Sensors & Vitality (Physical Activity)

DBB170 - Sensors for physiology

Prof. dr. Steven Vos[1,2] & dr. Joost Oomen[1]

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Technische Universiteit Eindhoven University of Technology

Where innovation starts

Fontys Sporthogeschool

Lectoraat Move to Be

Who am I?

- Joost Oomen
- Movement Science and Biological Health Science (UM)
- PhD Human Biology (Genetic variation in energy expenditure) (UM)
- Lecturer / Researcher Fontys School of Sport Studies
  - Measuring (in)activity in real life
  - And laboratory setting
  - Behaviour changes in human (in)activity
- Sports and activity minded in general

Physiology

- Human Body

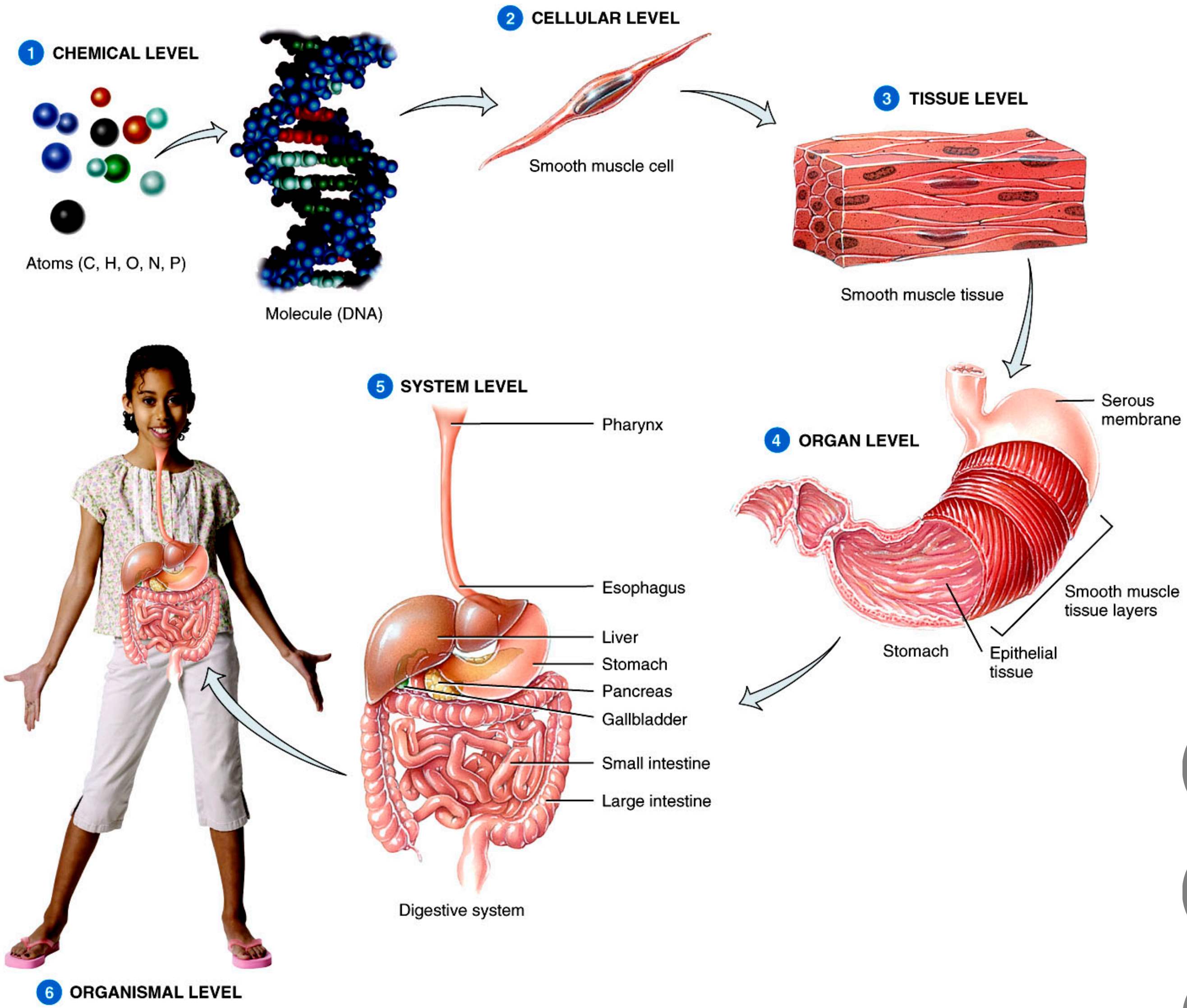

Figure 01.01 Tortora - PAP 12/e

Physiology and Health

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30 minuten bewegen

www.30minutenbewegen.nl

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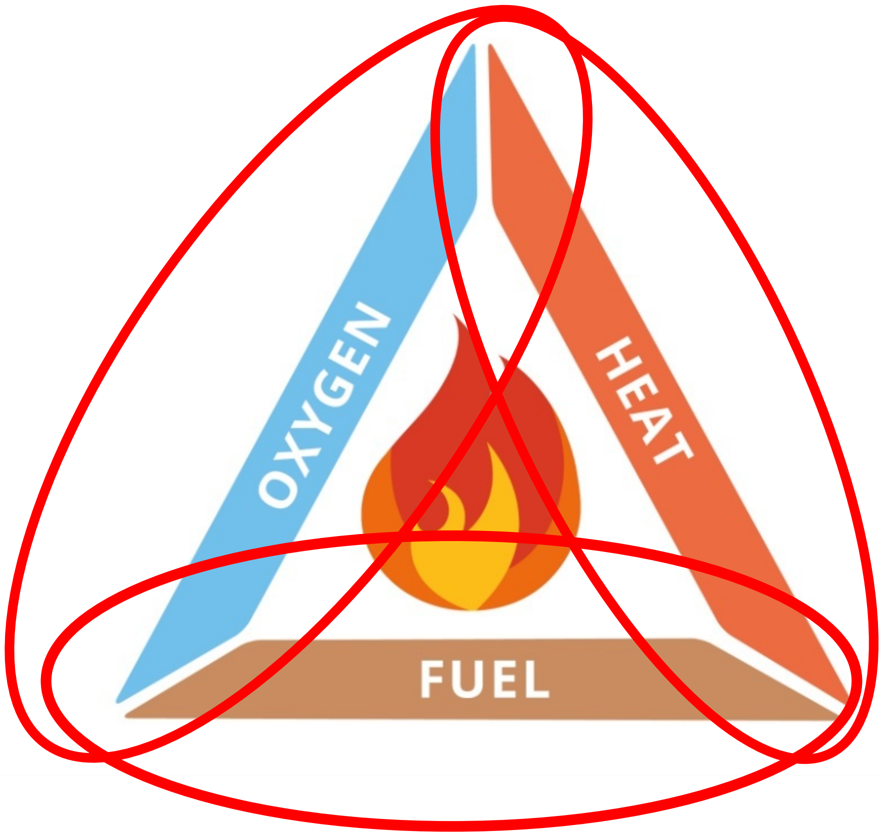
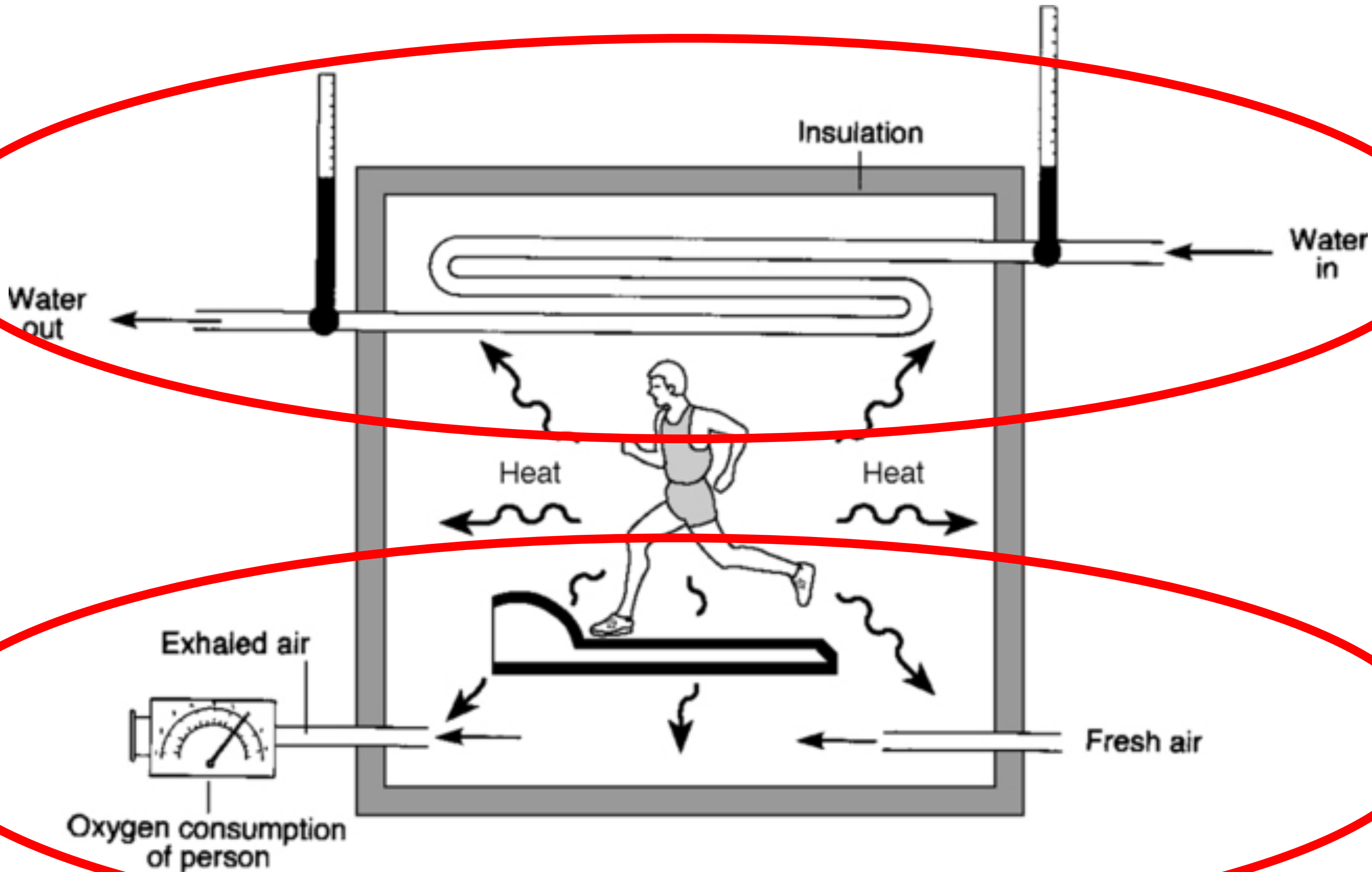
Health related physical activity (NNGB)

For adults based on daily movement of the body to exceed **200 kcal** above resting **energy metabolism**

Energy metabolism





Insulation
Water in
Water out
Heat
Heat
Exhaled air
Fresh air
Oxygen consumption of person

Health related physical activity (NNGB)

- For adults based on daily movement of the body to exceed 200 kcal above resting energy metabolism

- Problems with this definition?
  - How to measure resting energy expenditure?

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Health related physical activity (NNGB)

- For adults based on daily movement of the body to exceed 200 kcal above resting energy metabolism

- Problems with this definition?
  - How to measure resting energy expenditure?
  - How to measure moving energy expenditure?

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Activity energy expenditure

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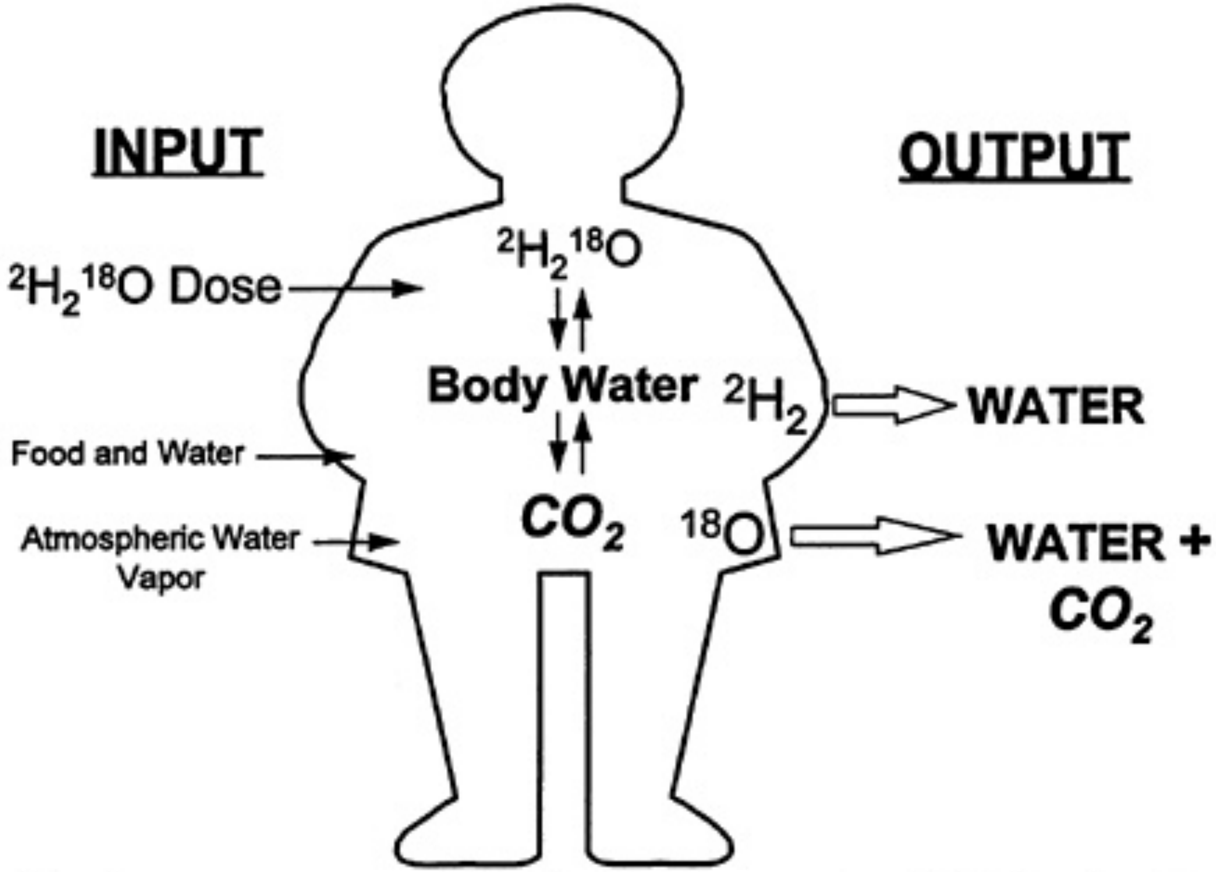
Alternative

Free living possibility



^{18}O elimination (water + CO_2) - $^2H_2$ elimination (water) = CO_2 Production

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Rather impractical in real life situations BUT

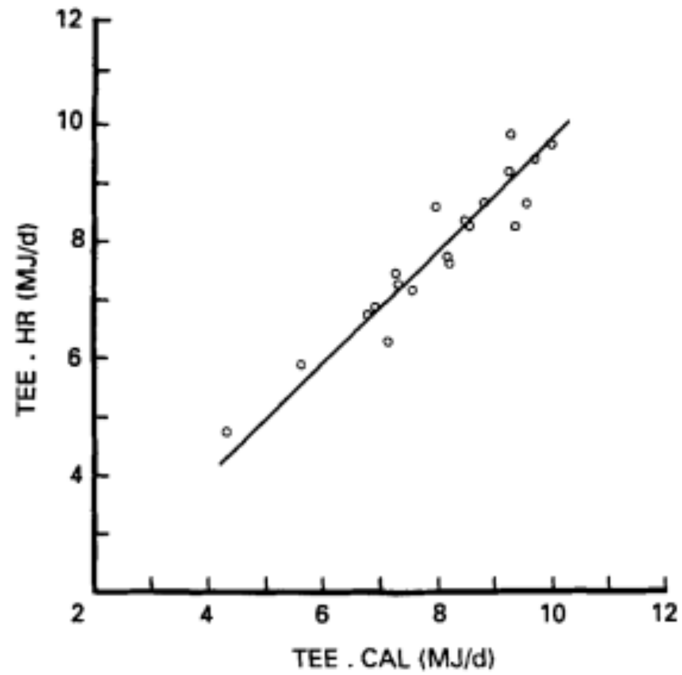
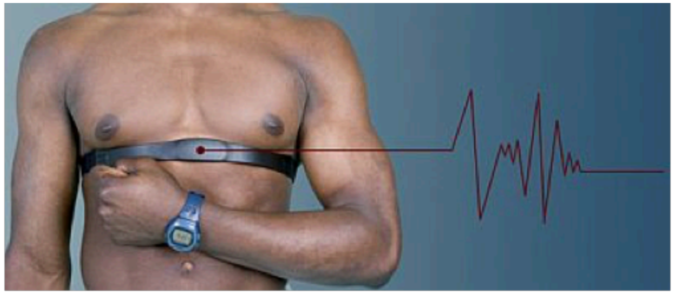
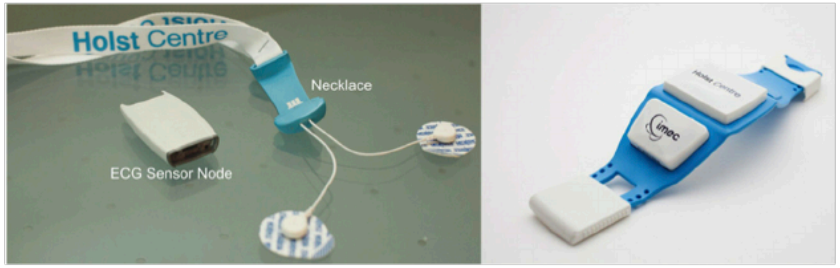


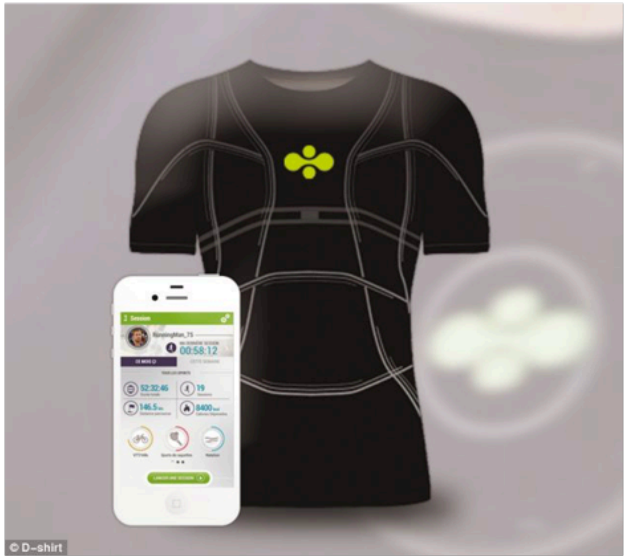
Fig. 1. Correlation between total energy expenditure (TEE) derived from the heart rate (HR; TEE . HR) and whole-body calorimetry (CAL; TEE . CAL) methods (*n* 20). *r* 0·943, slope 0·868, intercept 927 kJ, SE of estimate 458 kJ. For details of methods, see pp. 176–177.

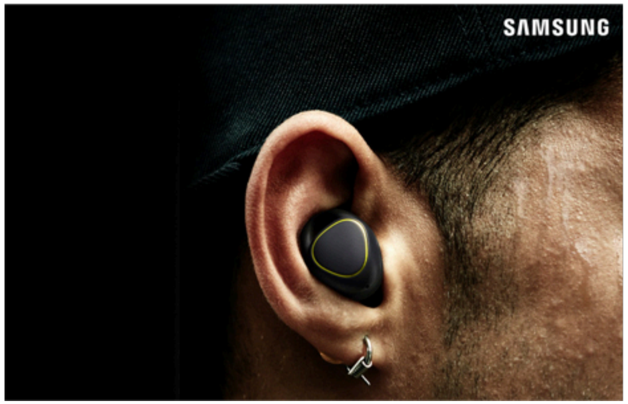
Cheesay (1989)

So heart rate could be an alternative?









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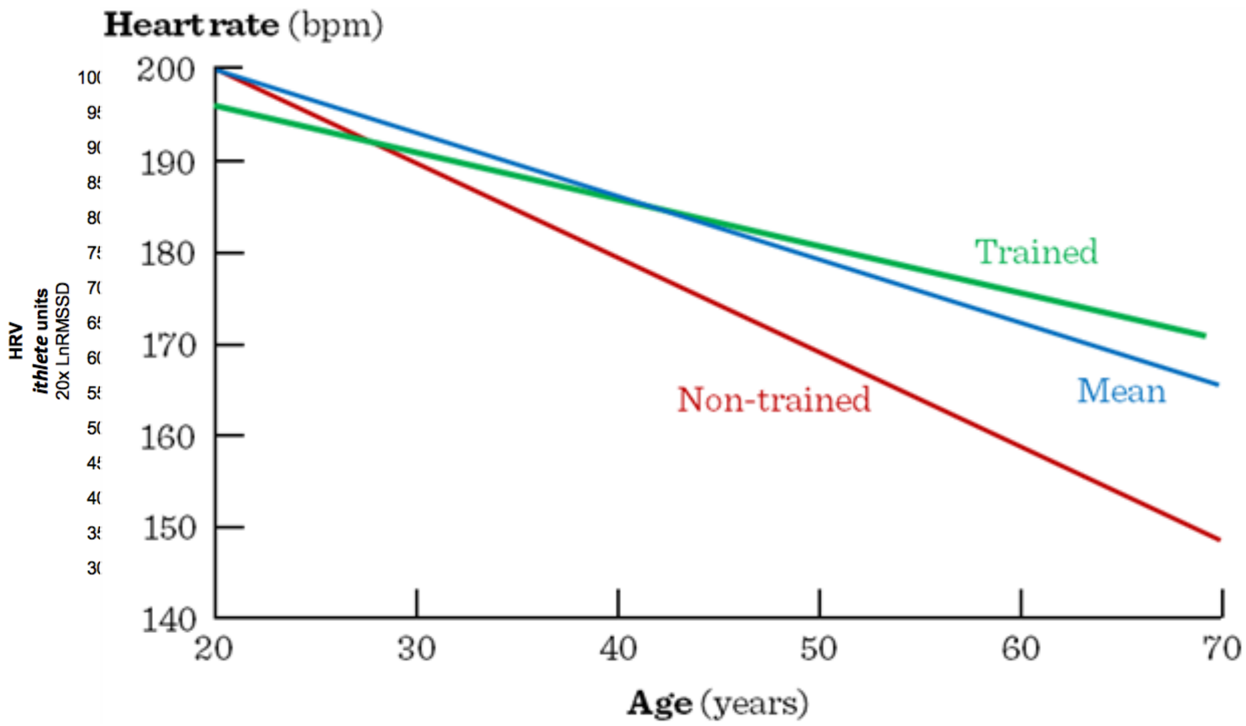
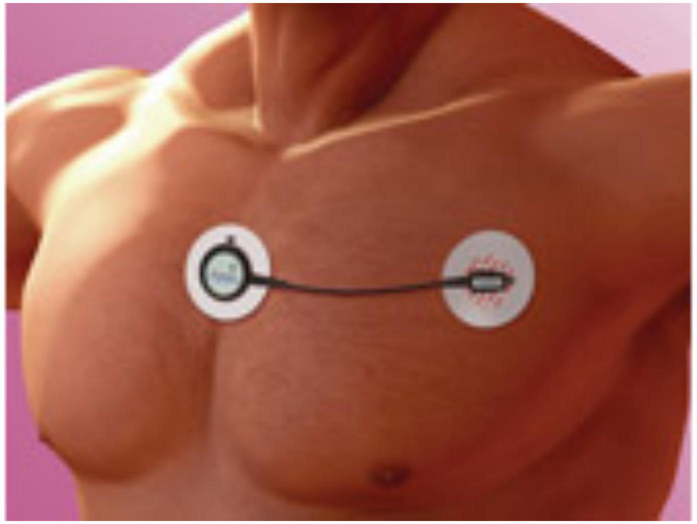
Heart rate dependent of....?

- Metabolism
- Age
- Trained status
- Stress
- Medicine
- ....



Not only heart rate……. Combination with?



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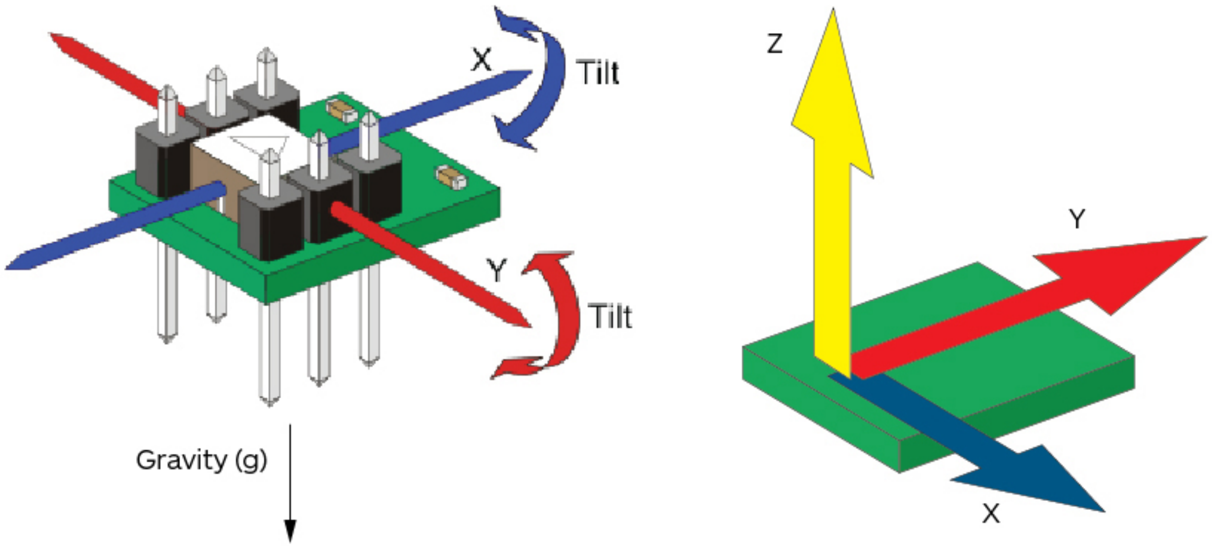
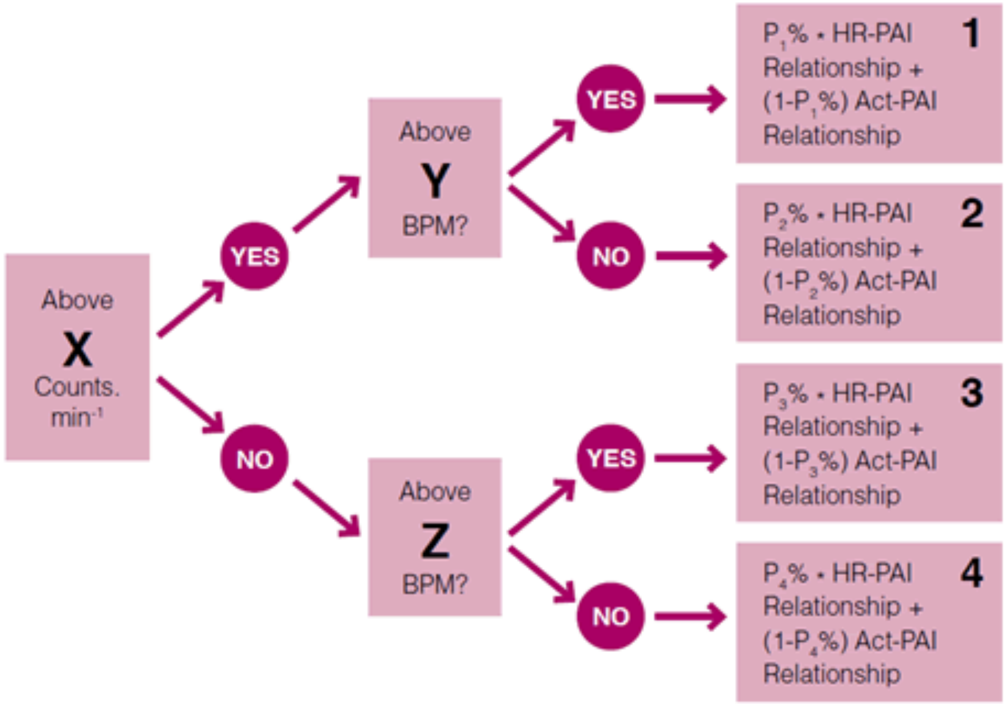
Accelerometer



Diagrams illustrating the axes of 2-axis (left) and 3-axis accelerometers. This particular 2-axis sensor is also capable of tilt measurement.
Image credit: Parallax | Kerry Wong

Branched chain equation



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This method is….

- Valid
- Accurate

But….

- Needs individual calib
- Stickers are not user f
- Not ideal for consum

ORIGINAL COMMUNICATION

Reliability and validity of the combined heart rate and movement sensor Actiheart

S Brage[1]*, N Brage[2], PW Franks[1], U Ekelund[1] and NJ Wareham[1]

[1]*MRC Epidemiology Unit, Institute of Public Health, University of Cambridge, UK; and* [2]*Institute of Sports Science and Clinical Biomechanics, University of Southern Denmark, Odense, Denmark*

Accurate quantification of physical activity energy expenditure is a key part of the effort to understand disorders of energy metabolism. The Actiheart, a combined heart rate (HR) and movement sensor, is designed to assess physical activity in populations.

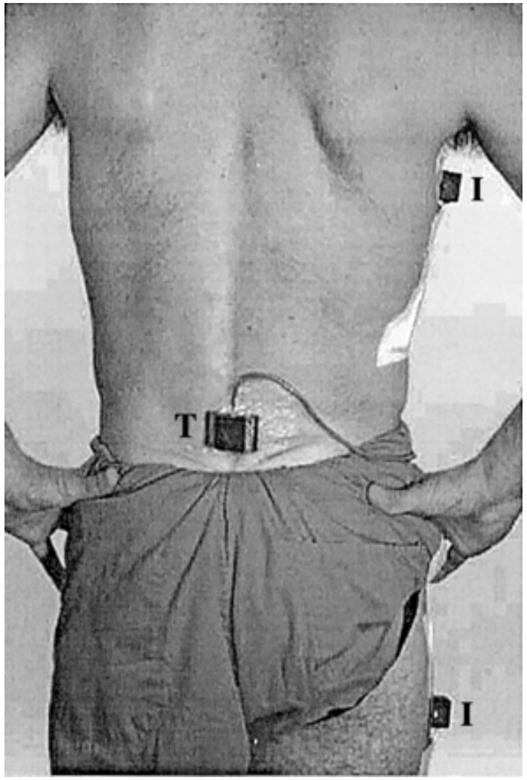
Objective: To examine aspects of Actiheart reliability and validity in mechanical settings and during walking and running.

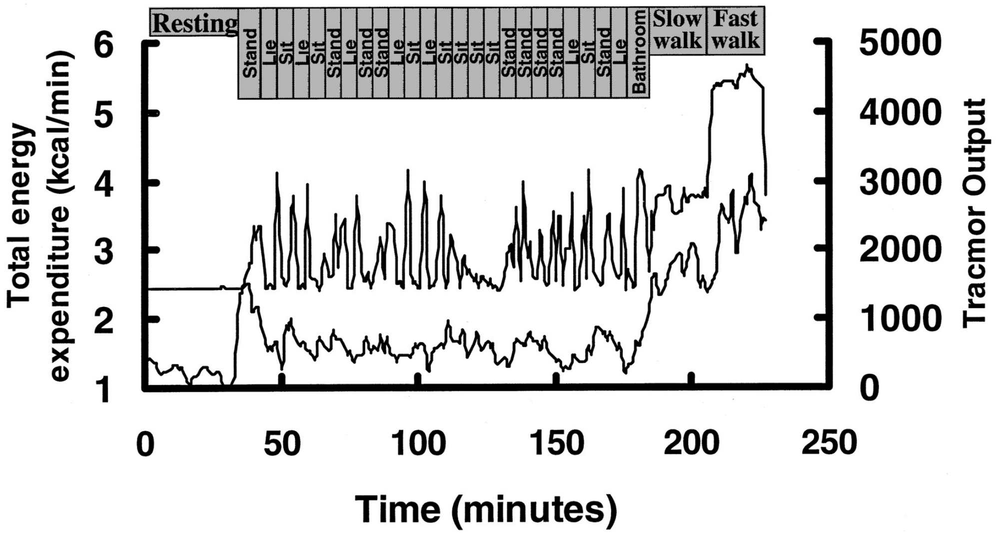
Methods: In eight Actiheart units, technical reliability (coefficients of variation, CV) and validity for movement were assessed with sinusoid accelerations (0.1–20 m/s^2) and for HR by simulated R-wave impulses (25–250 bpm). Agreement between Actiheart and ECG was determined during rest and treadmill locomotion (3.2–12.1 km/h). Walking and running intensity (in J/min/kg) was assessed with indirect calorimetry in 11 men and nine women (26–50 y, 20–29 kg/m^2) and modelled from movement, HR, and movement + HR by multiple linear regression, adjusting for sex.

Results: Median intrainstrument CV was 0.5 and 0.03% for movement and HR, respectively. Corresponding interinstrument CV values were 5.7 and 0.03% with some evidence of heteroscedasticity for movement. The linear relationship between movement and acceleration was strong ($R^2 = 0.99$, $P < 0.001$). Simulated R-waves were detected within 1 bpm from 30 to 250 bpm. The 95% limits of agreement between Actiheart and ECG were −4.2 to 4.3 bpm. Correlations with intensity were generally high ($R^2 > 0.84$, $P < 0.001$) but significantly highest when combining HR and movement (SEE < 1 MET).

Conclusions: The Actiheart is technically reliable and valid. Walking and running intensity may be estimated accurately but further studies are needed to assess validity in other activities and during free-living.

And only an accelerometer?





Levine (2001)

Basic physics

$$F = m * a$$

$$W = F * \triangle s$$

$$W = m * a * \triangle s$$

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To be able to inform user about NNGB

For adults based on daily movement of the body to exceed **200 kcal** above **resting energy metabolism**

- Formula Harris and Benedict

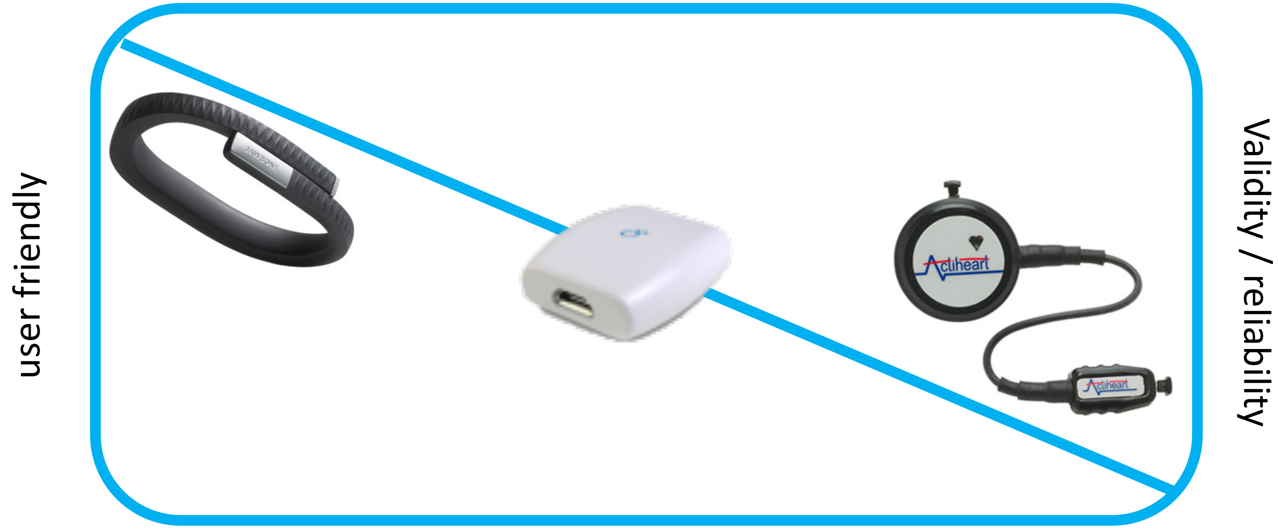
The Harris–Benedict equations revised by Mifflin and St Jeor in 1990:[4]

Men	BMR = (10 × weight in kg) + (6.25 × height in cm) - (5 × age in years) + 5
Women	BMR = (10 × weight in kg) + (6.25 × height in cm) - (5 × age in years) - 161

To calculate energy expenditure from body movement you need:

- Body Mass
- Accelerations
- Distance

Activity Trackers



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Actigraph

Estimating Energy Expenditure Using Body-Worn Accelerometers: a Comparison of Methods, Sensors Number and Positioning

Marco Altini[1], Julien Penders[2], Ruud Vullers[2] and Oliver Amft[3]

***Abstract*—Several methods to estimate Energy Expenditure (EE) using body-worn sensors exist, however quantifications of the differences in estimation error are missing. In this paper, we compare three prevalent EE estimation methods and five body locations to provide a basis for selecting among methods, sensors number and positioning. We considered (*a*) counts-based estimation methods, (*b*) activity-specific estimation methods using METs lookup, and (*c*) activity-specific estimation methods using accelerometer features. The latter two estimation methods utilize subsequent activity classification and EE estimation steps. Furthermore, we analyzed accelerometer sensors number and on-body positioning to derive optimal EE estimation results during various daily activities. To evaluate our approach, we implemented a study with 15 participants that wore five accelerometer sensors while performing a wide range of sedentary, household, lifestyle, and gym activities at different intensities. Indirect calorimetry was used in parallel to obtain EE reference data. Results show that activity-specific estimation methods using accelerometer features can outperform counts-based methods by 88% and activity-specific methods using METs lookup for active clusters by 23%. No differences were found between activity-specific methods using METs lookup and using accelerometer features for sedentary clusters. For activity-specific estimation methods using accelerometer features, differences in EE estimation error between the best combinations of each number of sensors (1 to 5), analyzed with repeated measures ANOVA, were not significant. Thus, we conclude that choosing the best performing single sensor does not reduce EE estimation accuracy compared to a five sensors system and can reliably be used. However, EE estimation errors can increase up to 80% if a non-optimal sensor location is chosen.**

***Index Terms*—Accelerometers, Energy Expenditure**

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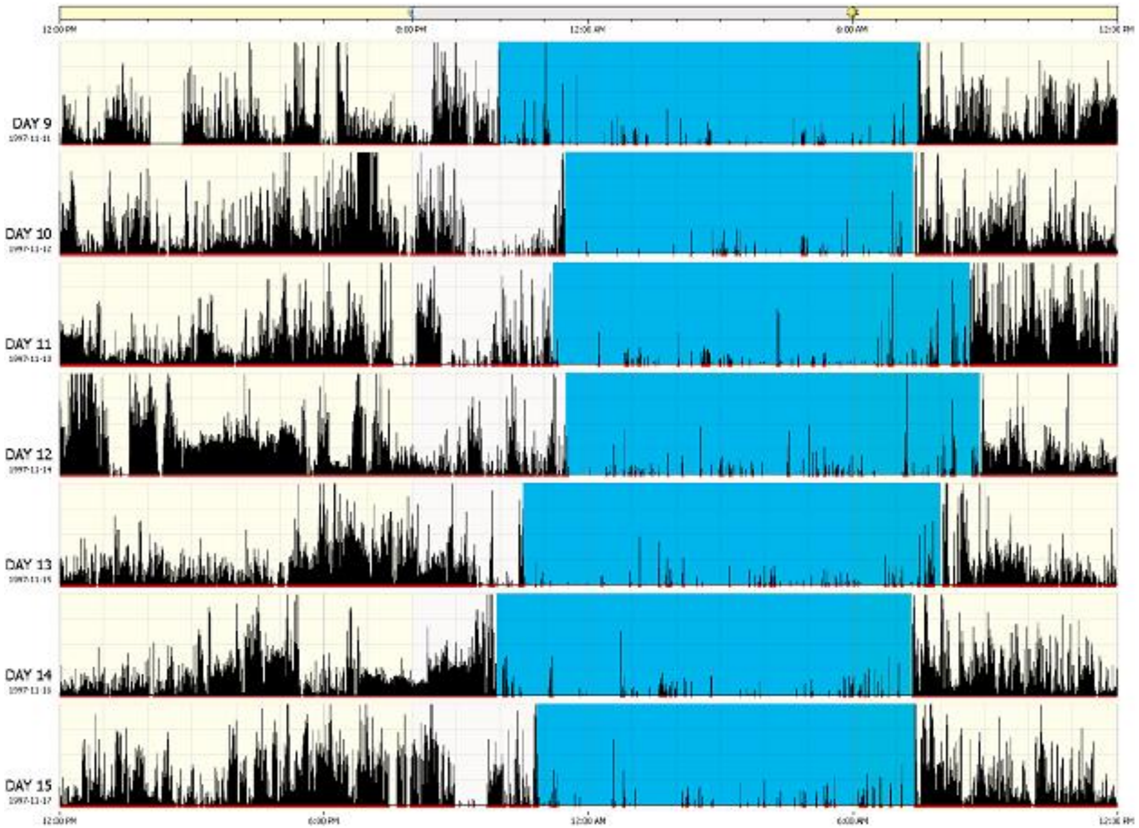
Data output



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But.....

- Only valid when whole body moves
- No good distinction between kind of movements
- Distance not easy to measure without GPS or being indoor (issue with all accelerometers)

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Basal Digestion: Physical

Physical activity	**MET**
Light intensity activities	**< 3**
sleeping	0.9
watching television	1.0
writing, desk work, typing	1.8
walking, 1.7 mph (2.7 km/h), level ground, strolling, very slow	2.3
walking, 2.5 mph (4 km/h)	2.9
Moderate intensity activities	**3 to 6**
bicycling, stationary, 50 watts, very light effort	3.0
walking 3.0 mph (4.8 km/h)	3.3
calisthenics, home exercise, light or moderate effort, general	3.5
walking 3.4 mph (5.5 km/h)	3.6
bicycling, <10 mph (16 km/h), leisure, to work or for pleasure	4.0
bicycling, stationary, 100 watts, light effort	5.5
Vigorous intensity activities	**> 6**
jogging, general	7.0
calisthenics (e.g. pushups, situps, pullups,jumping jacks), heavy, vigorous effort	8.0
running jogging, in place	8.0
rope jumping	10.0

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Problems with MET

Physical activity	MET
Light intensity activities	**< 3**
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running jogging, in place	8.0
rope jumping	10.0

- By definition 1 MET = 3,5 ml O_2/kg/min (Rest)
- Measured in rest in 1 subject (age 40, weight 70 kg)
- Resting metabolic rate more dependent on muscle mass than body weight
- Overestimation of 20-30%
- Individual 'calibration' necessary

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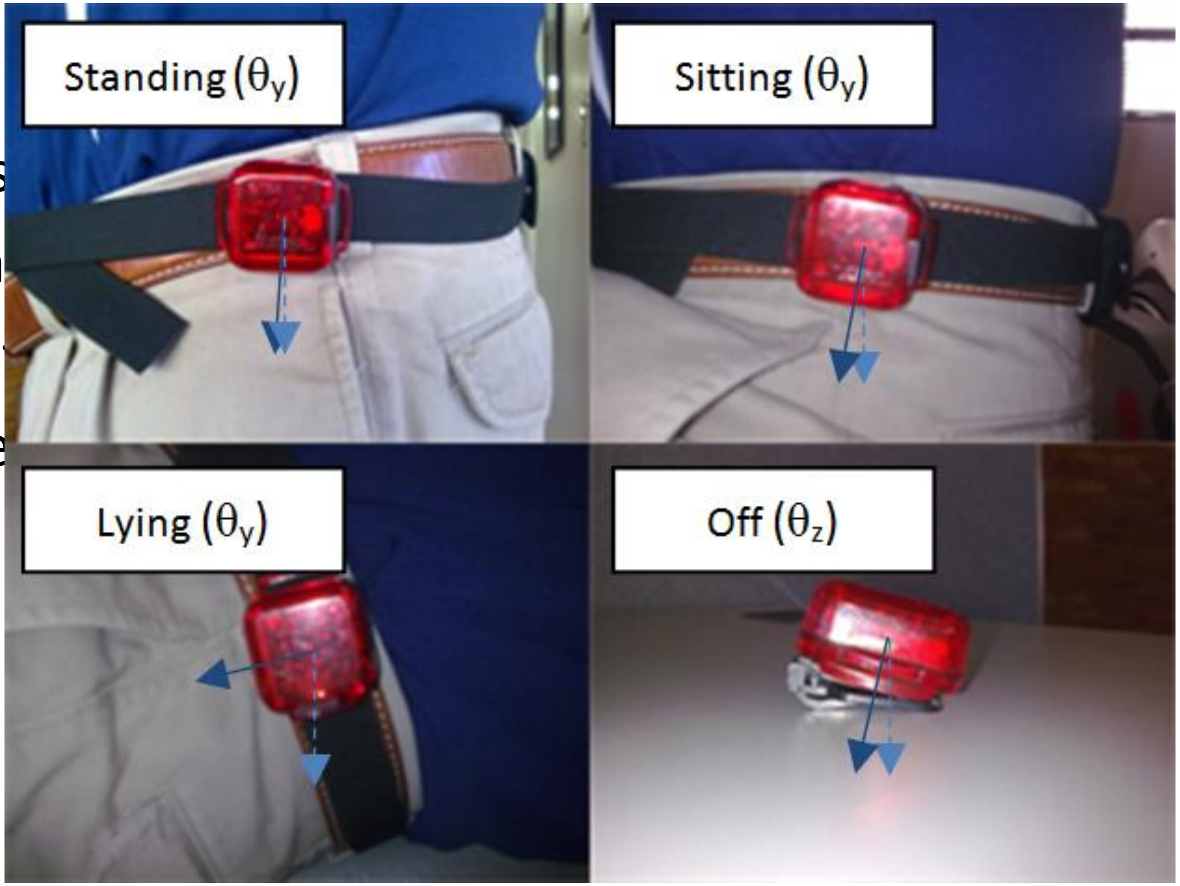
Alternative

- Accelerations
- Determine m
- Determine in
- Calculate Ene



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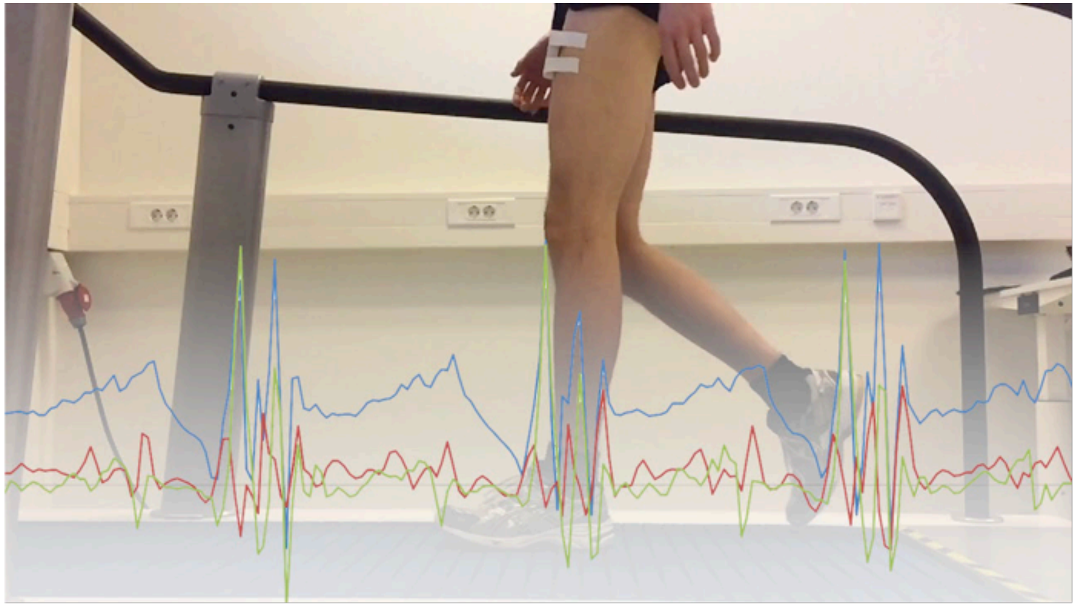

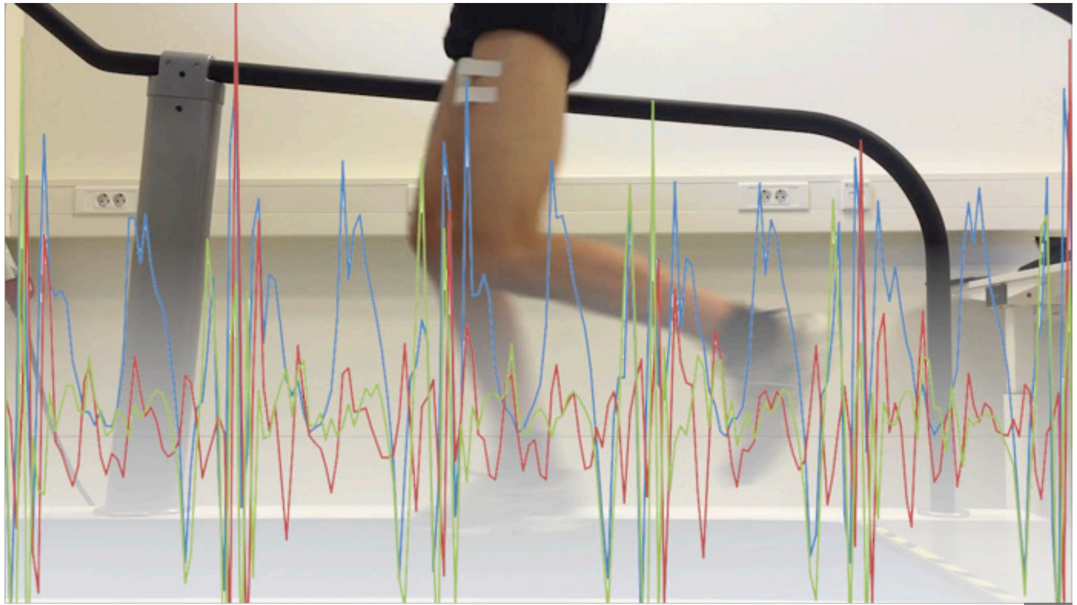

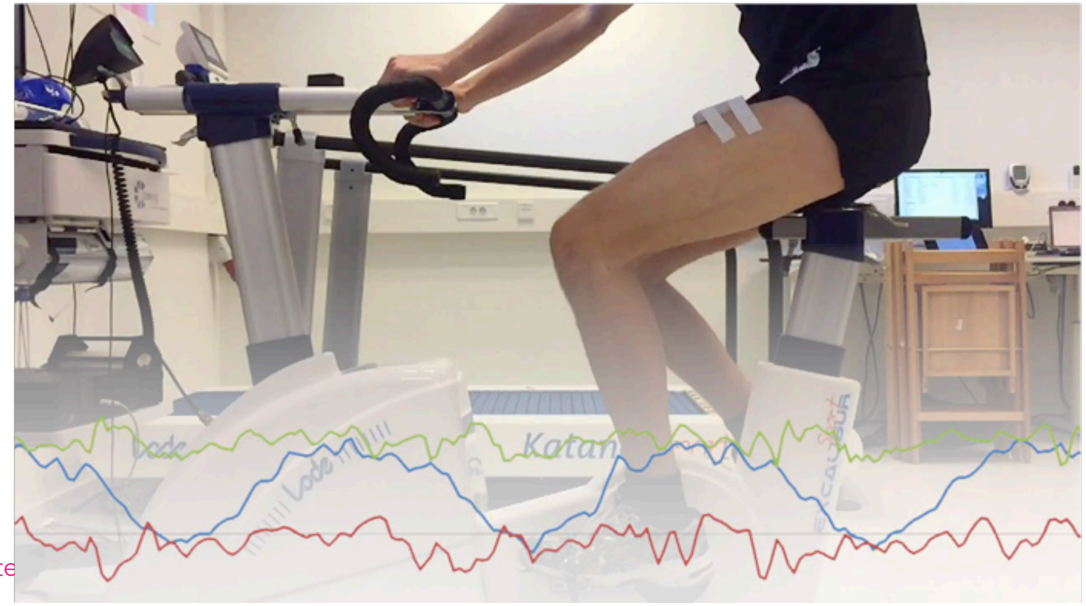

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Pattern recognition

- Orientation in the gravity field (Standing, sitting, lying)
- Identify the movement (walking, running, cycling)
- Intensity of the movement
- Calculation of the energy expenditure (based on resting energy expenditure to correct for individual differences)

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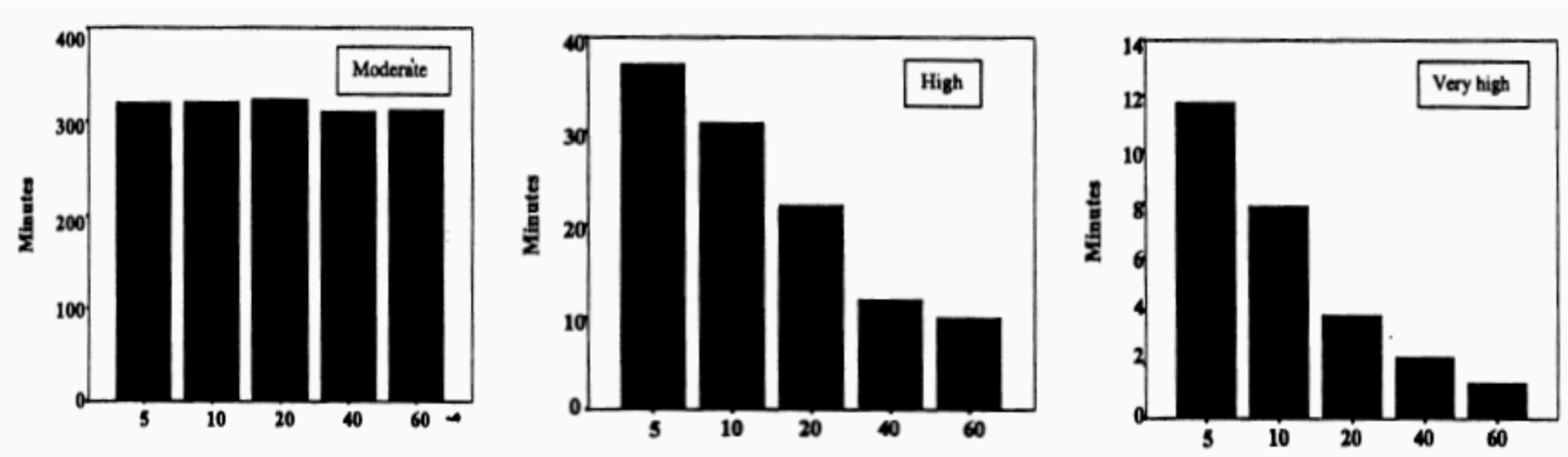
Things to take into account

Hardware

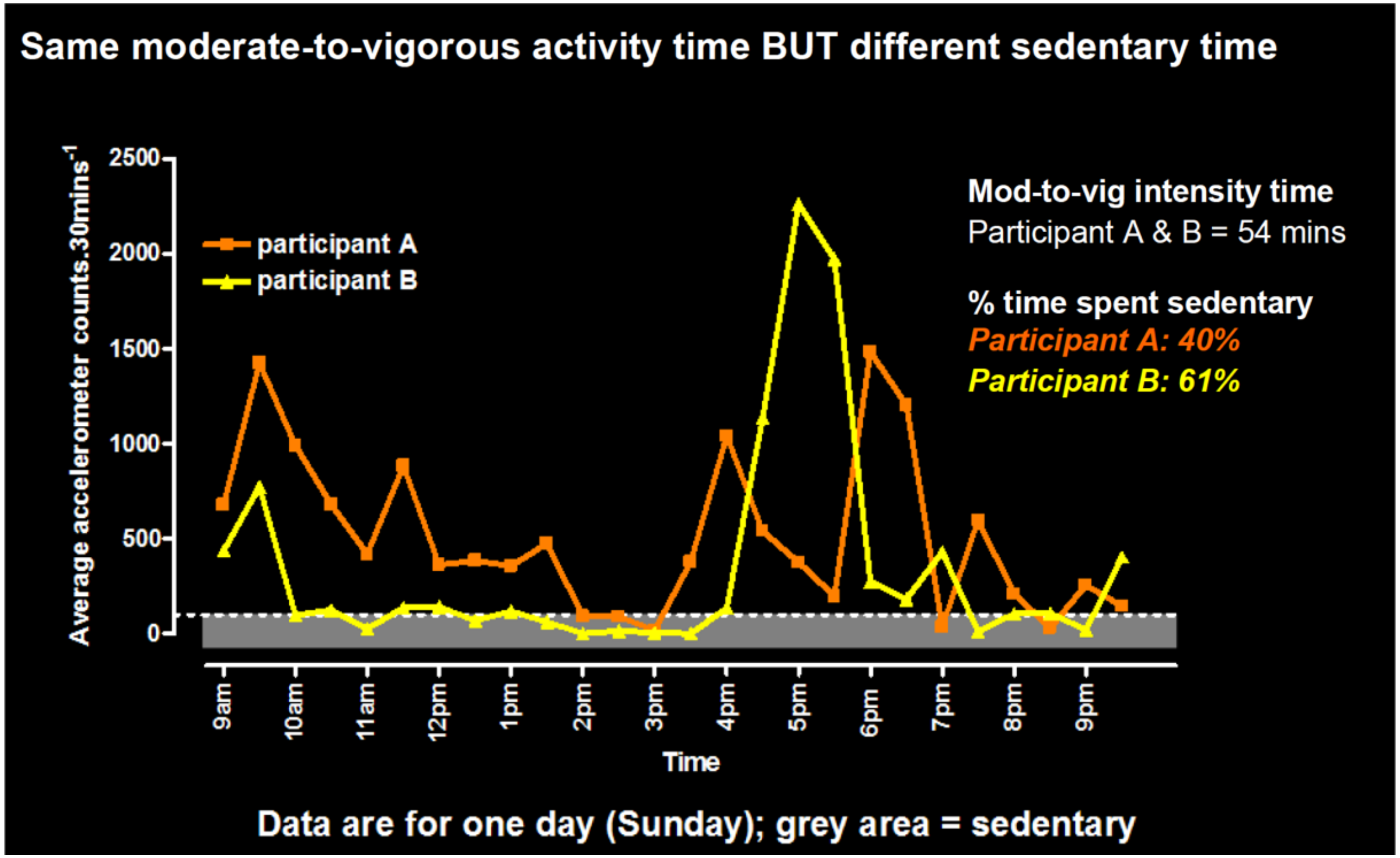
- Communication possibilities (with phone or between multiple devices)
- Gravitation maximum(2G-8G)
- Frequency rate (12-50 Hz)
- Storage capacity
- Battery life (depends on all of the above)

Things to take into account

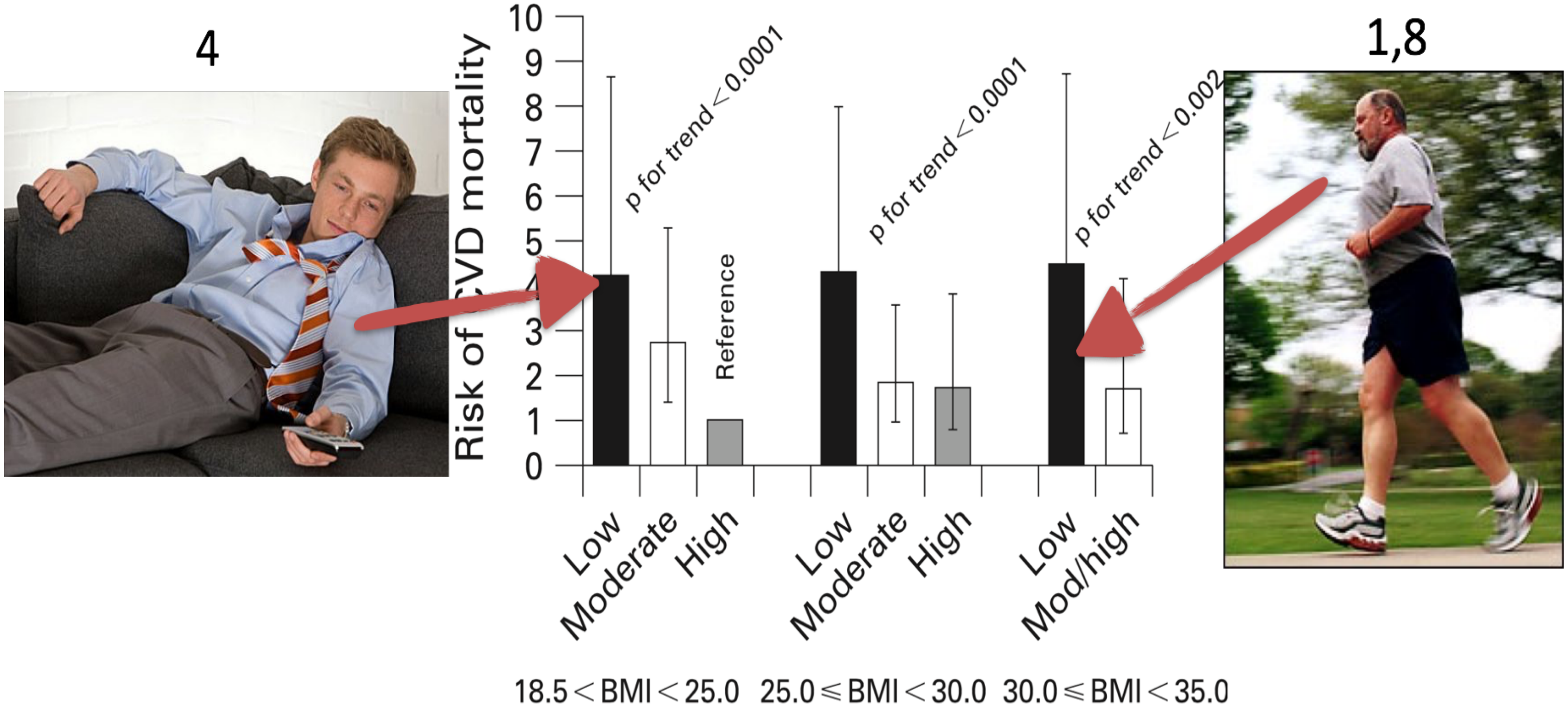


Nilsson, Ekelund, Yngve,& Sjostrom (2002) *Pediatric Exercise Science*,14,87-96

Sedentary behaviour



Health impact of sedentary behaviour



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How to measure sedentary behaviour with an accelerometer?

- Where to locate?
- How to determine that you are sitting?
- How long of consecutive sitting is unhealthy?

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Introduction Activ8

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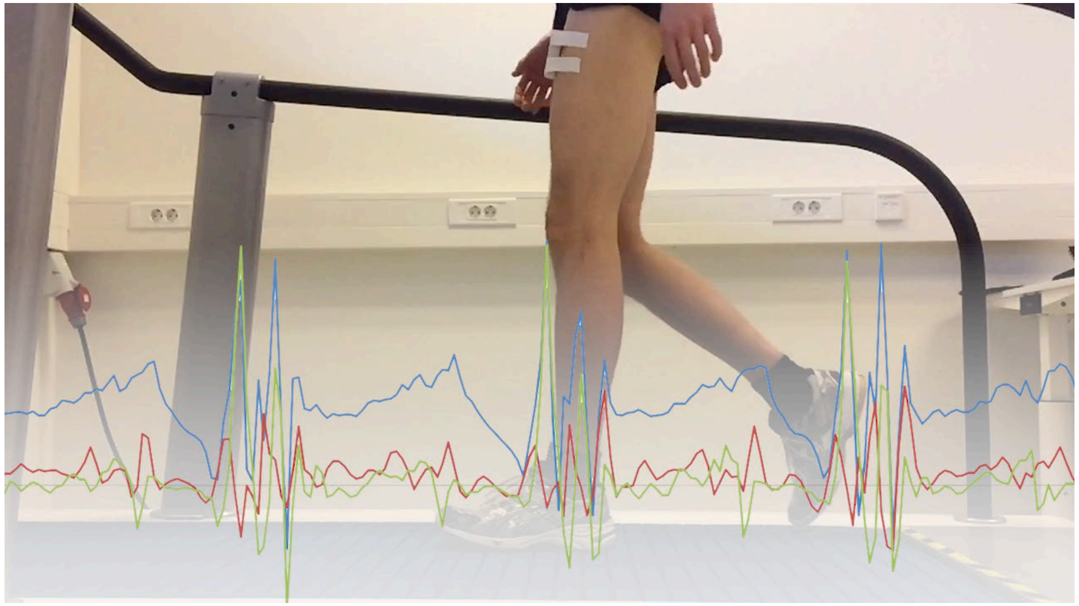

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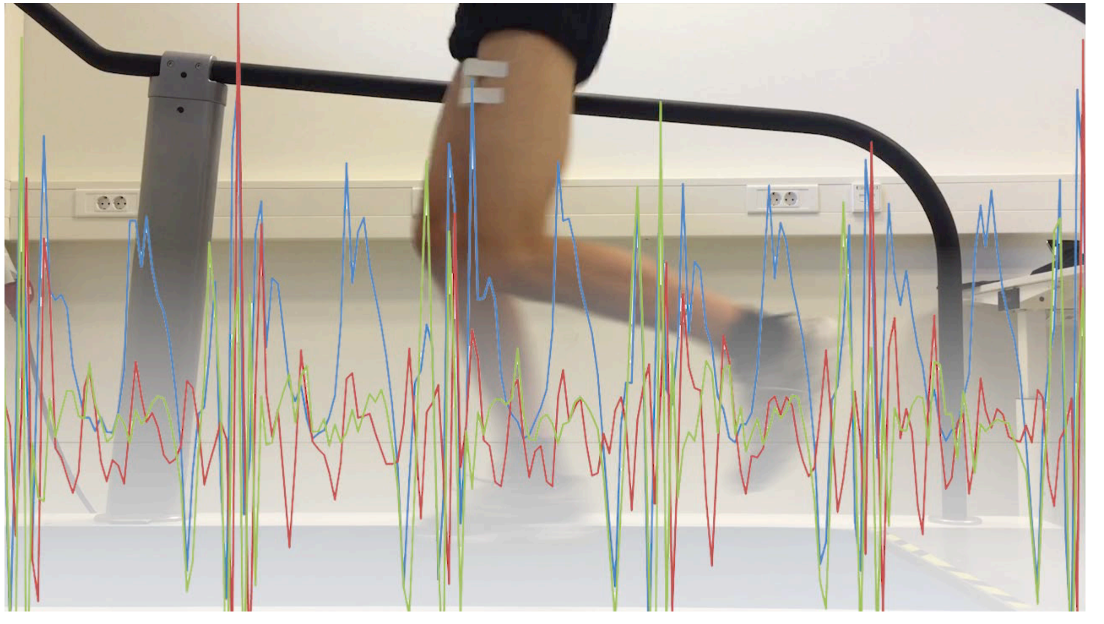

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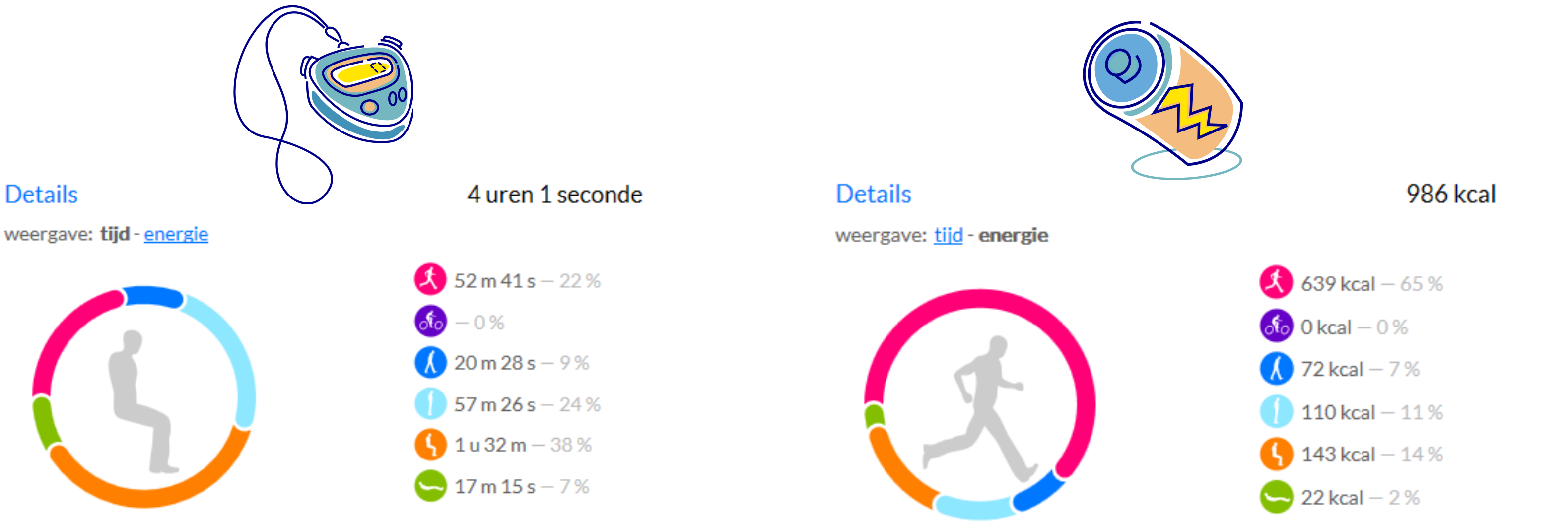
Example dashboard



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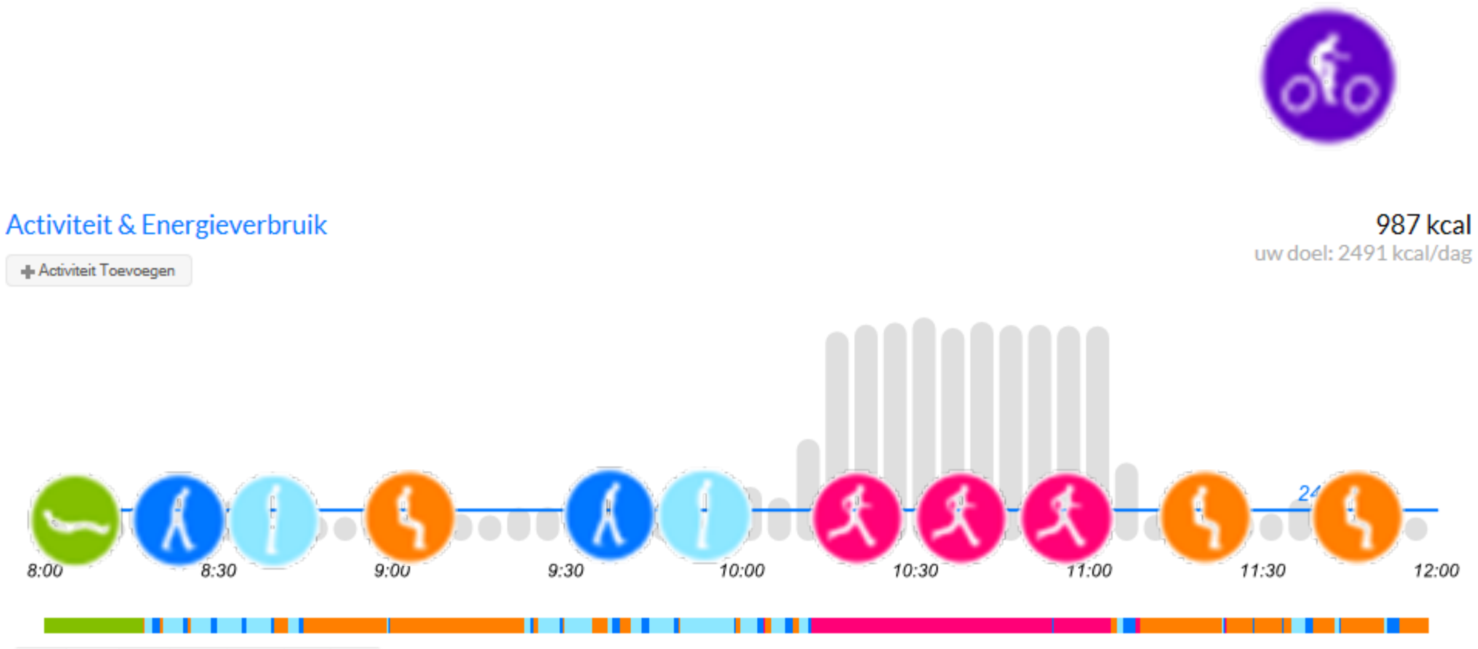

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Things to know before you start

- Target group
  - IT capabilities
  - Willing to upload frequently
  - Willing to charge battery frequently
  - What behaviour do they want to change
- Accuracy or feasibility?
- Hardware possibitilies (Size, Frequency, Sensitivity, Battery)

Questions regarding the user?

- What works for the individual user? What motivates him/her?
- What kind and amount of information does the user need?
- How can the user interface reach all goals?