May 20th, 11:00 AM

Validating and Testing Wearable Sensors to Assess Physical Activity and Sedentary Behavior in the Center for Personalized Health Monitoring

Patty Freedson
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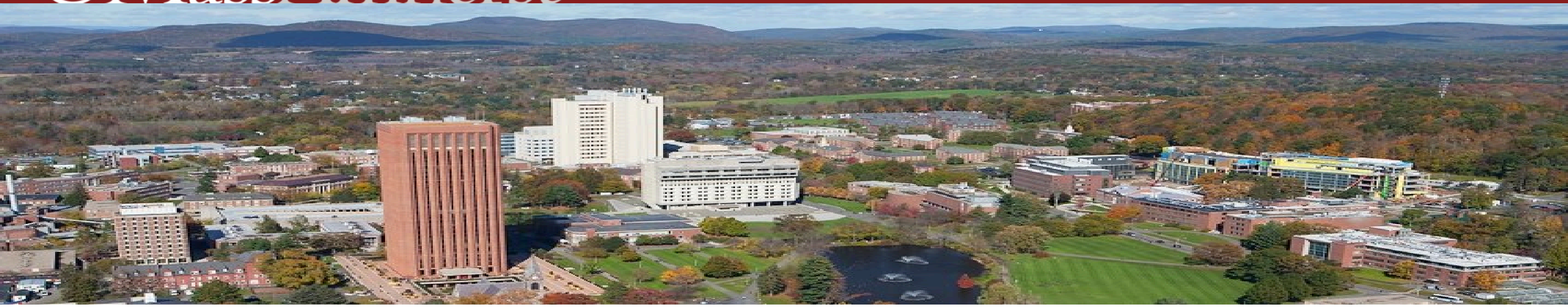

Validating and Testing Wearable Sensors to Assess Physical Activity and Sedentary Behavior in the Center for Personalized Health Monitoring

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May 20, 2014

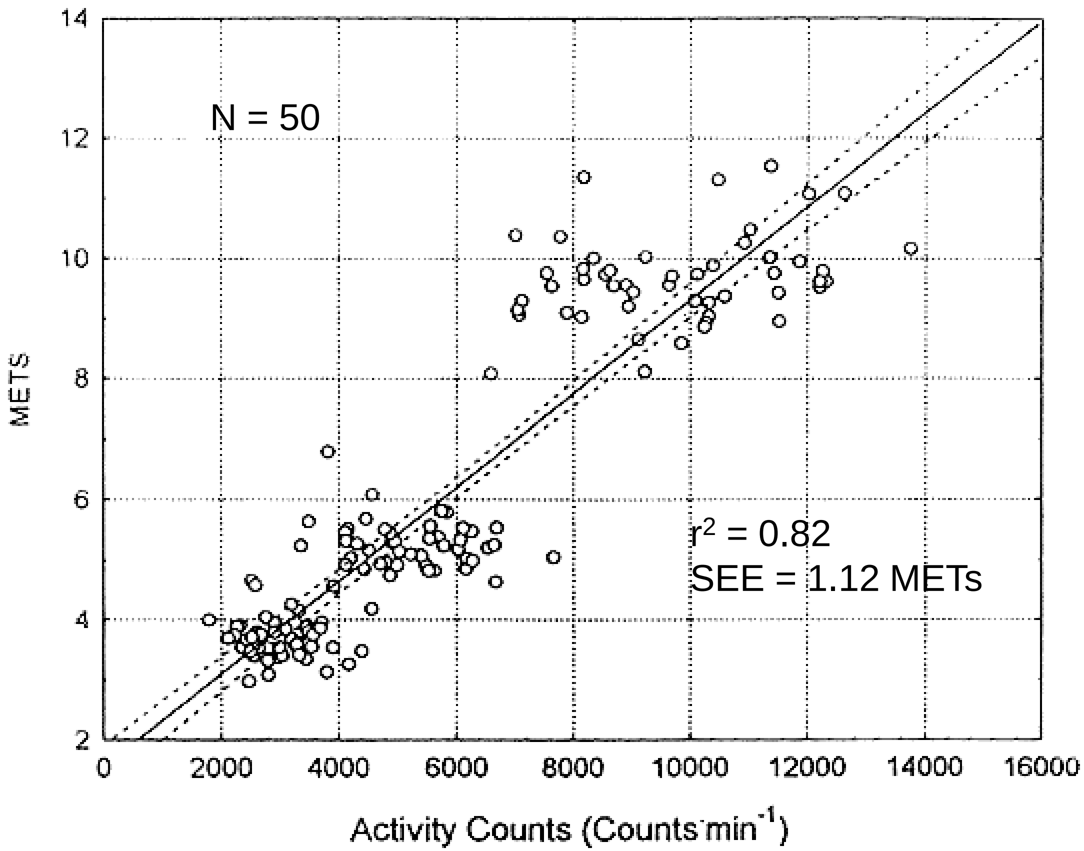
Outline

- Introduction
- Validation of wearable sensors
- Testing of wearable consumer activity trackers
- Capability of sensor evaluation in Human Testing Center in Center for Personalized Health Monitoring (CPHM)

Human testing facilities in the Center for Personalized Health Monitoring

- Research on wearable monitors to develop algorithms to translate sensor signals into meaningful and biologically valid output for clinical applications
  - Establishing meaning to personal biomarkers of health
- To determine the functionality and wearability of sensors
- Evaluation to determine how human movement affects brain, muscle, bone, tendons, ligaments and supporting structures and systems
- Translation: Evaluation of sensors for the commercial pipeline by establishing accuracy, effectiveness and usability of sensors
  - Usefulness of the 'Quantified Self'

Relationship between Actigraph counts and METS

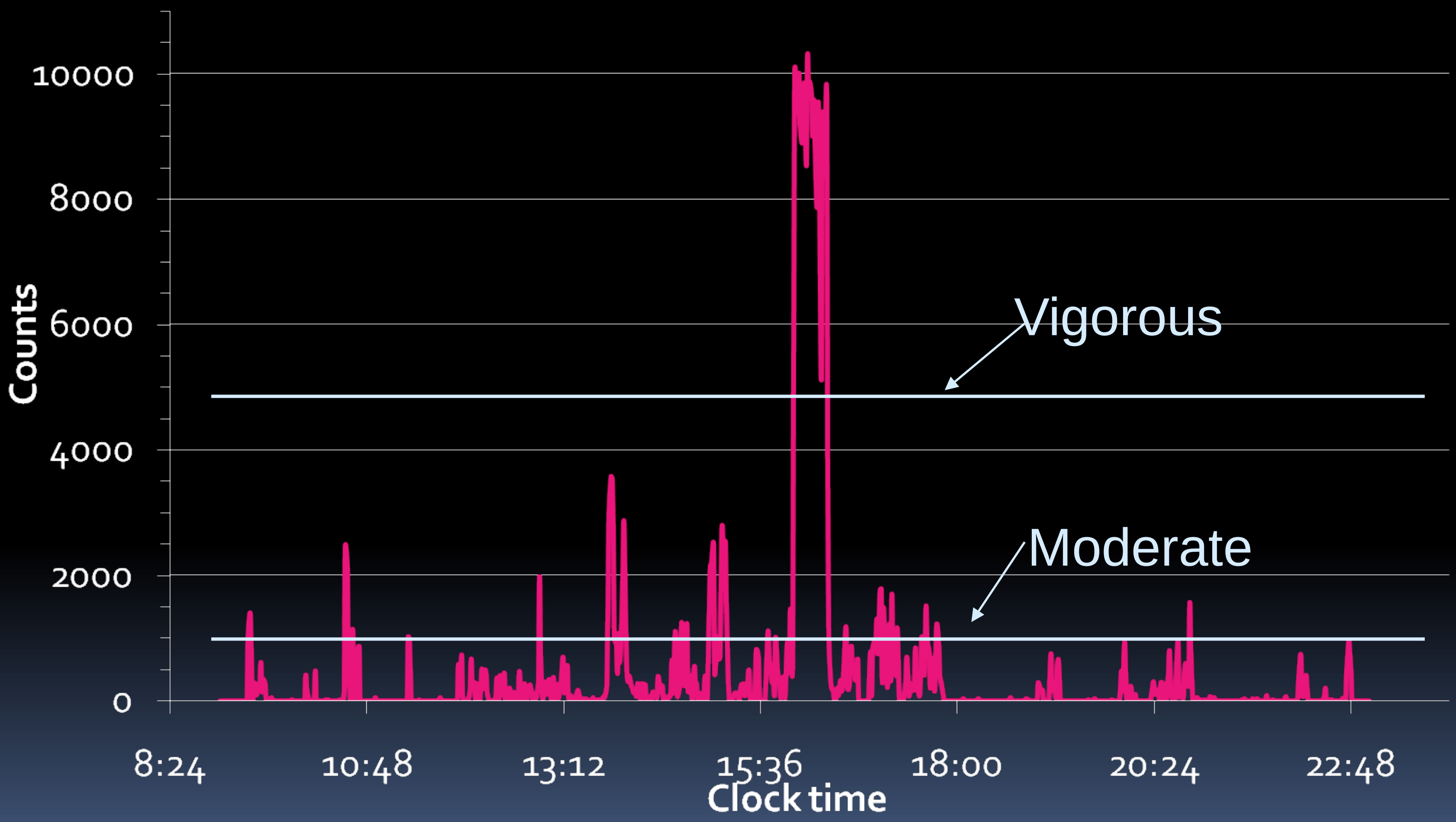


Activity Intensity	MET Range	Activity Counts (cnts·min^{-1})
Light	<3.00	<1952
Moderate	3.00–5.99	1952–5724
Hard	6.00–8.99	5725–9498
Very hard	>8.99	>9498

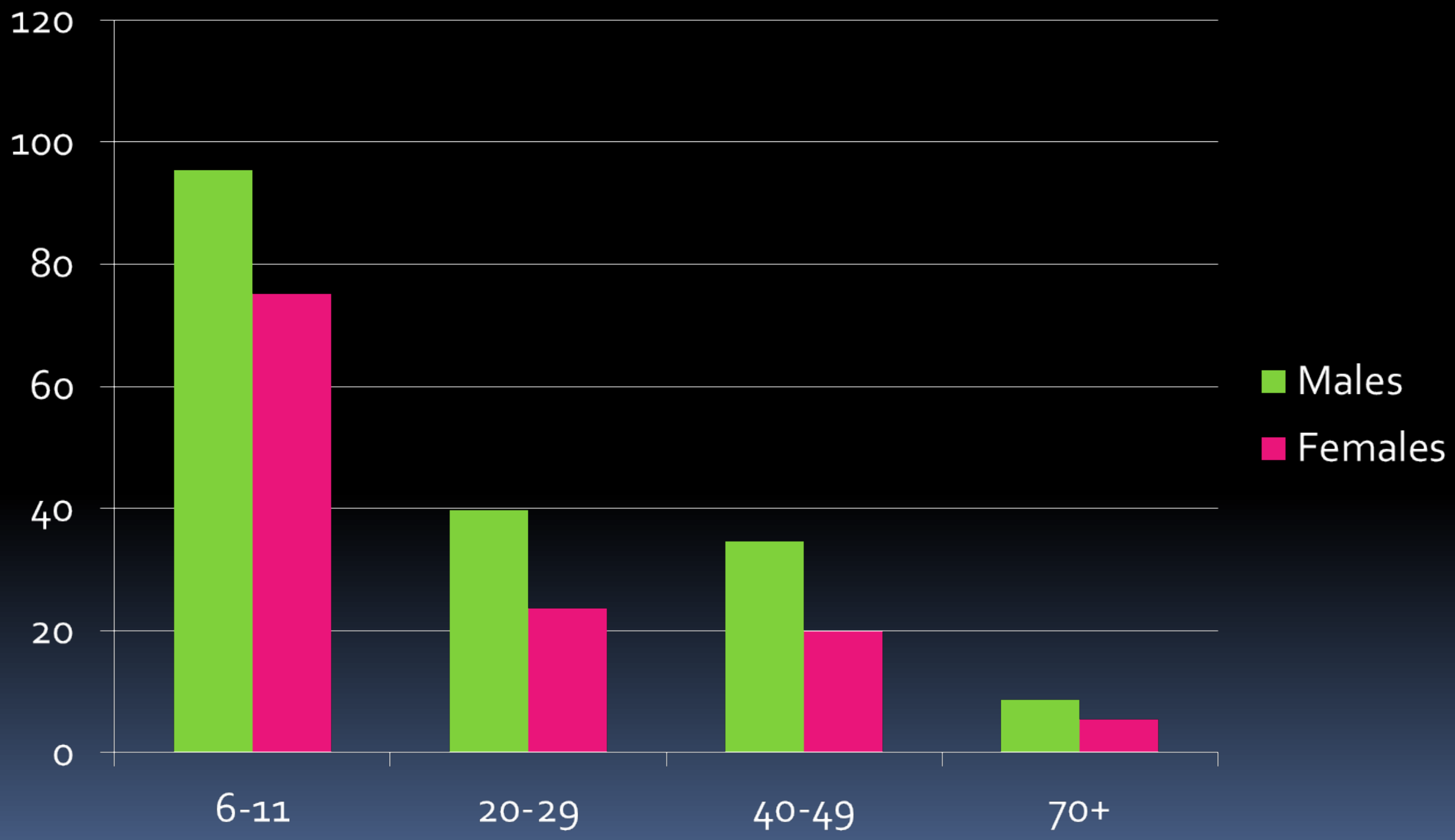
Regression
95% confid.

Freedson et al., MSSE, 1998

Activity counts and cutpoints



Minutes of moderate to vigorous physical activity: NHANES 2003-2004

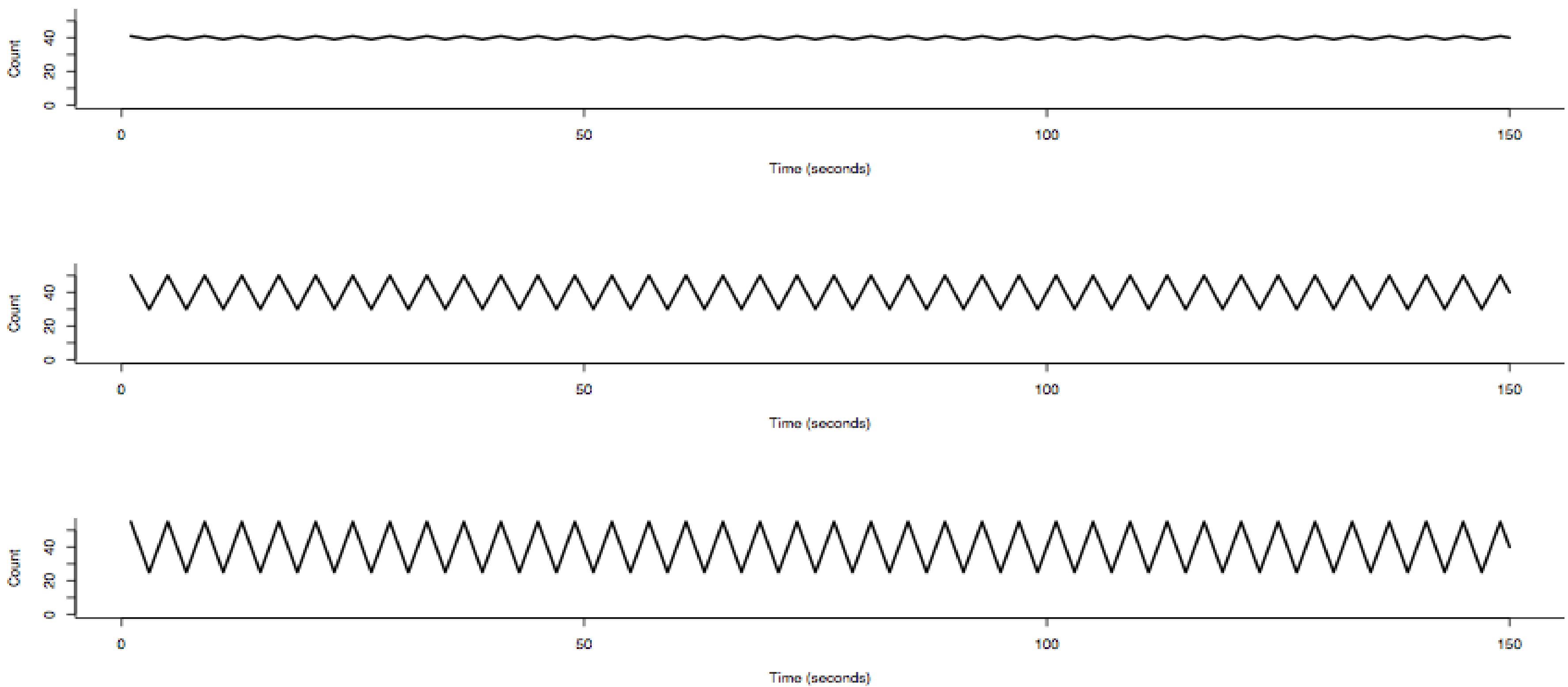


Troiano et al., MSSE 2008

Traditional Data Processing of Accelerometer Data

- Provide physiological meaning to accelerometer data
- Linear regression models
  - Predict point estimate of energy expenditure
  - Classify activity intensity
- Extensively used in the literature to characterize/quantify physical activity behavior
- Numerous revised regression models
  - Confusion in the literature
- Method fails to discriminate intensity levels properly
  - Similar counts with different energy expenditure
    - Walking uphill vs walking on level ground
  - Different counts with same energy expenditure

Illustration of a Fundamental Problem Using Average Counts



These three time series of simulated accelerometer data have the same total or mean counts per minute. They would all be classified as “moderate” activity using typical data processing methods, but they could represent activities with substantially different energy costs.

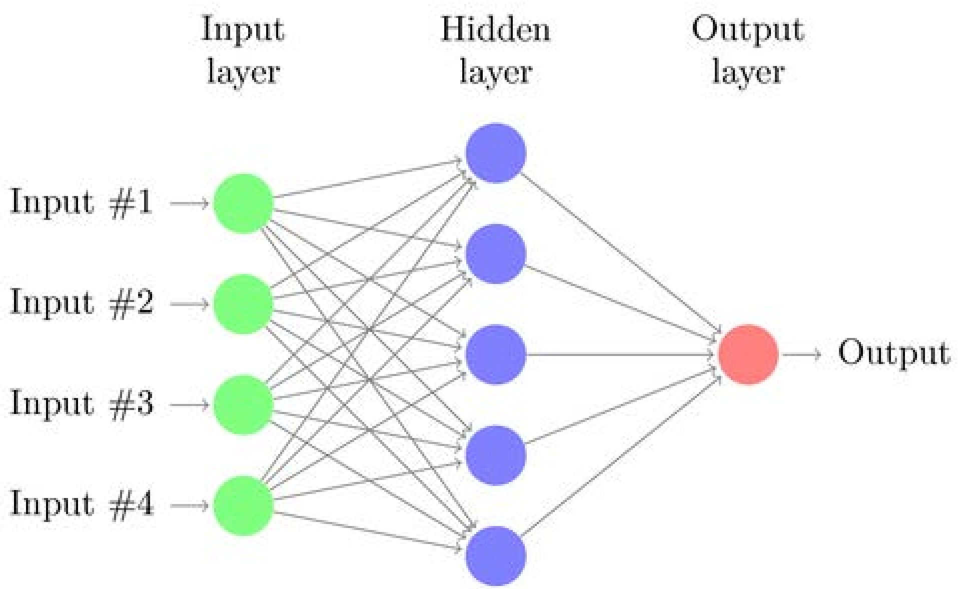
How Can We Maximize the Information Collected?

- Use entire sequence and pattern of accelerometer signal
  - Use features of signal
  - Process with pattern recognition algorithms

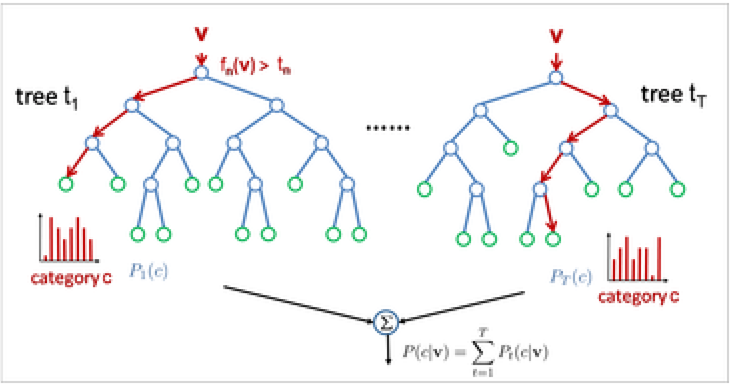
- Continual 'learning' by example
  - Powerful
  - Flexible

Advanced Data Processing: Machine Learning

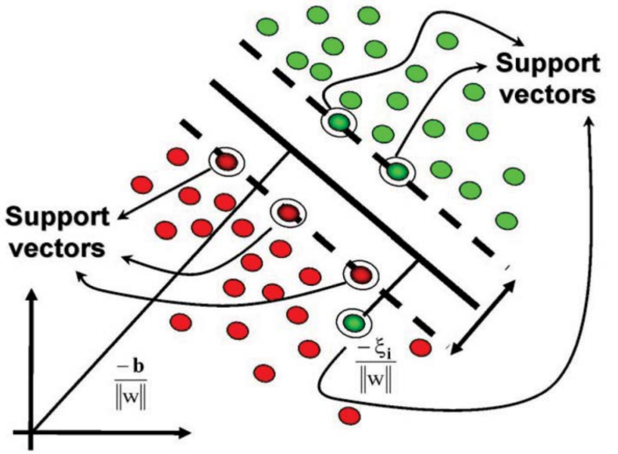
Artificial Neural Network



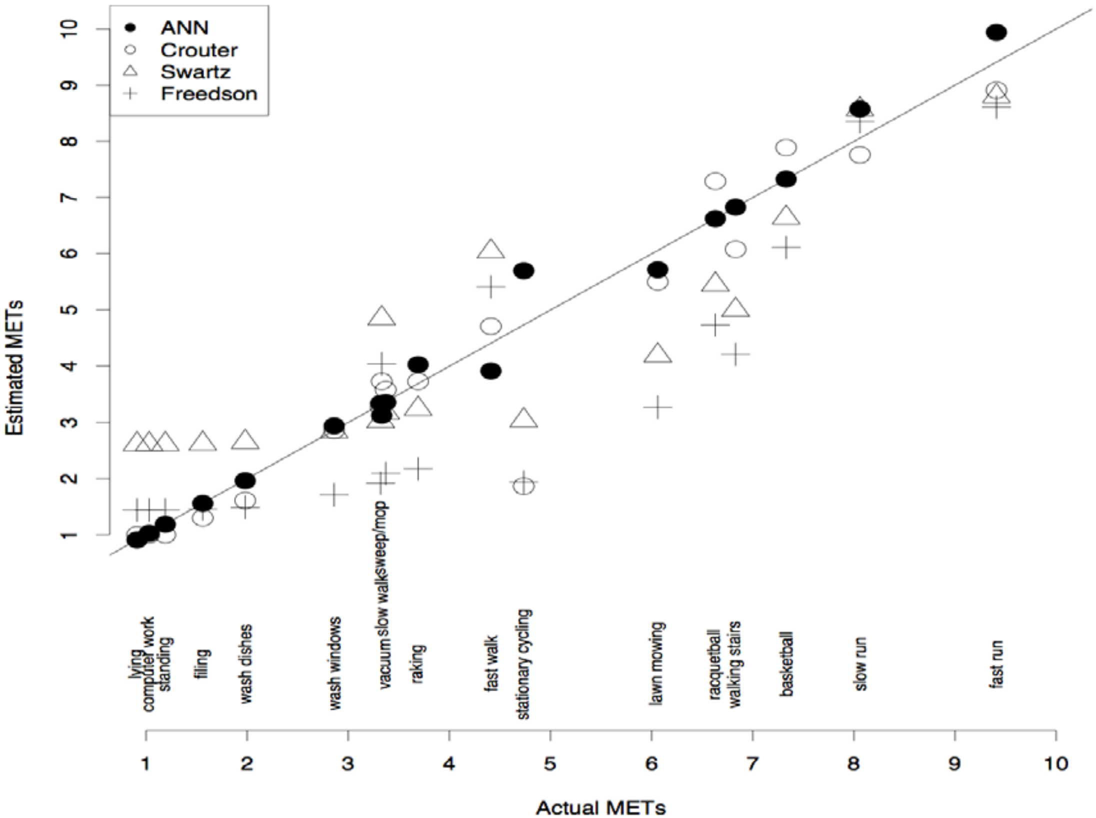
Random Forest



Support Vector Machine



Estimated METs Using the ANN and Linear Regression Equations



We tested the method on data from Crouter et al. (2006).

48 subjects did a variety of activities.

Indirect calorimetry used to estimate average PAEE for each person & activity.

Leave 1 out cross validation:
method never fit and evaluated on same subject's data.

Staudenmayer et al, JAP, 2009

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Artificial neural network trained to estimate METs and applied to independent dataset

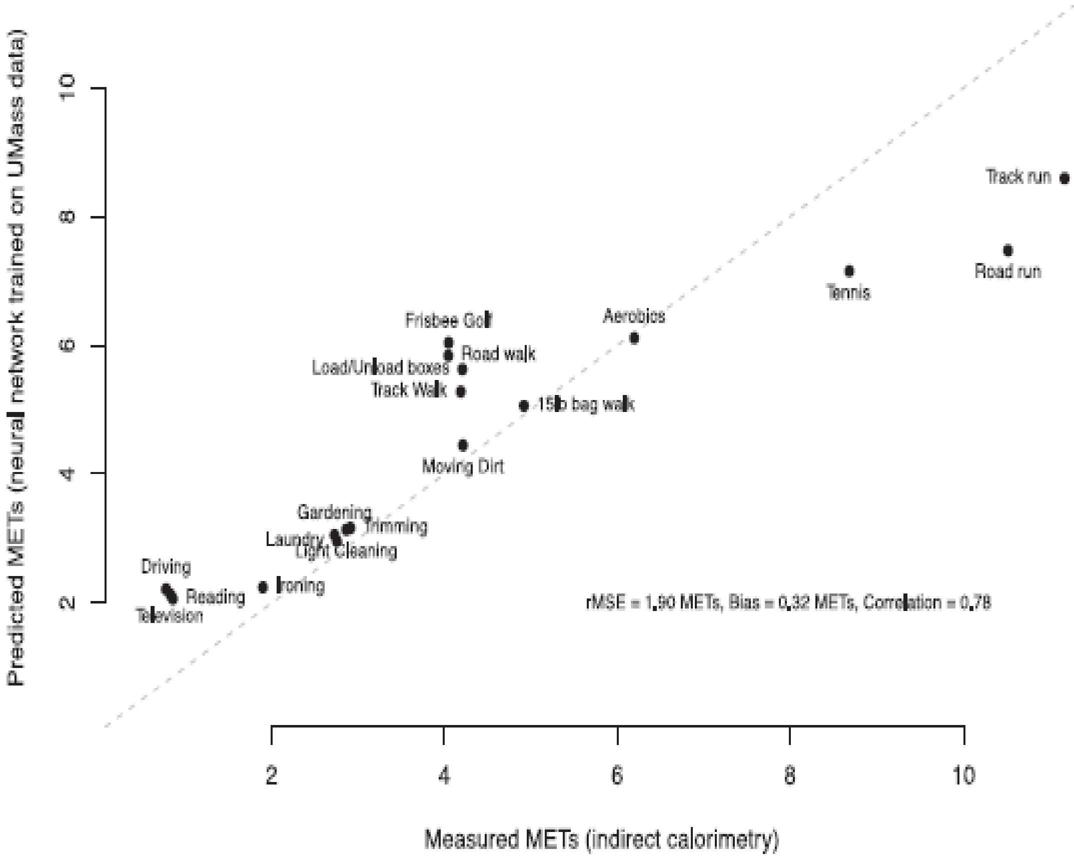
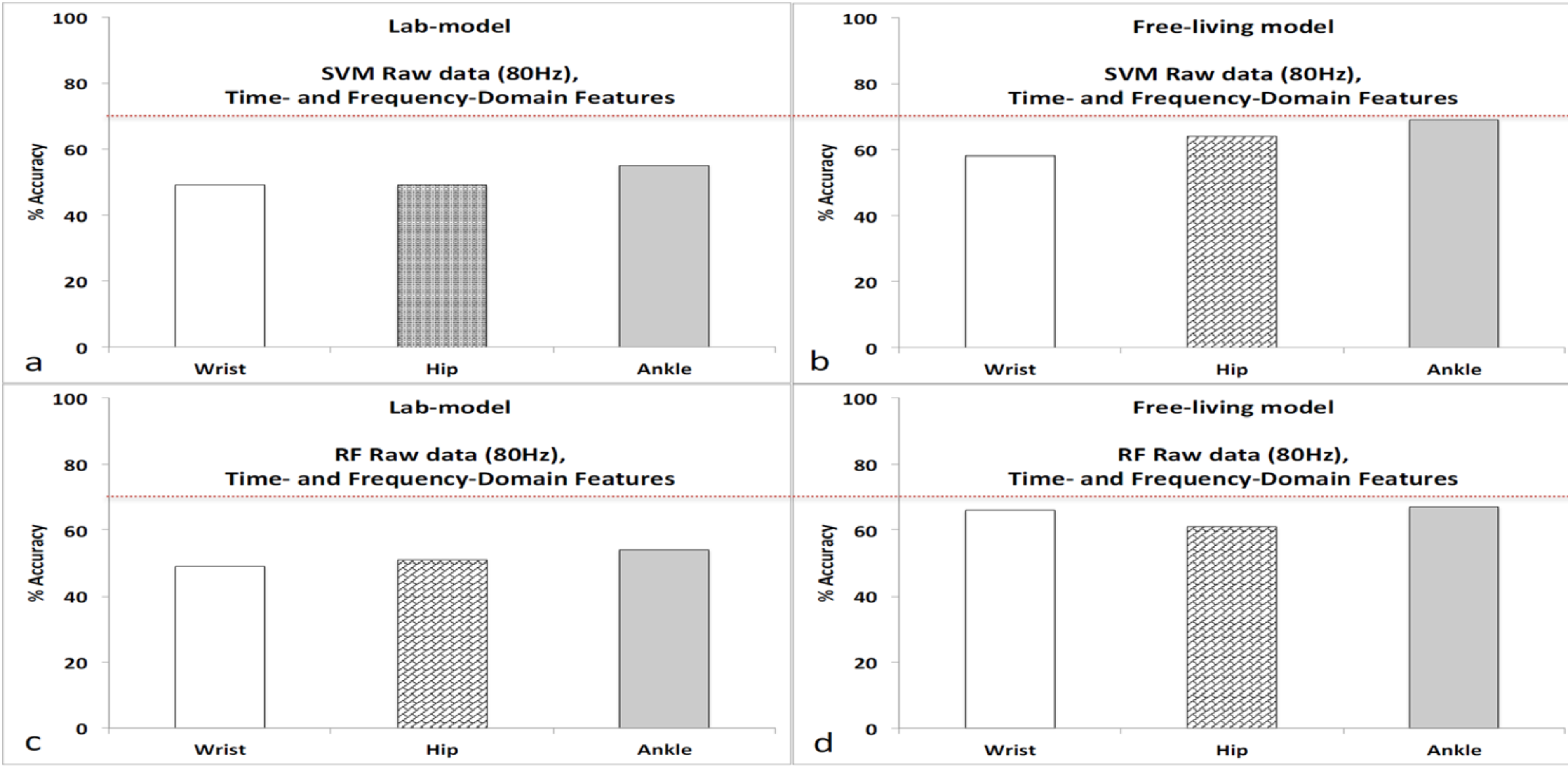


Fig. 1. Measured metabolic equivalents (METs) vs. METs predicted from neural network (nnetMET). The nnnetMET was developed on University of Massachusetts (UMass) data set (n = 277) and applied to University of Tennessee (n = 65) data set. The bias was 0.32 METs, and the root mean square error (RMSE) was 1.90 METs.

Freedson et al, JAP, 2011

Machine learning models to detect activity types developed and tested in lab and free living settings in older adults



Sasaki, et al, In Preparation

Consumer wearable sensors to estimate activity and sleep

Fitbit One

Samsung Gear Fit

Fitbit flex

Garmin Vivofit

Nike Fuel

Jawbone Up

Misfit Shine

Withings Pulse

Basis Carbon Steel

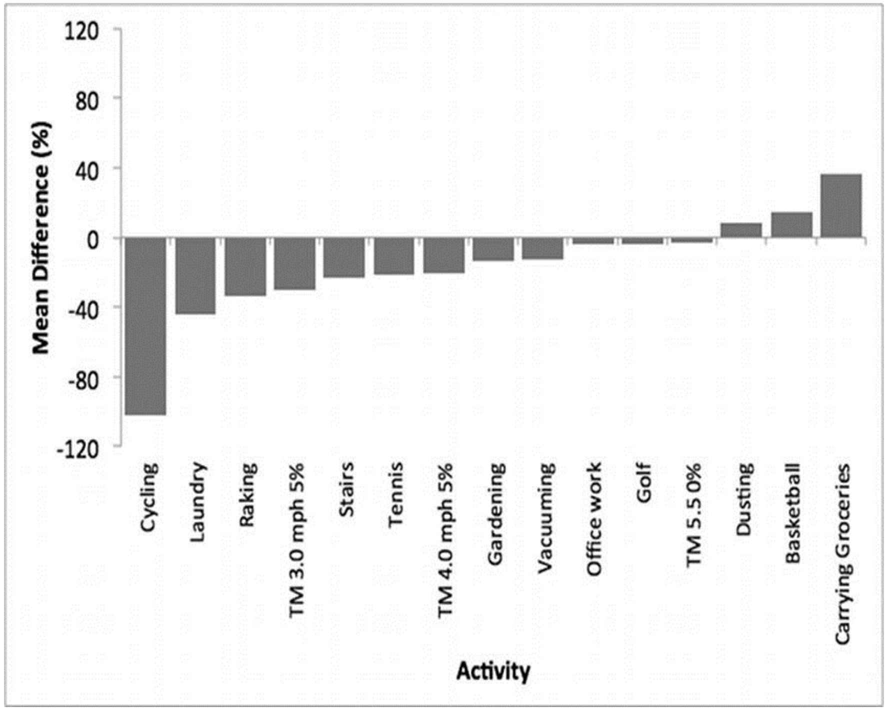
Polar loop

Accuracy of the Fitbit in estimating energy expenditure

Methods

- N = 20 college-age participants
- Performed treadmill walking and running and other activities
- Compared ee from indirect calorimetry to fitbit estimate of ee

Fitbit EE vs Indirect calorimetry

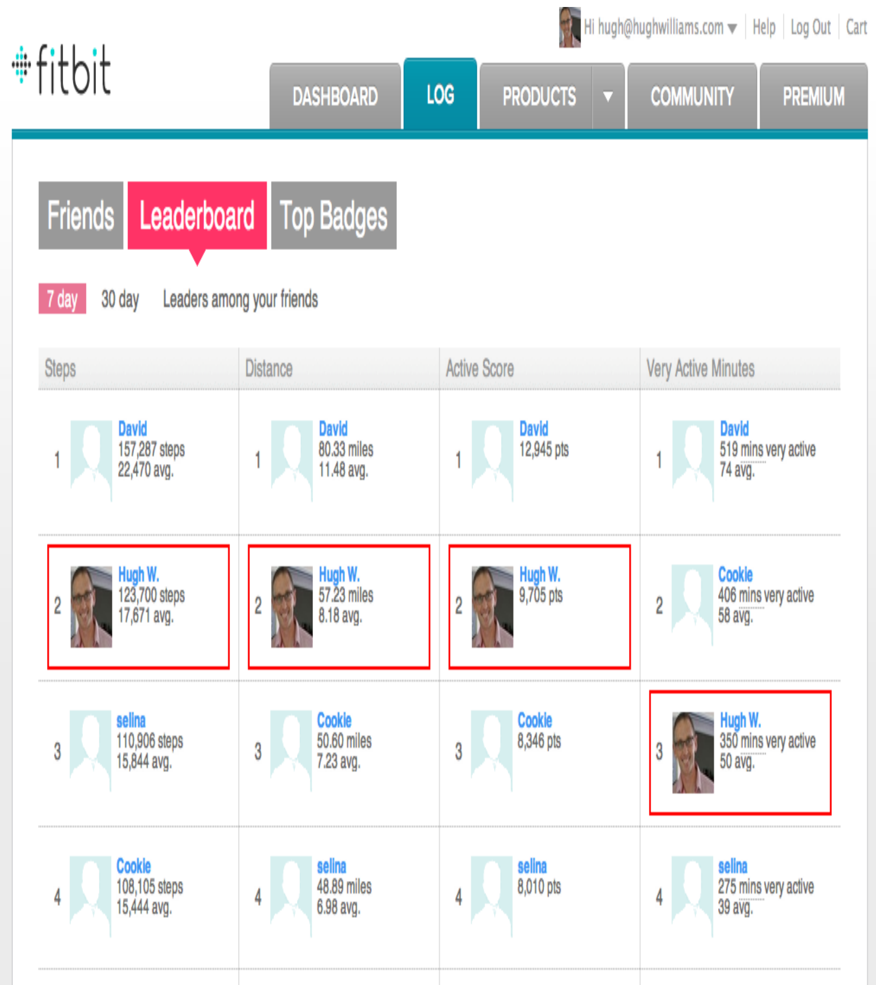


Sasaki et al., JPAH, ahead of print, 2014

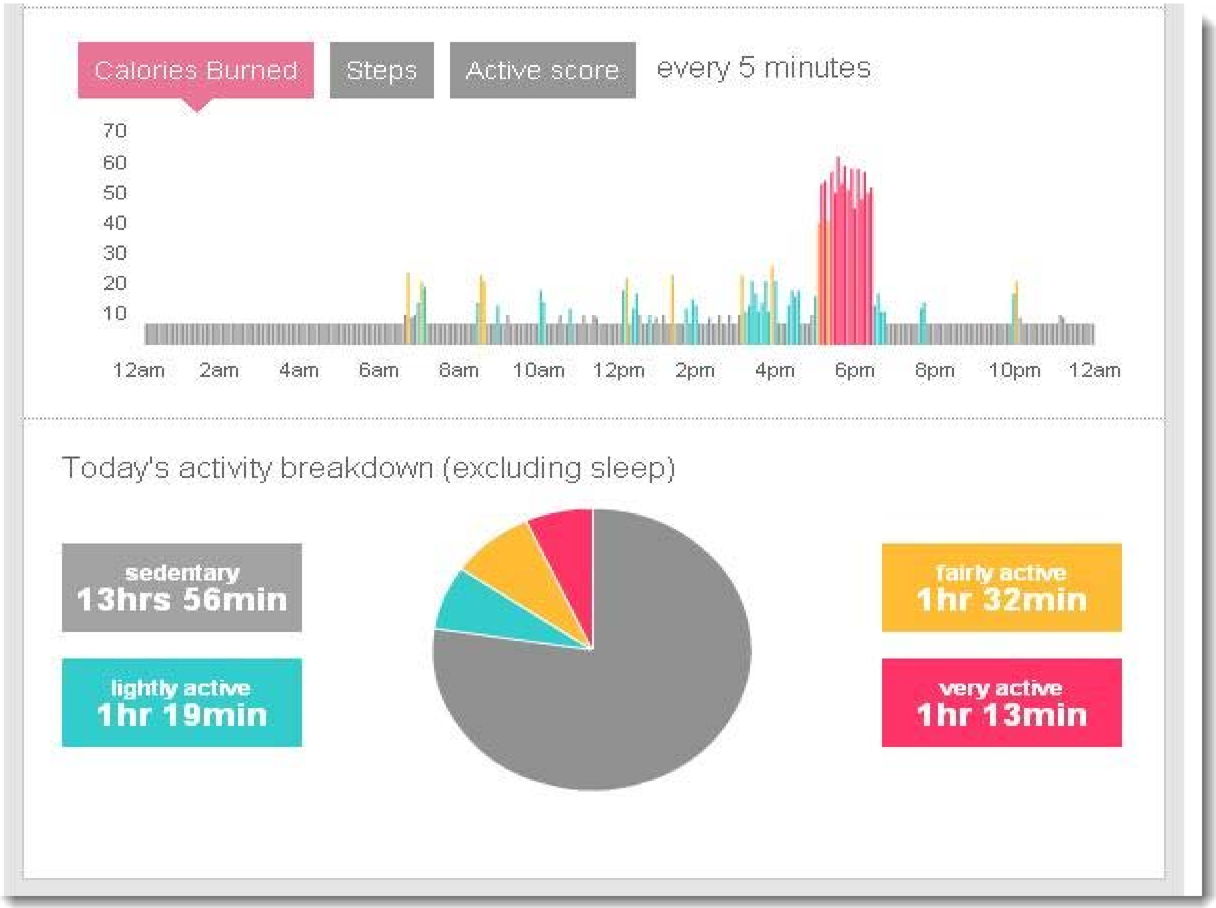
Fitbit social media application

Compete or share with friends

Up for a little healthy competition? Bring friends and family in on the fun so you can compare stats, share progress, and cheer each other on. Your leaderboard refreshes all day long in the Fitbit App so you know exactly how many more steps you need to rise to the top.



Fitbit output wirelessly transmitted to smart phone or computer: sleep and activity data

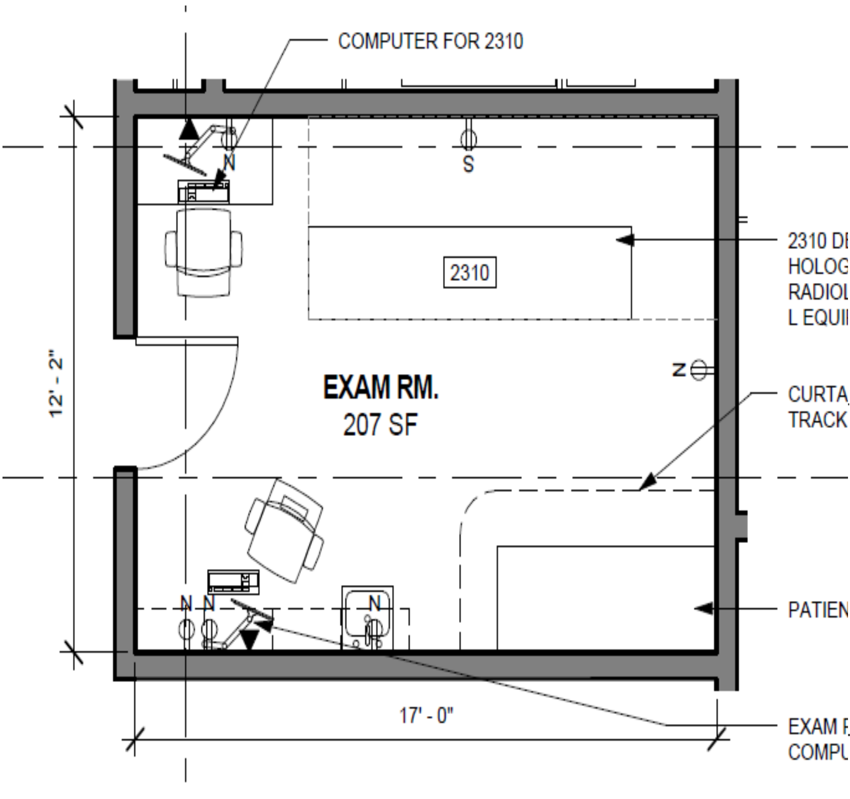


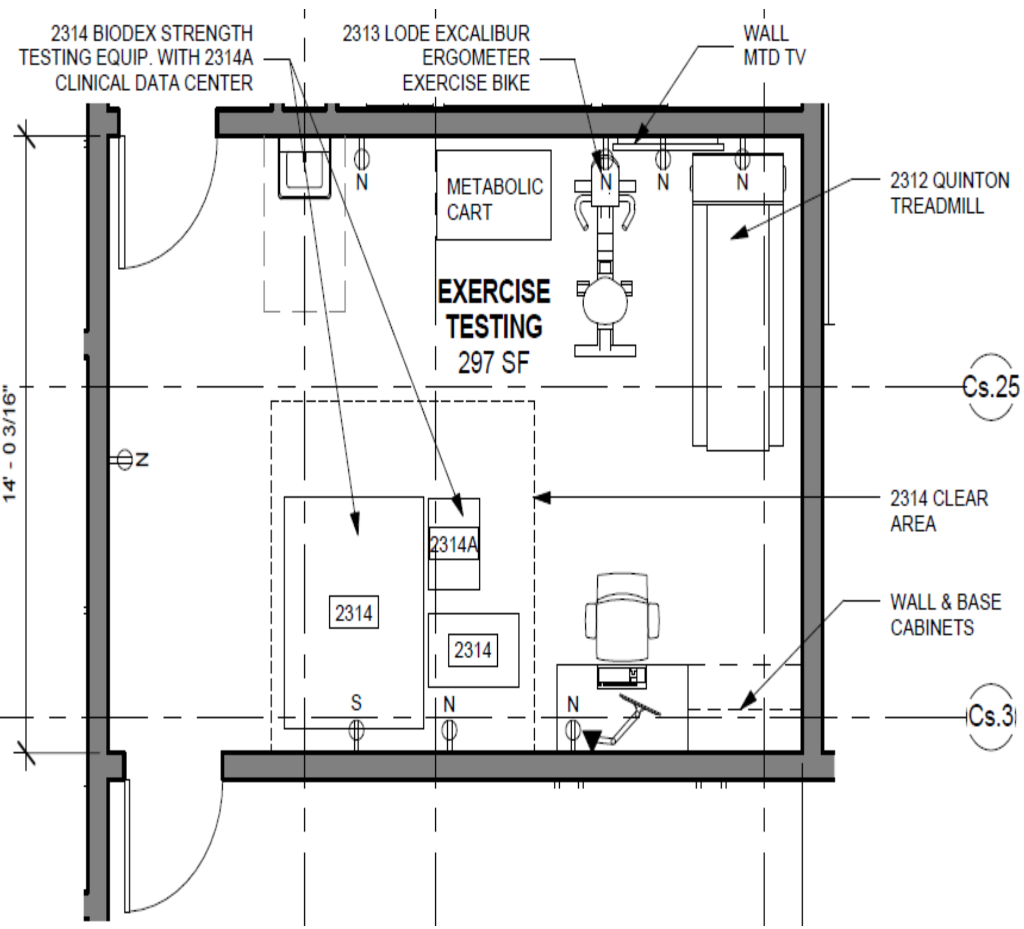
How does this relate to the CPHM?

- This work uses off the shelf activity sensors
- We have established ourselves as leaders in the activity monitor testing and algorithm development space
- Most of our previous work is in lab settings

- In CPHM we will have the capacity to:
  - Test many types of sensors built in house collaborating with electrical and computer engineering, polymer science, computer science, mathematics and statistics, other disciplines
  - Work with industry (e.g. medical device companies, activity monitor companies)
  - Test in real world instrumented home setting
  - Study clinical applications
    - Use in interventions for self monitoring
    - Social media for motivation and sustaining behavior change

Human testing facilities in CPHM





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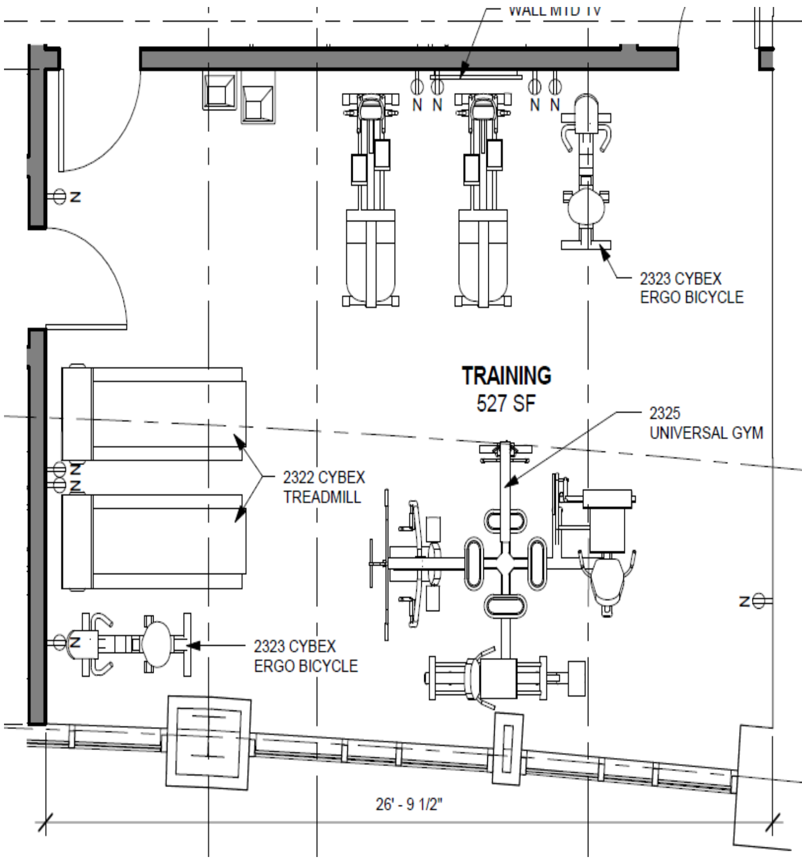
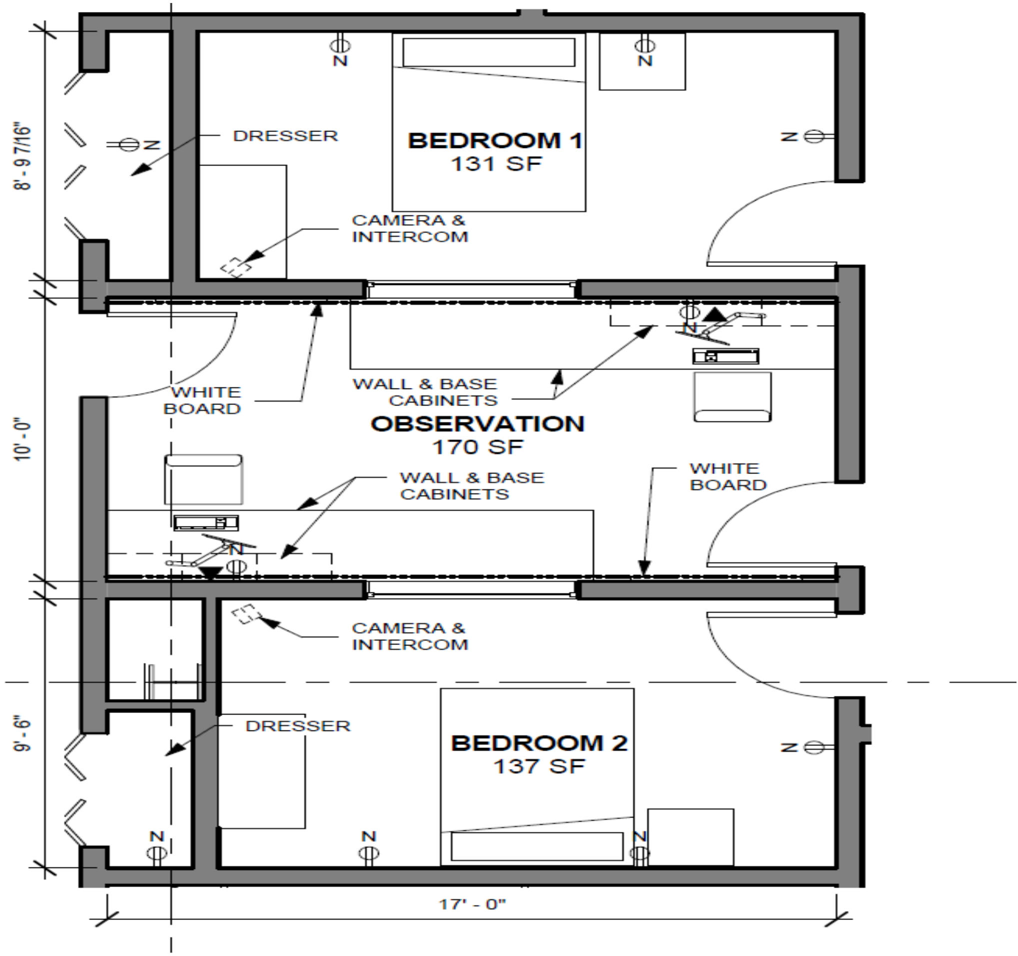
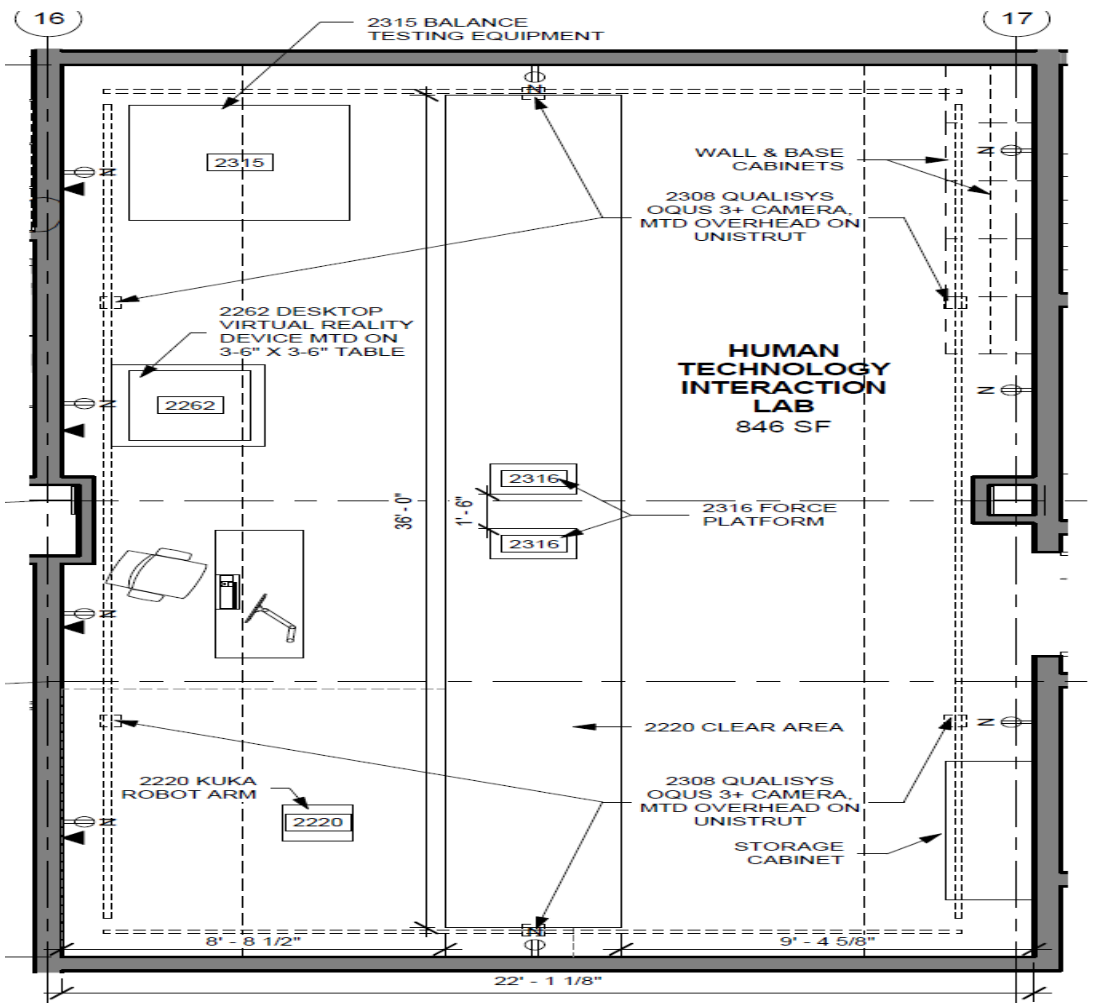
Human testing facilities in CPHM

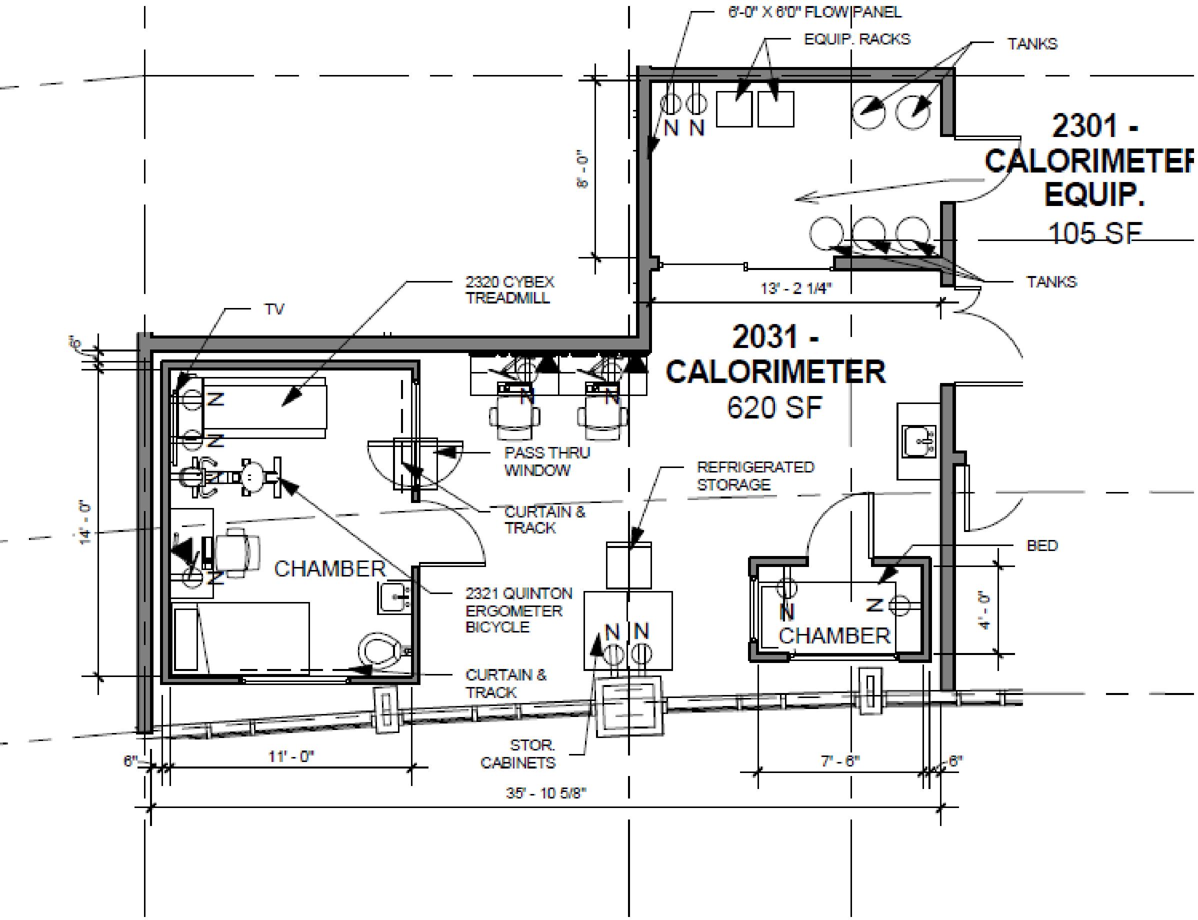




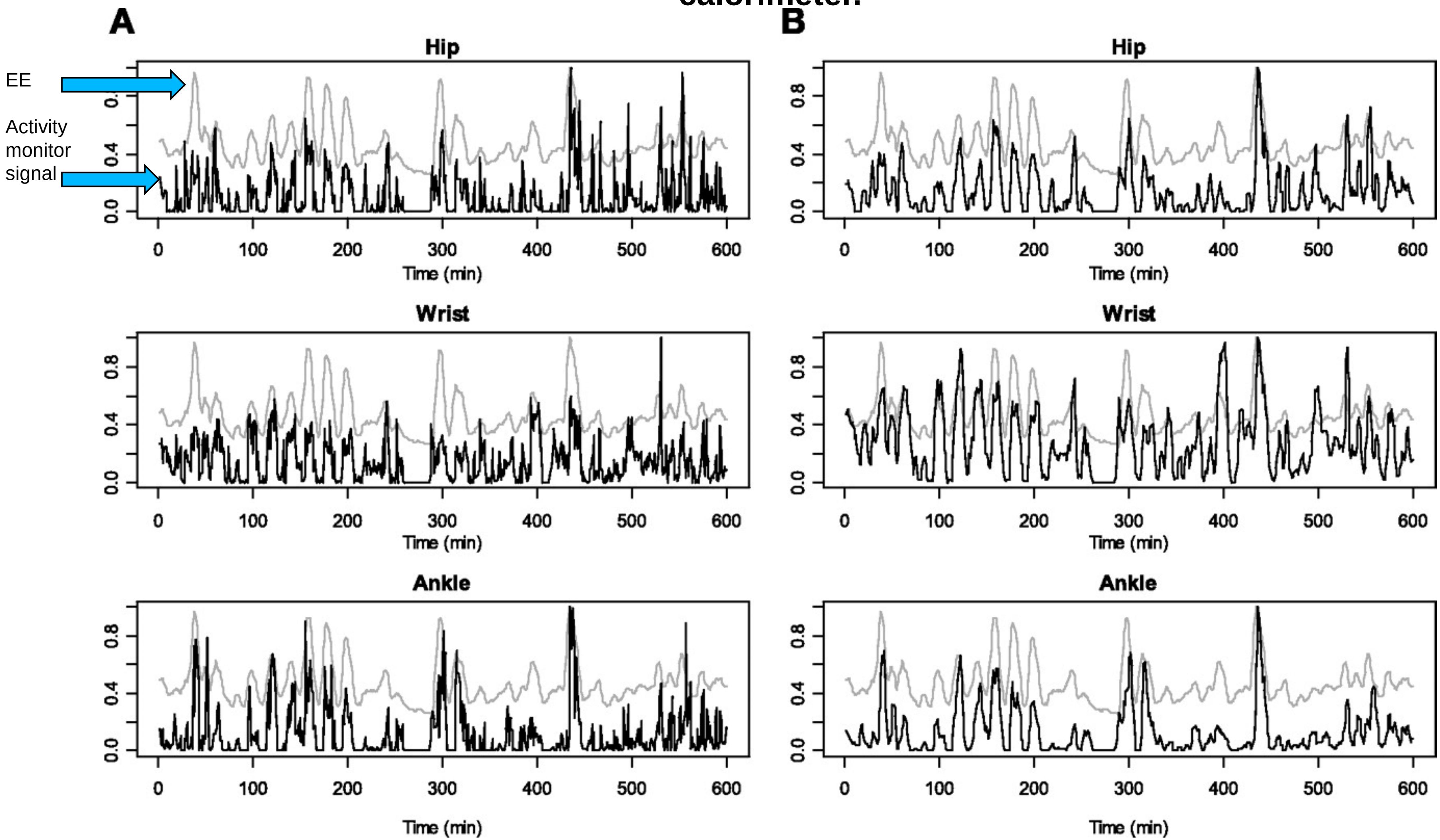
Human testing facilities in CPHM



Human testing facilities in CPHM



Normalized overlaid plot for a representative participant (10-year-old boy, weight = 76.5 kg, height = 155 cm) obtained during first 600 min of the ~24-h stay in the whole-room indirect calorimeter.



Choi L et al. J Appl Physiol 2010;108:314-327

AHA Scientific Statement

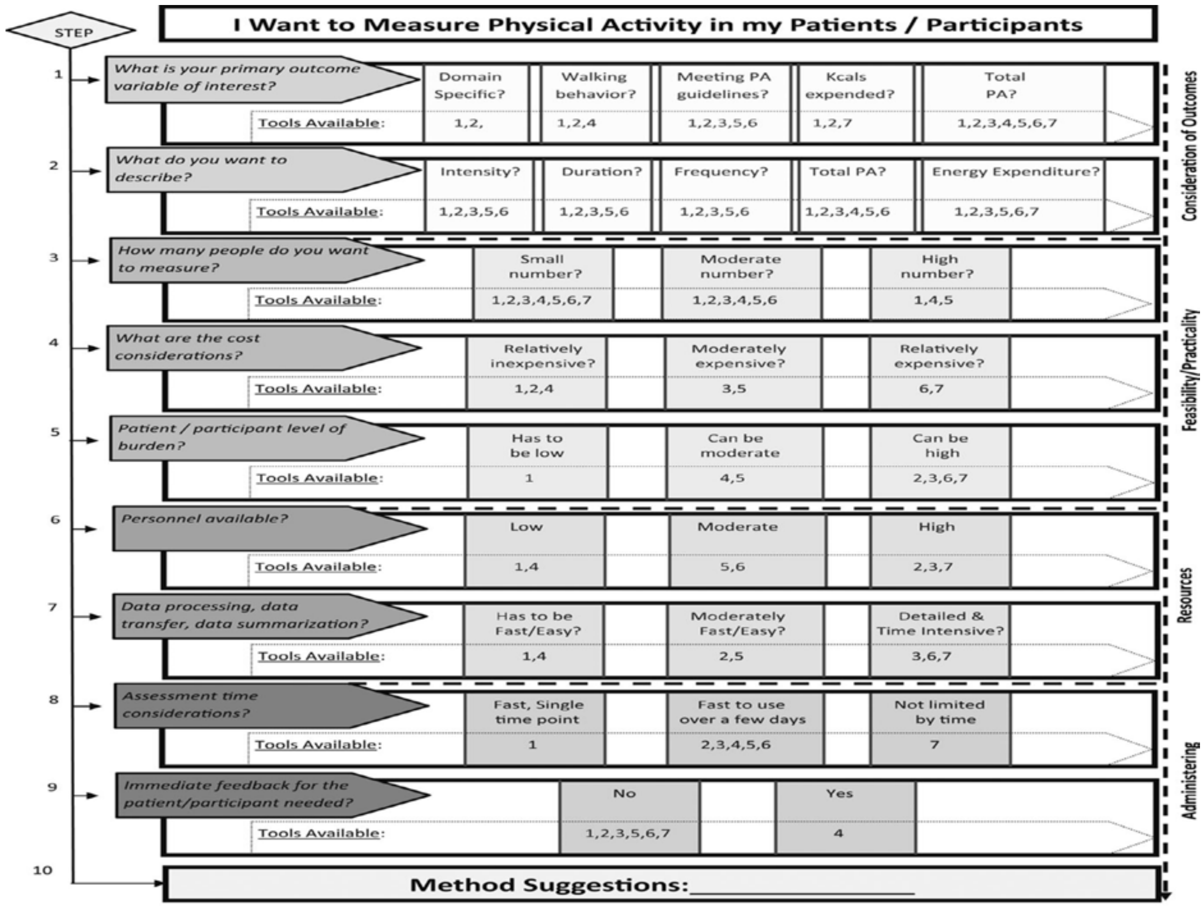
Guide to the Assessment of Physical Activity: Clinical and Research Applications

A Scientific Statement From the American Heart Association

Scott J. Strath, PhD, Chair; Leonard A. Kaminsky, PhD, Co-Chair;
Barbara E. Ainsworth, PhD, MPH, FAHA; Ulf Ekelund, PhD; Patty S. Freedson, PhD;
Rebecca A. Gary, RN, PhD; Caroline R. Richardson, MD; Derek T. Smith, PhD;
Ann M. Swartz, PhD; on behalf of the American Heart Association Physical
Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular,
Exercise, Cardiac Rehabilitation and Prevention Committee of the Council on Clinical Cardiology, and
Council on Cardiovascular and Stroke Nursing

Circulation 128: 2259-2279, 2013

Decision matrix guide to selecting a physical activity measurement instrument



Note: 1=Physical activity questionnaires; 2=Physical activity logs/diaries; 3=Heart Rate Monitoring; 4=Pedometers; 5=Accelerometer; 6=Multi-unit Sensors; 7=Doubly Labeled Water

American Heart Association.

Strath S J et al. *Circulation*. 2013;128:2259-2279

Acknowledgements

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