

Wearables at Leiden University and LUMC



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Park Vossenbergh - QoL in Dementia Care



Procedures - Gear - Software

- ▶ Consent
- ▶ GPS - Privacy Circle

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- ▶ Hardware: Samsung Gear Fit 2 Pro
- ▶ Software: LIACS home-brew:

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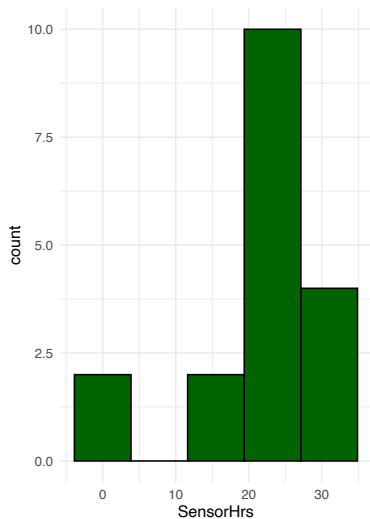
```
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```
- ▶ People:



Richard van Dijk (LIACS RSE),
Renelle Bourdage (Student Intern),
Monique Willemse (Thesis Student)



Collected Data - Movement Sensors



► 16 participants

► 5 hrs of labels

Next Steps

- ▶ sparse labels, unsupervised ML challenge
- ▶ physical activity model? hard-thresholded model?
- ▶ but first: post-processing, quality checks, error and noise estimation

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Acceptability and feasibility of wearables in youth mental health units

Klodiana Daphne Tona | WIP 18-05-2021



Universiteit
Leiden
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Department of Child and Adolescent Psychiatry,
Leiden University Medical Center,
Leiden, The Netherlands.

How do youngsters with mixed mental health problems perceive the use of wearables in mental healthcare units?



Tona, K.D., Sanne van den Driesschen, Laura Nooteboom, Eddo Velders, Robert Vermeiren, Kirsten Hauber



Introduction

New technologies & wearables can:

- Be used at the service of (mental) healthcare
- Enhance resilience in youth, better future for next generation
- Some work has been done and more is under process

BUT

What do young people believe?

- Feasibility
- Acceptability
- Needs
- Suggestions



Methods

A mixed methods study:

- Focus groups (Qualitative)
- Questionnaire (Quantitative)
- In depth information about participants' knowledge, experiences and opinions on the use of wearables in child and youth psychiatry.
 - Four focus groups: 3 at Curium-LUMC and 1 at YOUZ
 - N= 20
 - Participants: adolescents with (a history of) psychological, developmental or personality problems (depression, autism spectrum disorder, borderline, suicidality)

Results (just a taste...)

Research and target group:

- Research is important but...
- The wearable must be well researched and work well before you can test it for vulnerable young people
- If it doesn't work properly, you can get stressed out
- Carefully design the amount of provided information:
e.g., “I can get frustrated with it, if the wearable asks a question too often”.

Results (just a taste...)

The use of a wearable:

- Youngsters must be able to take off the wearable
- They prefer a wearable that is subtle & aesthetically pleasant, such as a smart watch (“I would not use a stone like device”)
- They differ in opinion as to whether it should be clear that the wearable is for assistance with a (mental) health condition
 - do not want other people to see it -> “to avoid stigmatization”
 - it is not a problem if people see it -> “you want people to accept you, whatever you wear.”

Results (just a taste...)

The use of a wearable in treatment:

Youngers:

- Prefer to not communicate with friends via the wearable.
“It is your treatment and not your means of communication. You have other means for that”.
- Find it easier to indicate how they feel via a telephone or tablet than face-to-face.

The wearable:

- Should be adjusted personally.
“You must also be able to hang photos, music or sounds in it.”
- Should be an addition to the treatment, not substitute it.
- Can send a standard text message to unit, for example 'help'.

Results (just a taste...)

The use of a wearable in treatment:

➤ **Free will & technology:**

the wearable can help detect that they are in crisis, but the final decision is up to the youngsters:

- Detection of increased heartbeat -> computer gives you the choice if you want to ask someone for help -> you can click “yes” or “no”
- “The wearable should not call for help immediately if you are in crisis and have a very high heart rate. *The wearable may not conclude anything*, but must ask a question such as "something is wrong, are you afraid?" "are you okay?" - You can also click it away yourself.”

Thus...

What do youngsters believe?

- Feasibility

Do they think it is feasible?



- Acceptability

Do they accept the usage of wearables?



- Needs



- Suggestions



Thank you!

Questions?

Email me:

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K.D. Tona
Clinical Psychology Unit
Leiden University

D-ActWheels project

Iris Yocarini | WIP 18-05-2021



Universiteit
Leiden
The Netherlands



VRJE
UNIVERSITEIT
AMSTERDAM



revalidatie | reumatologie



Hogeschool van Amsterdam



Discover the world at Leiden University

D-ActWheels project

Goal: increase energy expenditure estimation (EEE) for wheelchair users



D-ActWheels project

Data collection

Triaxial accelerometers

- **activ8** (right wrist and wheel) and **geneactive** (left wrist)

Photoplethysmography (PPG)

- Fitbit (right wrist)



Figure by BSc student Lorenzo Spierings (2020)

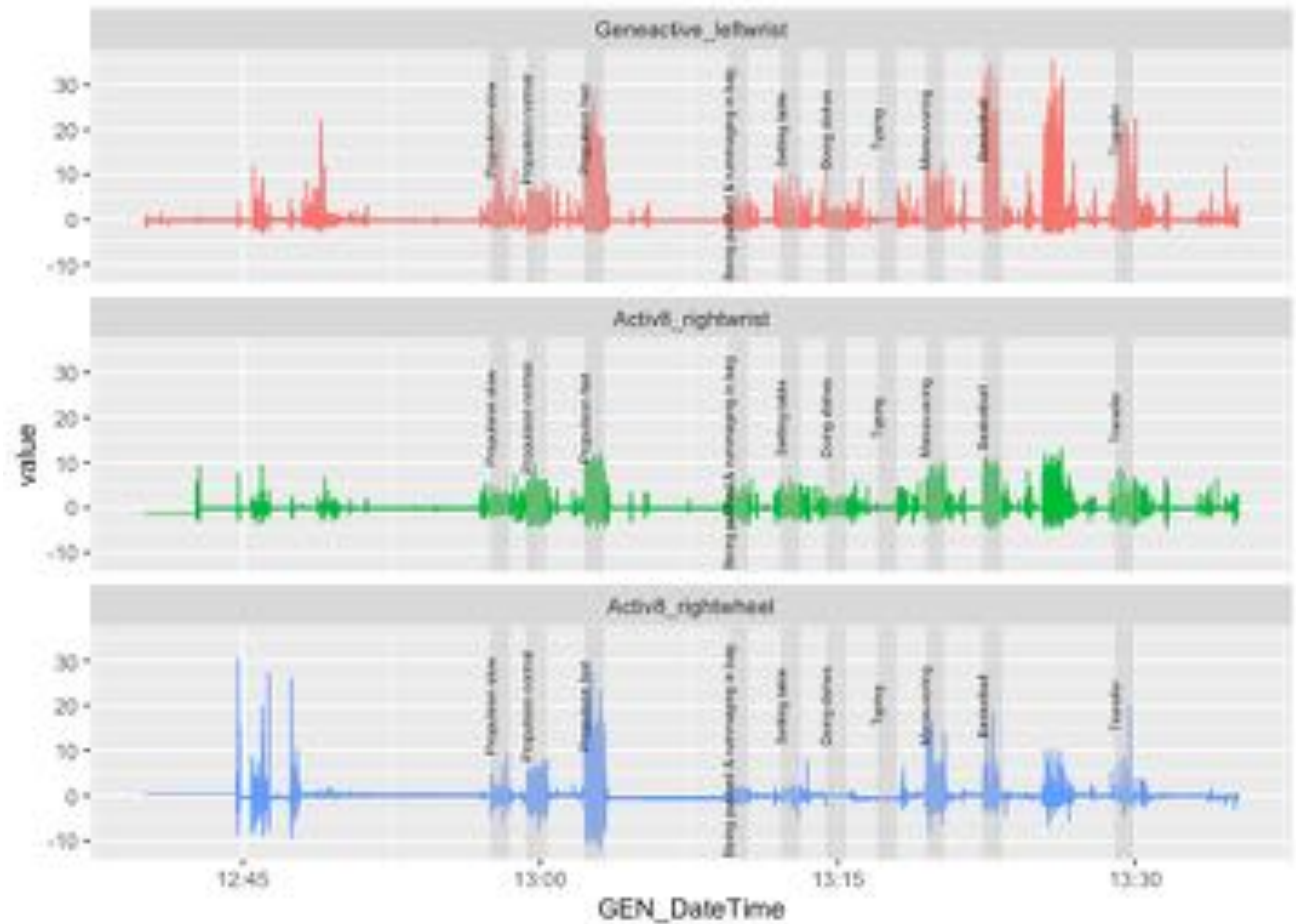
D-ActWheels project

Activities in protocol

- 11 daily activities
- Self-selected strength activities

Participants

- 33 - spinal cord injury
- 11 - lower limb amputation



Human activity classification

Integrating heart rate data with accelerometer data
to classify wheelchair activities

Classification of wheelchair activities

Daily activities distinguished into propulsion vs. non-propulsion

1. Propulsion vs. no propulsion
2. Propulsion: high, medium, low intensity activities

Challenges in integration different sensors

- Imputation missing data
- Level of accurate and meaningful compression (up/down sampling)
- What feature of time serie is most important

Classification of wheelchair activities

Most studies use only sensor data such as accelerometer, gyroscopes or magnetometers for HAR

Add heart rate data

- Heart rate measured by wristworn sensor
 - Practically more relevant, yet alternative available: chest strap heartrate monitor measured breath-by-breath
- Measure of activity intensity

Decision-level integration approach

- Assess added value of heart rate in classification of wheelchair activities

Late fusion

Decision-level fusion

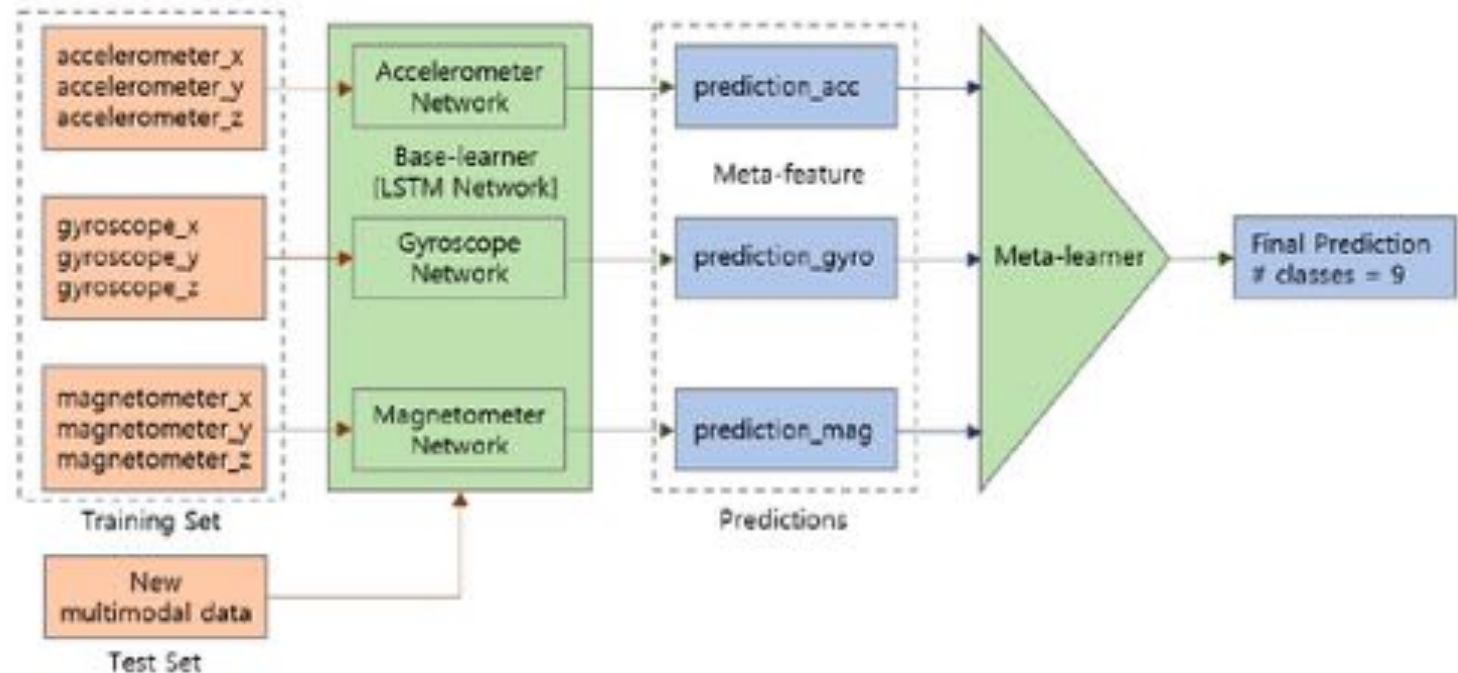


Figure 5. Classifier-level ensemble for multimodal sensor fusion. Prediction results from each sensor modality are used as meta-features for the meta-learner.

Chung et al. (2019) sensor data acquisition and multimodal sensor fusion for HAR using DL

Energy expenditure estimation

Activity-specific or not?

D-ActWheels project

Further exploration

- Difference LLA and SCI group
- Integrating demographic (static) information to model person differences

Thank you!

Questions? Email me:
i.e.yocarini@liacs.leidenuniv.nl



Leiden University
Medical Center

Activity Recognition and Energy Expenditure Estimation towards a Healthy Ageing, the GOTO study

WIP 18/05/2021

Stylianos Paraschiakos

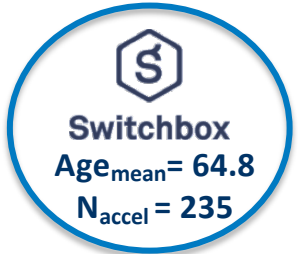
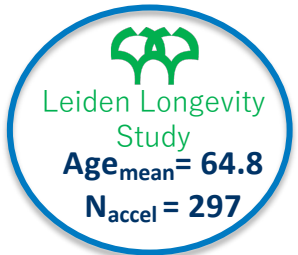
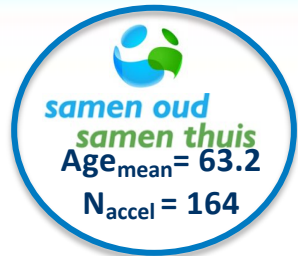
s.paraschiakos@lumc.nl



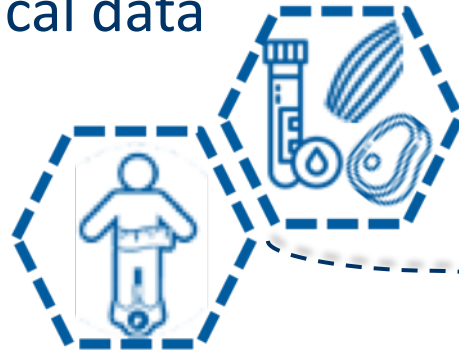
Universiteit Leiden
LIACS



LUMC Studies: Lifestyle and Clinical Data



Clinical data



Lifestyle data



Profiling



Health Outcomes

Growing Old TOgether Study (GOTO)

A lifestyle intervention



*samen oud
samen thuis*

$N_{\text{accel}} = 164$

$\text{Age}_{\text{mean}} = 63.2$

$\text{BMI}_{\text{mean}} = 26.3$

+12.5%

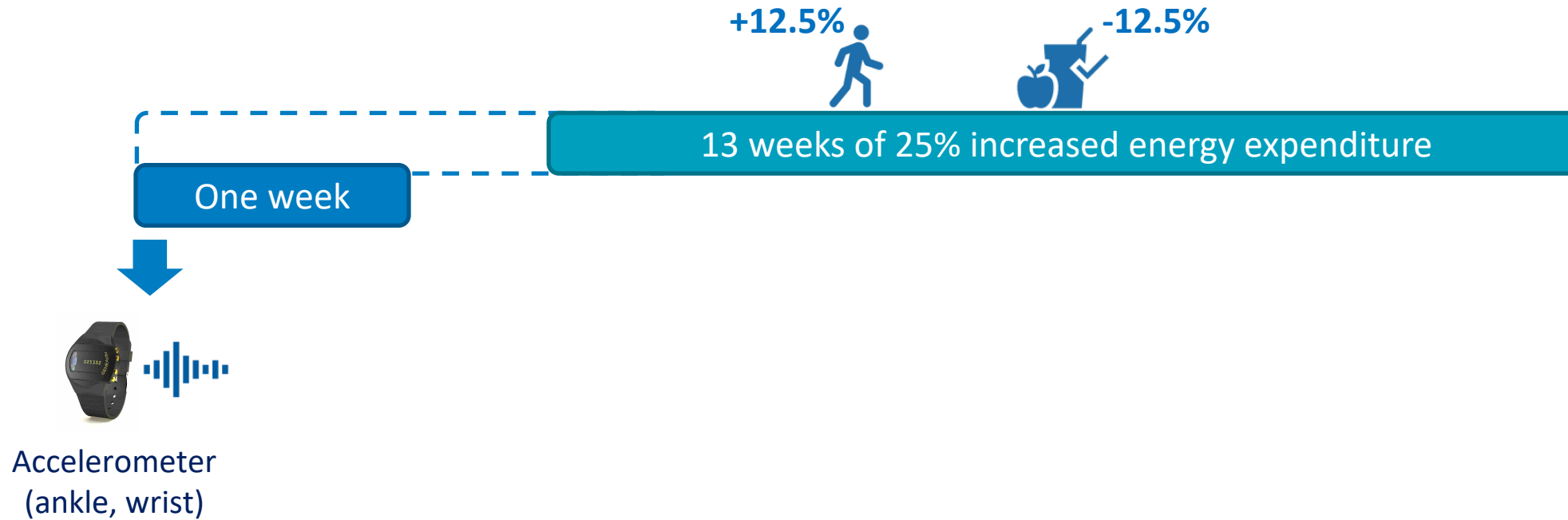


-12.5%



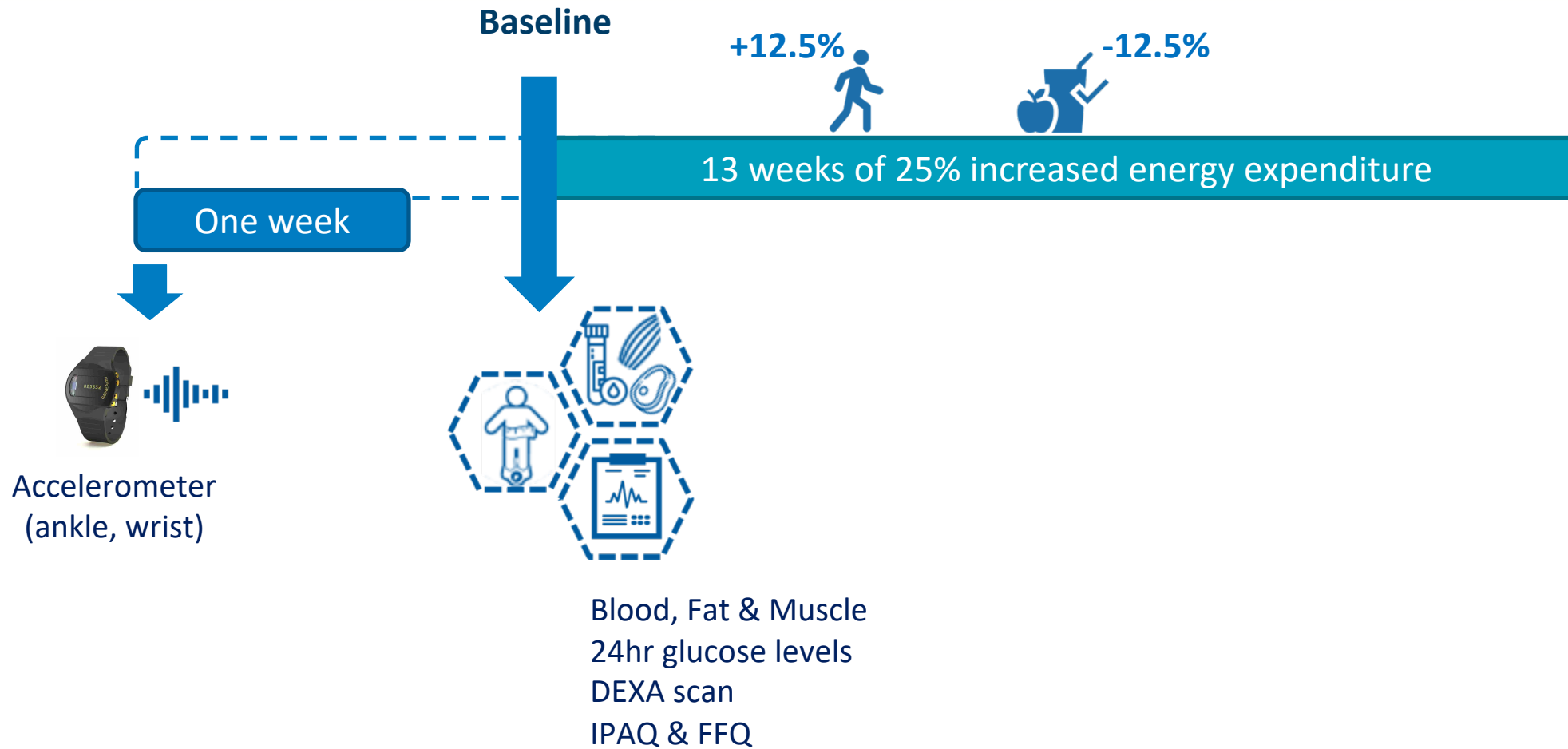
13 weeks of 25% increased energy expenditure

A lifestyle intervention: Growing Old TOvergether Study (GOTO)



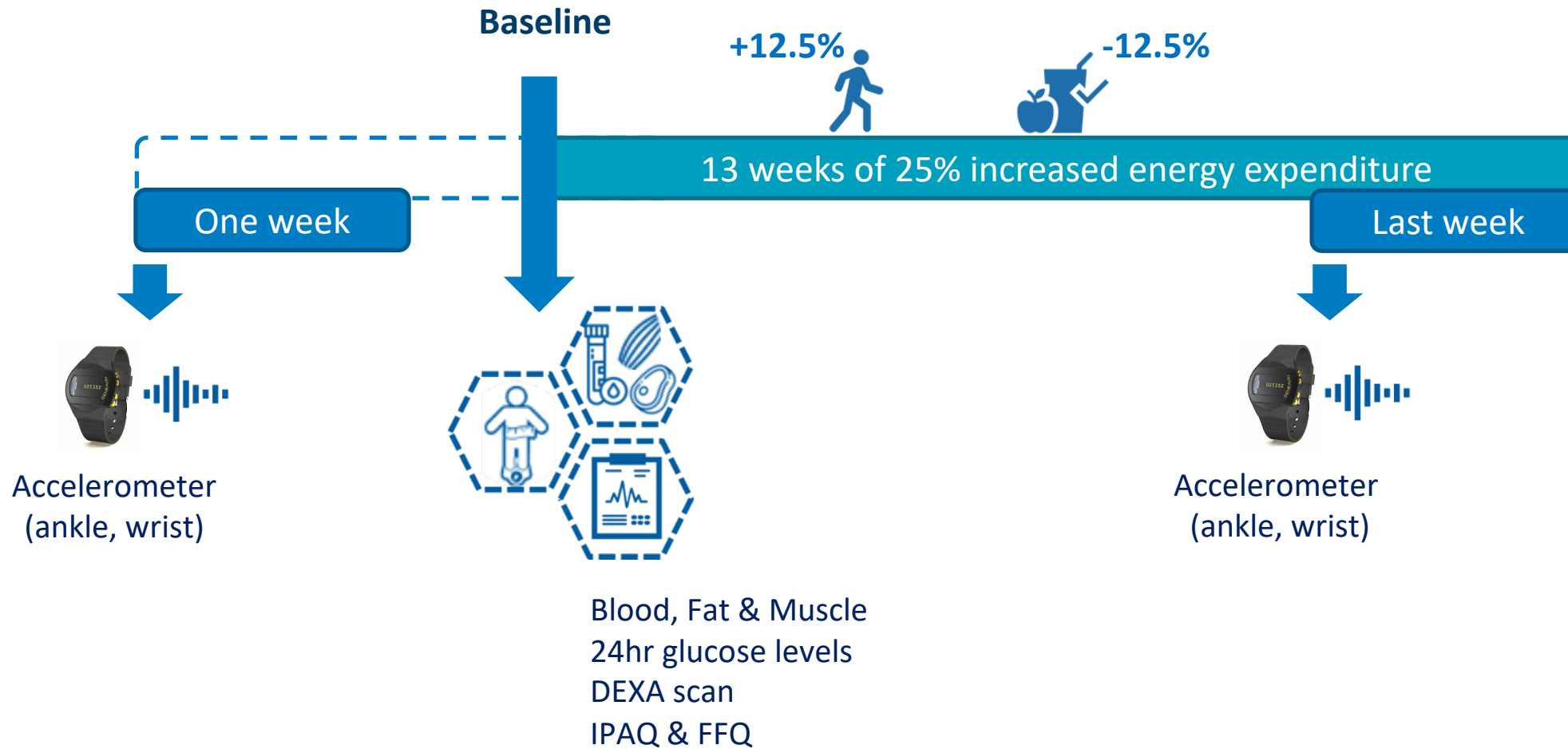
Growing Old TTogether Study (GOTO)

A lifestyle intervention



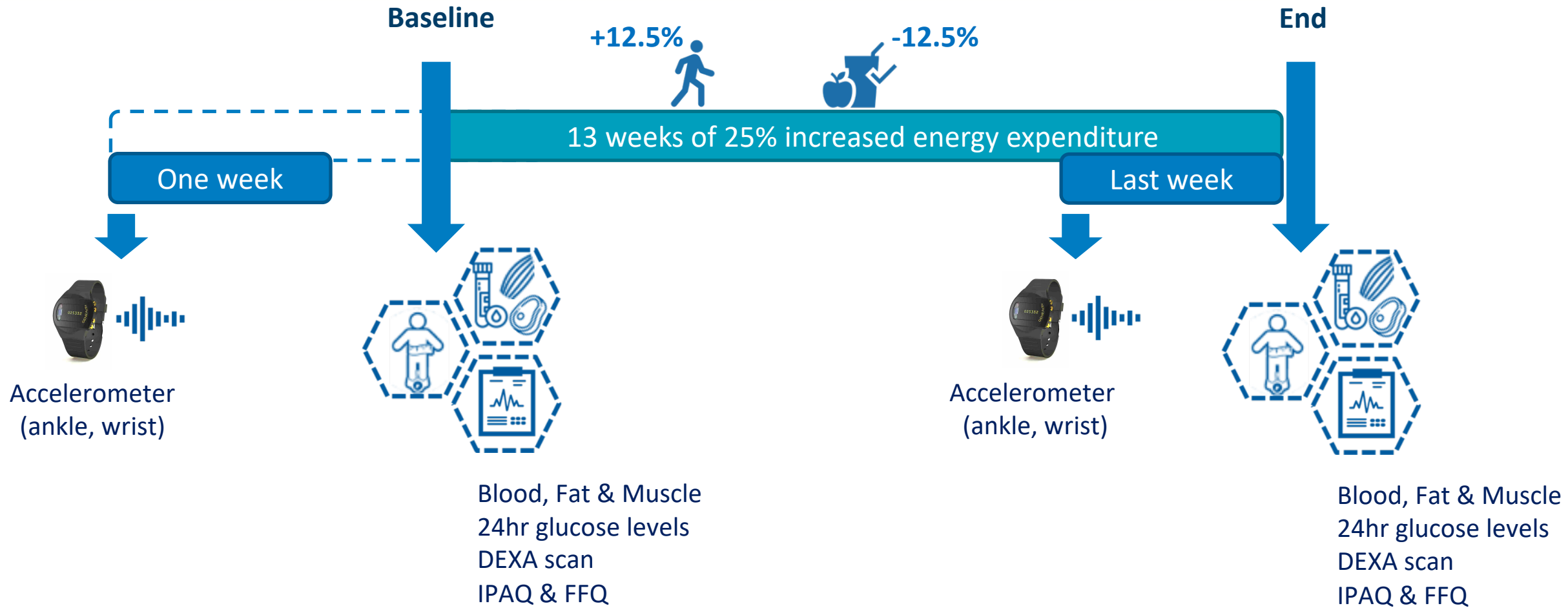
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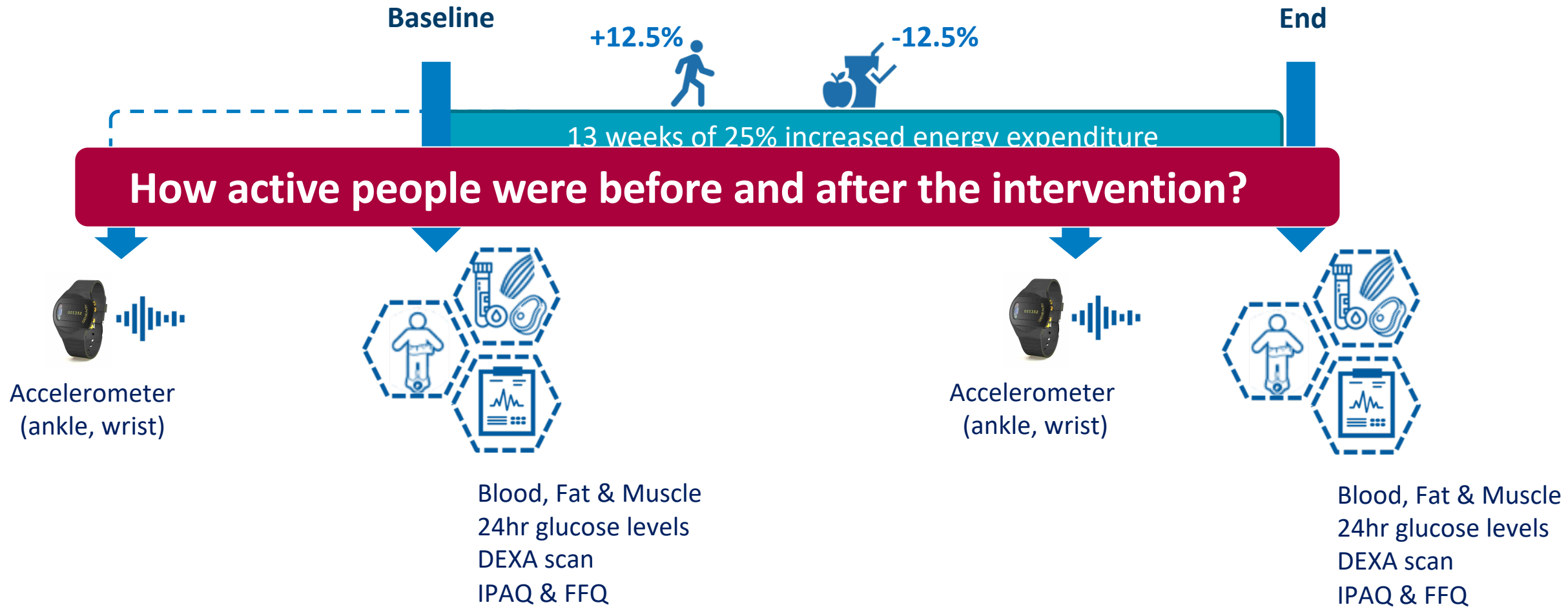
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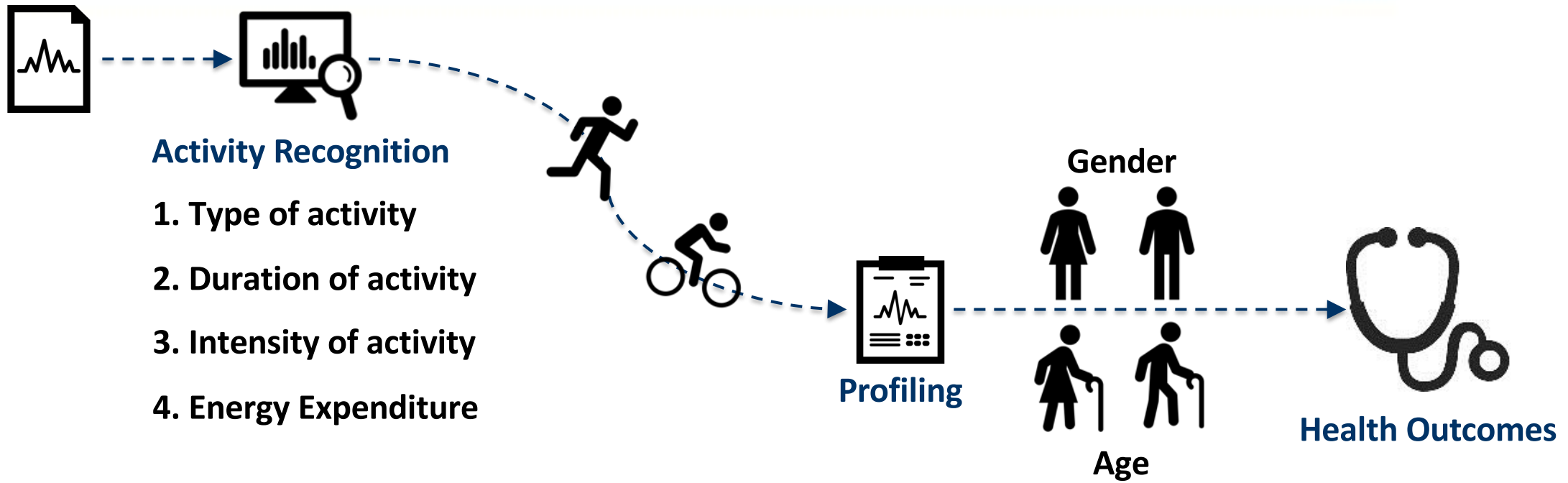
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GOTO Accelerometer Data

How active people were before and after the intervention?



ACCEL DATA

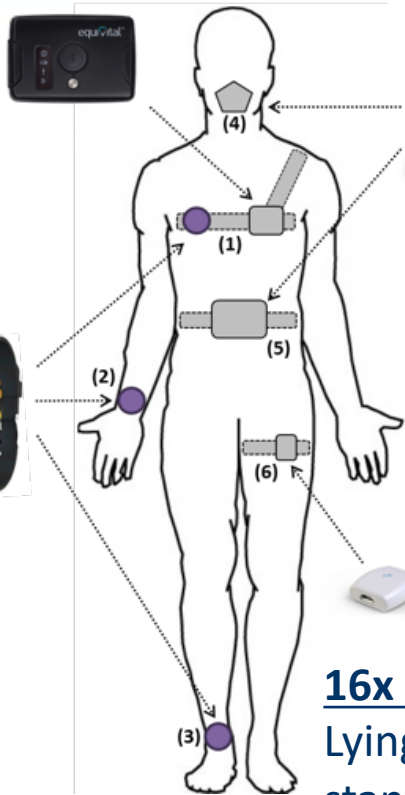
AR & EE
MODELING

PROFILING

COMBINE
HEALTH DATA

GOTOv (validation) study:

Lab Conditions Data Collection



N = 35 (60.0% male)
Mean Age = 63.2
Mean BMI = 27

4x Devices in 6 Body Locations:

GeneActivs [1,2,3]

Equival [1]

COSMED K4 b² [4,5]

Activ8 [6]

16x Performed activities:

Lying down, sitting,
standing, households,
walking, cycling



GOTOV Human Physical Activity and Energy Expenditure Dataset on Older Individuals

[Cite](#) [Download \(841.96 MB\)](#) [Share](#) [Embed](#) [+ Collect](#)

666
views

76
downloads

Dataset posted on 26.06.2020, 02:00 by Slagboom P. (Eline), Beekman M. (Marian), Stylianou Paraschiakos, Knobbe A. (Arno), Cachucho R. (Ricardo)

Wearable sensor-based data of physical activities and indirect calorimetry for 35 (14 female, 21 male) healthy older individuals (over 60 years old). The data has been collected from different body locations and devices: 3x GeneActivs accelerometers (ankle, wrist, and chest), 1x Equival (chest) and COSMED (mask and belt on chest). The 35 individuals followed a protocol of 16 activities of daily living for approximately an hour and a half in a semi-lab environment. These include different types or paces of indoor and outdoor activities with low (lying down, sitting), mid (standing, household activities) and high (walking and cycling) levels of intensity. Additionally, some activities can be specified at different granularities. The study took place at LUMC, between February and May 2015.



GOTO modeling Overview



1. Model Developement

a. Activity Recognition (AR)

- Random Forest with Accordion features [\[Paraschiakos et al, UMUI – June 2020\]](#)
- AR model using GRU layers robust to missing data [\[Okai and Paraschiakos et al, EMBC 2019\]](#)



Open Access | Published: 23 June 2020

Activity recognition using wearable sensors for tracking the elderly

Stylianos Paraschiakos , Ricardo Cachucho, Matthijs Moed, Diana van Heemst, Simon Mooijaart, Eline P. Slagboom, Arno Knobbe & Marian Beekman

User Modeling and User-Adapted Interaction 30, 567–605 (2020) | [Cite this article](#)

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Building robust models for Human Activity Recognition from raw accelerometers data using Gated Recurrent Units and Long Short Term Memory Neural Networks

Publisher: IEEE

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Jeremiah Okai ; Stylianos Paraschiakos ; Marian Beekman ; Arno Knobbe ; Cláudio Rebelo de Sá [All Authors](#)

2
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98
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GOTO modeling Overview



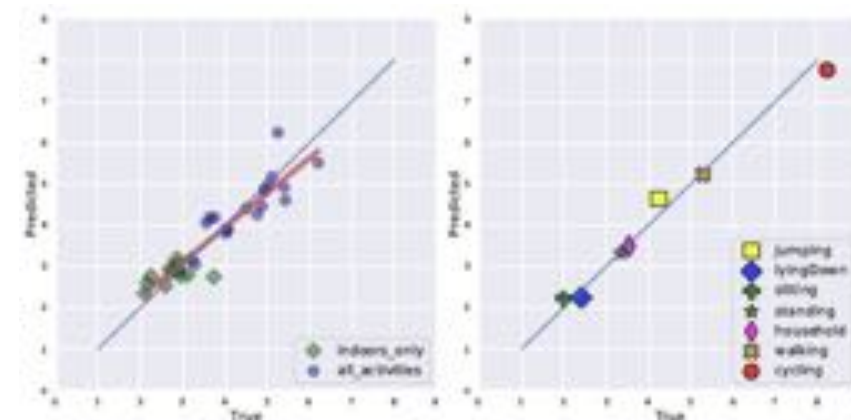
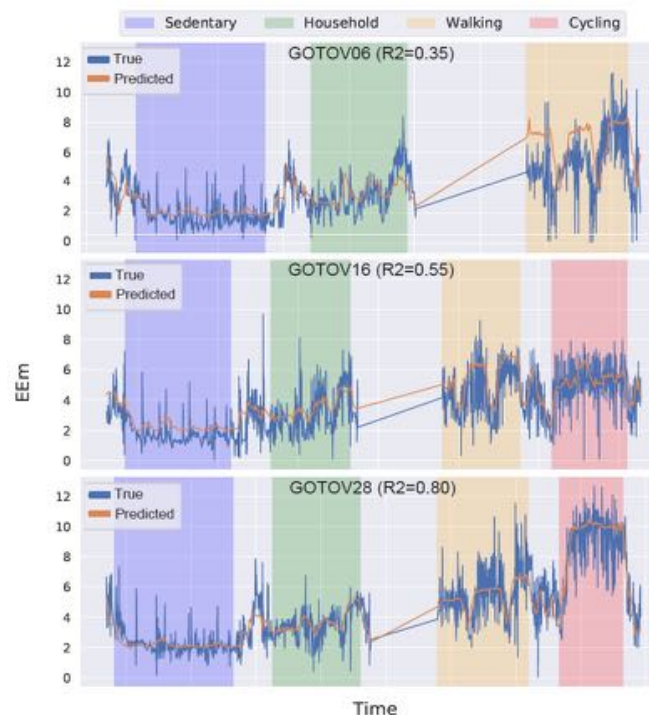
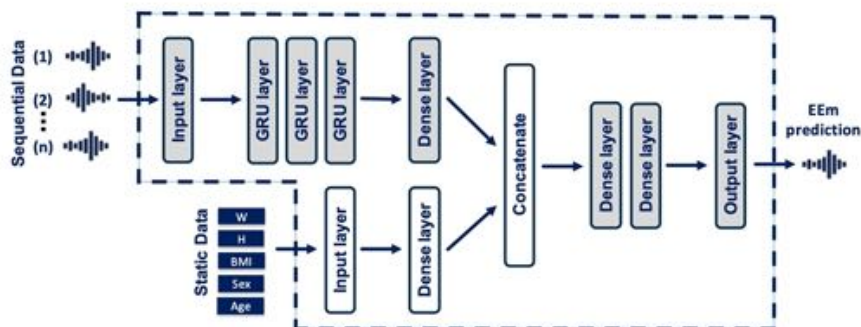
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b. Energy Expenditure (EE)

- RNN-GRU model combining sensor data, demographics and activity predictions [[Paraschiakos et al, DMKD under review](#) ([pre-print link](#))]



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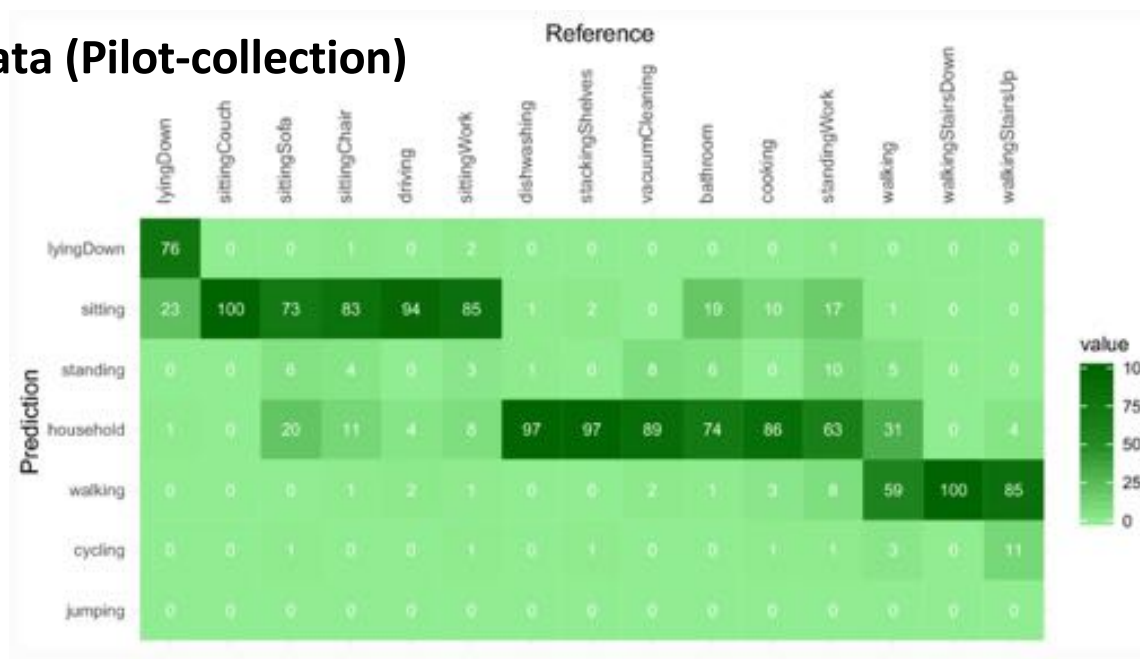
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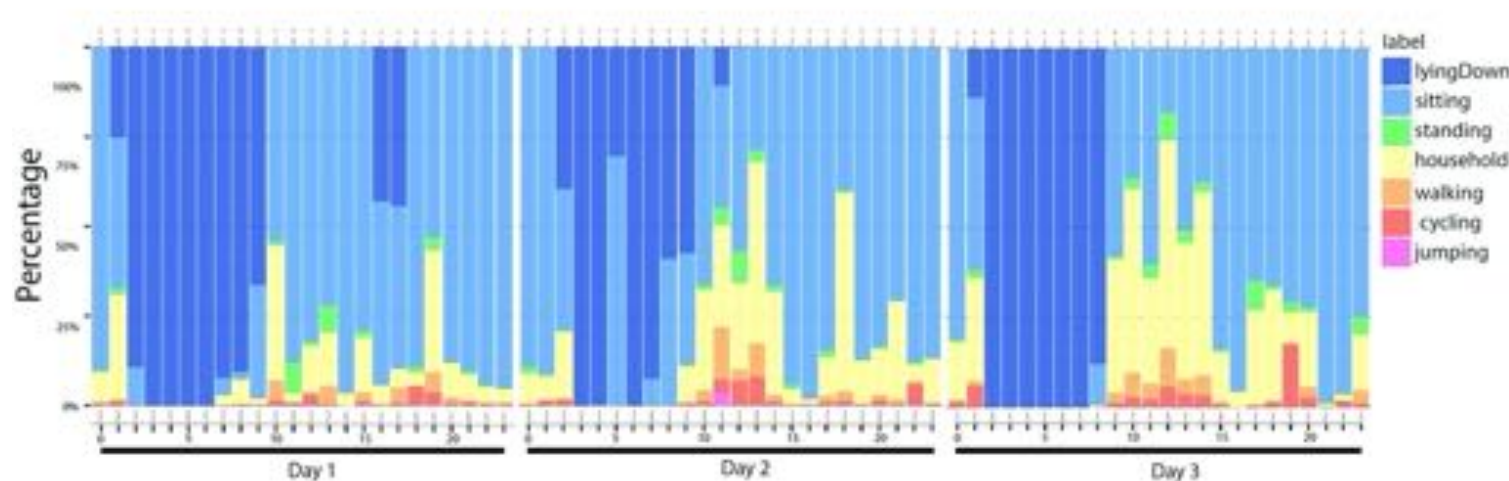
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- Data QC
- Predictions QC
- Create activity profiles
- Compare activity profiles per group (e.g. age, BMI, gender, clinical variables)



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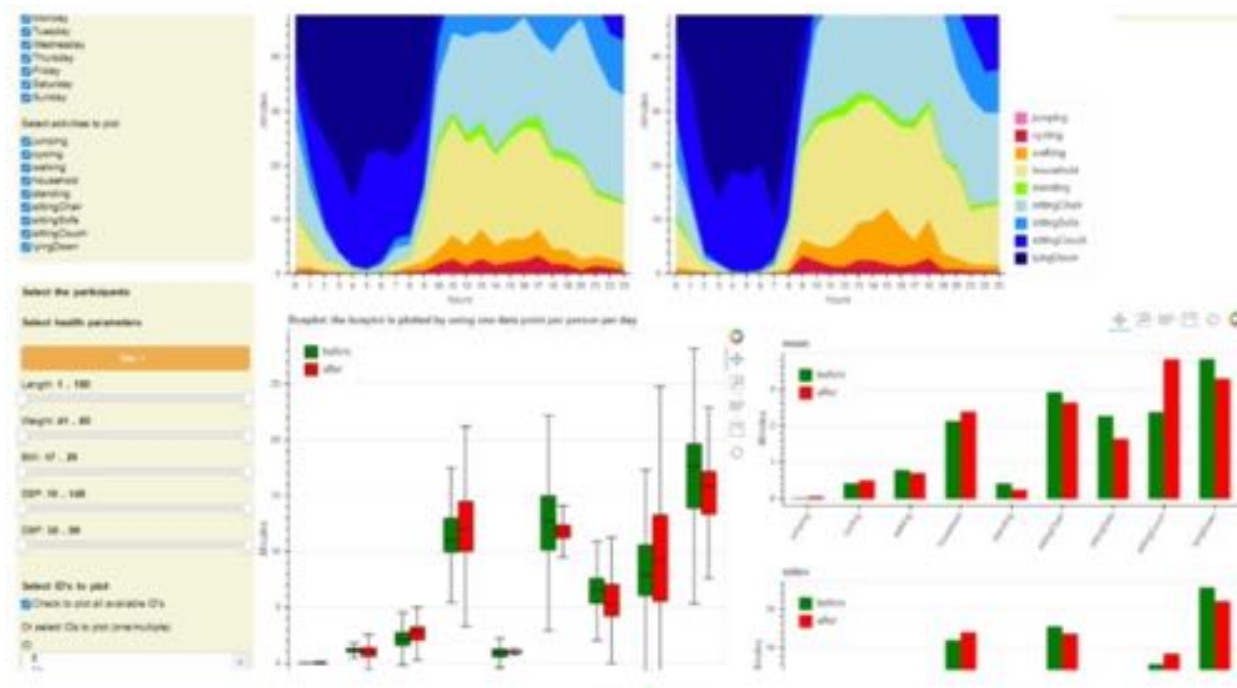
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4. GOTO Dashboard



Thank you!



Eline Slagboom



Marian Beekman



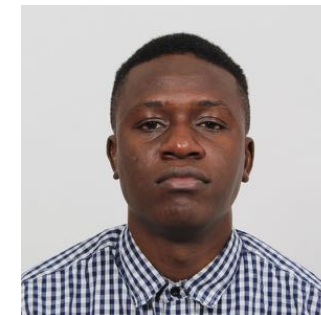
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Jeremiah Okai

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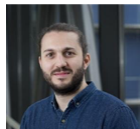


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