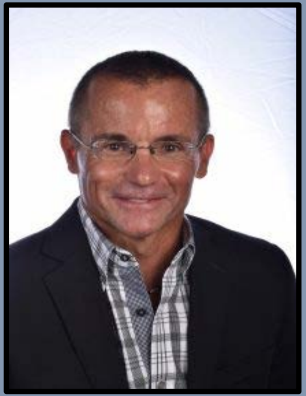
Steps – 9500 steps/d



Summary and Future Directions

- ✓Increase use of wearables to measure sleep in clinical research
- ✓Strategies to improve congruence between devices
- ✓Use more information (raw data) from the devices
- ✓Integrating All Behaviors

Primary Mentor



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Stepping into the Future

Julia Wrobel, PhD
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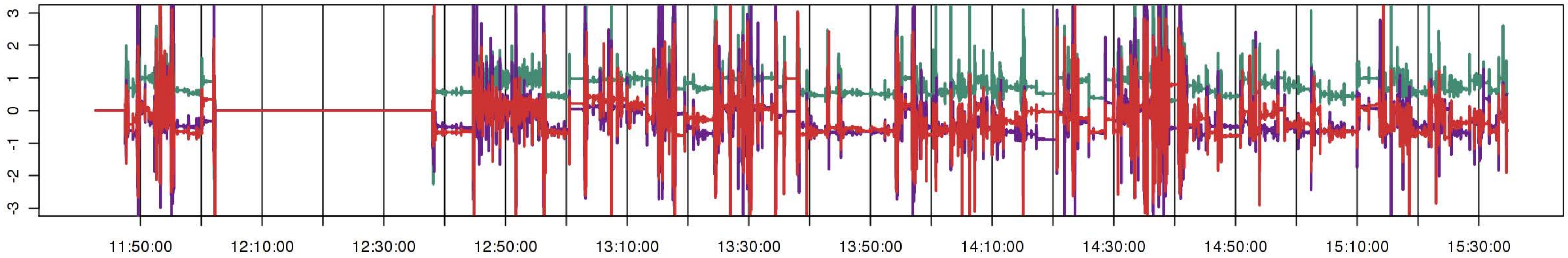
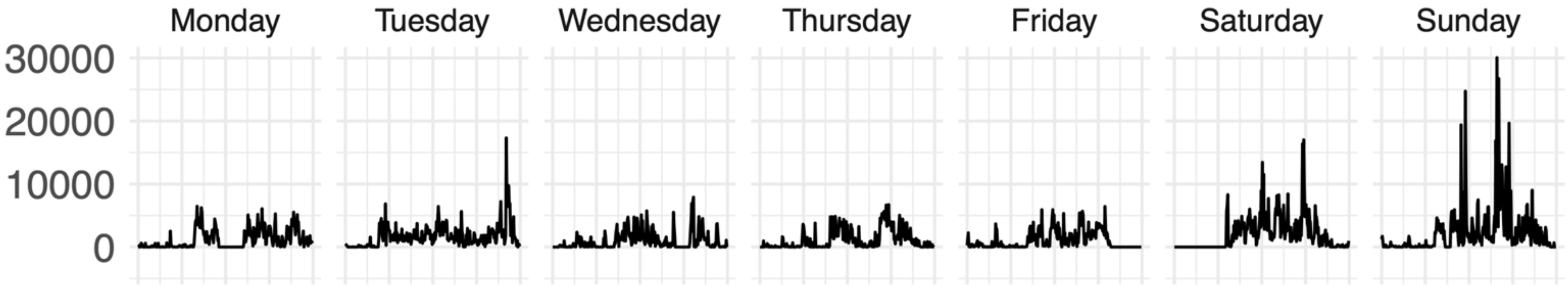
Department of Biostatistics and Informatics

What do wearables offer?

- Sleep
- Circadian Rhythmicity
- Heart Rate (ECG, BPM)
- Blood Glucose Monitoring
- Light, Temperature (Circadian markers)
- Electronic diary/Ecological momentary assessment (1-2-4 per day)
- Physical activity
  - Activity Counts
  - Sedentary behavior
  - Steps and Gaits

Accelerometer data processing pipeline

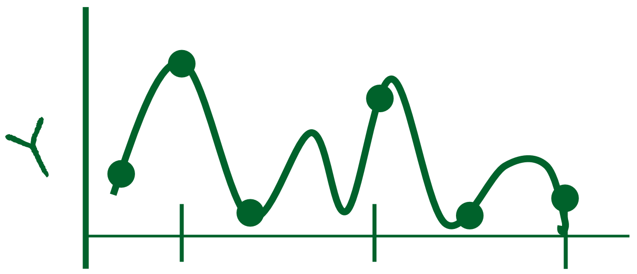




- **PA measures:** Total steps / counts, MVPA minutes,
- **Sedentary measures:** Sedentary time, number of sedentary bouts

Functional data analysis (FDA)

- Wearable devices record signal over 24-hour periods- the exact focus of FDA!
  - Outcome is curve or function $Y_i(t)$
  - For accelerometer data each curve/outcome is a 24-hour activity profile



- There are functional analogs of common data analysis tools
  - Functional regression, functional principal components analysis

Uses for FDA in wearables

- Less pre-processing of the raw data
  - Compare across different studies
  - Compare across devices, manufacturers, wear locations
- Better ways of imputing data
  - Missing data is a big problem in wearables
- Time-dependent interpretations, potentially across devices
  - Timing and consistency
  - Integrating all behaviors (jointly analyze PA, sleep, sedentary behavior)

sensors MDPI

Article

Diurnal Physical Activity Patterns across Ages in a Large UK Based Cohort: The UK Biobank Study

Julia Wrobel [1,*], John Muschelli [2] and Andrew Leroux [1]

- Goals of this analysis
  - Understand patterns of physical activity using functional data methods
  - Huge dataset (>80,000)- still computationally feasible?
  - Focused on age, gender differences in daily patterns of PA
  - Analyzed an "average" 24-hour day for each subject

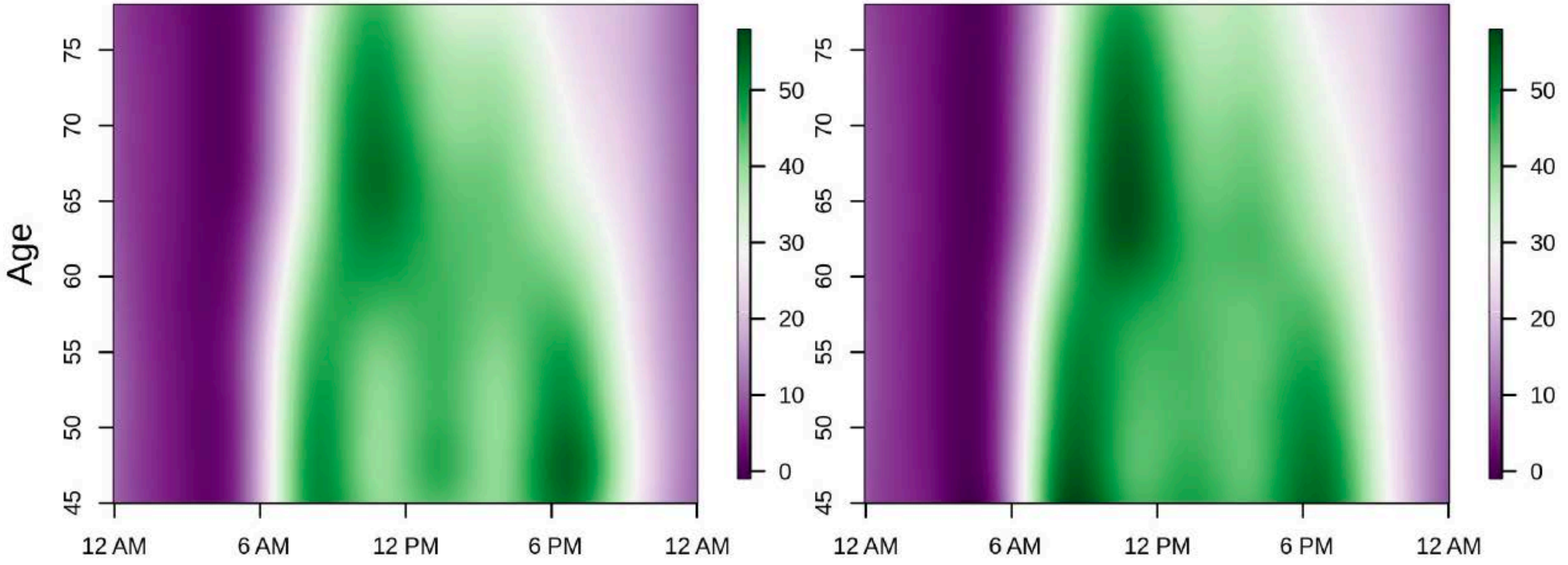
UK Biobank Accelerometry Data

- 88,793 subjects
  - 39,255 men and 49,538 women
  - 42-78 years of age (mean: 61.9 years of age)

- Raw data was aggregated and reproducibly
  - Euclidean norm minus one (ENMO) of raw tri-axial accelerometer data
    - Produces sub-second "activity count" that is open-source and reproducible
  - Averaged activity count at minute level for each subject
    - Produces 24-hour minute level trajectories or activity profiles

Diurnal patterns in physical activity across ages

- Average activity intensity across ages for males (left) and females (right)



UK Biobank Analysis Takeaways

- PA decreases with age for males and females
  - This decrease occurs predominantly in afternoon/evening hours
- Females have higher probability of being active, especially at older ages
  - Comes from FDA analysis of sedentary behavior in this data
- Similar patterns are seen in BLSA, NHANES
  - Suggests social/behavioral patterns shared across populations

Future Directions

- Would be interesting to see how covid-driven remote work disrupts these patterns in younger adults
  - Are these driven by 9-5 work habits? Or more physiological mechanisms?

- Need methods to extend more effectively across days
  - Developing these methods takes time!

Other ongoing "wearables" and FDA projects

- Using patterns of sedentary behavior to detect human **chronotypes**
  - **Chronotypes** are behavioral manifestations of circadian rhythms
  - Accelerometer data, separate timing and magnitude of PA
  - Subtypes in activity timing (morningness vs. eveningness)
  - Subtypes in activity magnitude (low activity vs. high activity)

- Clustering daily weigh-in data
  - Bluetooth scales as "wearable" data
  - Ongoing weight-loss study at CU Anschutz Wellness Center
  - Are certain patterns in weigh-ins associated with long-term weight maintenance?

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- Jennifer Schrack, PhD

fdawg

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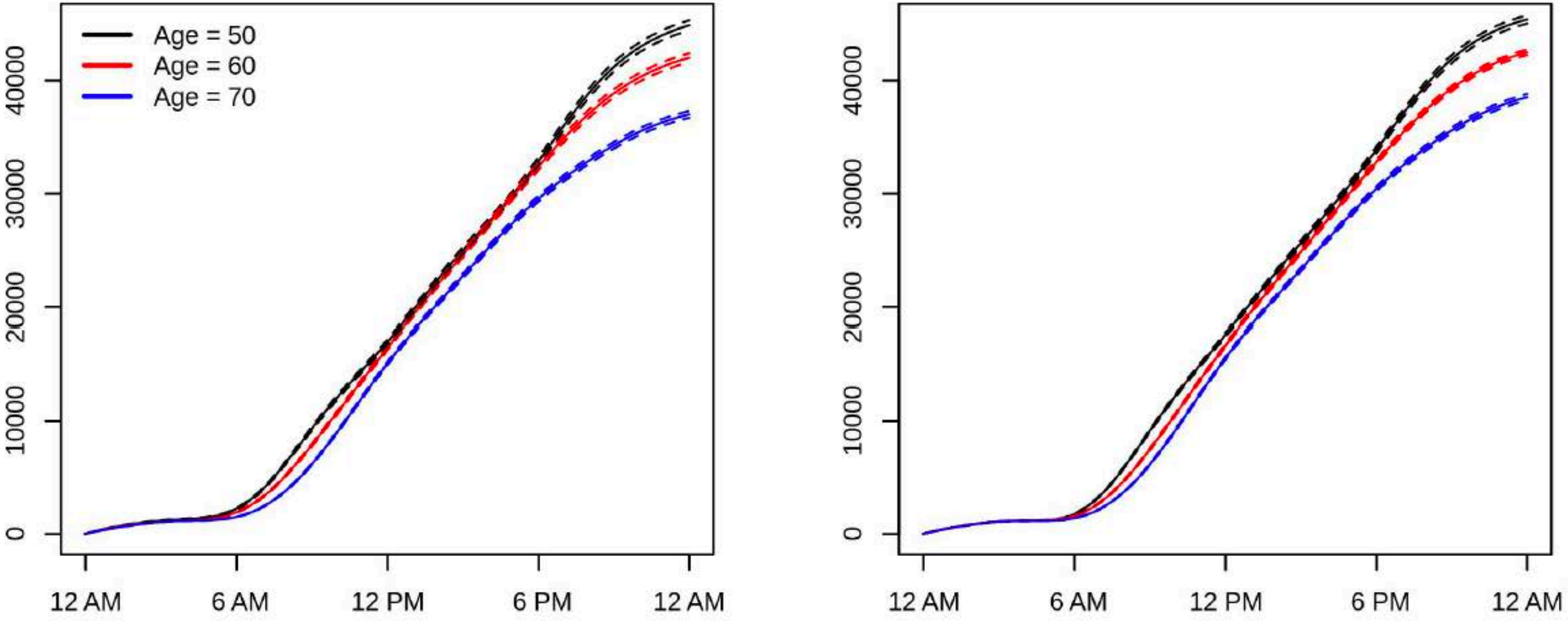
Activity drop off occurs mainly in evening hours

- Average cumulative activity intensity for males (left) and females (right)



Reproducibility and rigor …

- A good deal of this isn't settled

- Consider MVPA
  - How are counts generated?
  - How are cutpoints found?
  - Are these consistent across devices? Age groups? Placements

- Some general recommendations
  - Keep rawest form of data possible
  - Process using non-proprietary software
  - Follow a plan to ensure reproducibility