2025

FITSILVER

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Driftline ehf - CSEM SA

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Abstract

The FITSILVER project (Eurostars-3 Project E! 2671), co-funded by Iceland's Technology Development Fund and InnoSuisse, was a collaboration between Driftline ehf (Iceland) and CSEM SA (Switzerland) from 2023 to 2025. Aimed at addressing the health challenges of demographic ageing and leveraging Silver Economy opportunities, the project developed smart wearable technologies for automatic fitness and calorie tracking, with a focus on older adults.

FITSILVER integrated software development, activity classification, three scientific studies, and the creation of a prototype metabolic tracker, CALO. It introduced a novel heart rate–based method for individualized energy expenditure (EE) tracking and a proof-of-concept model for automatic energy intake (EI) tracking by detecting thermogenic food waves from heart rate dynamics.

Studies at the University of Iceland found Driftline's metabolic model (DMM) achieved a mean absolute error (MAE) of only 0.25% for EE during walking and running. DMM further achieved an MAE of 5.7% for EE estimation across mixed activities in CSEM's validation study, outperforming commercial fitness trackers that typically report 20–30% error.

The CALO prototype tracker (PPG and accelerometry) developed by CSEM, also delivered outstanding accuracy with a 7.7% MAE, showing the strength of CSEM's advanced activity detection algorithms. During exercise phases, the Driftline model maintained a lower error (8.2%) compared to CALO (24.7%), emphasizing the advantage of individualized heart rate-based modeling during mixed activities. Together, CSEM's technological innovations and Driftline's metabolic approach may represent a major step forward in wearable EE tracking.

Integrating Driftline's heart rate analysis into CALO or similar wearables could significantly improve EE estimation accuracy. Project deliverables included the CALO prototype, the FITSILVER app, three pending scientific publications, a national patent application, and two University degrees, including a PhD. A novel Metabolic Fitness Index (MFI), assessable through simple walking tests, was also introduced and shown to correlate with glycemic control and cardiorespiratory fitness.

Future efforts will focus on refining both EE and EI estimation, expanding validation, and preparing for market entry. FITSILVER lays the groundwork for next-generation metabolic monitoring solutions that support healthier aging and improved population health.

Preface

The FITSILVER project was initiated to address the growing health challenges posed by an ageing population. Through collaboration between Driftline ehf (Iceland) and CSEM SA (Switzerland), the project combined expertise in wearable technology, physiological modeling, and health analytics to create innovative solutions for fitness and metabolic monitoring. Supported by Eurostars and national funding agencies, FITSILVER focused on developing practical, science-based tools that empower older adults to manage their health proactively. This report summarizes the project's objectives, methodology, key findings, and future directions.

Introduction[1]

State of the market

Population Ageing Trends

Population ageing is a global phenomenon driven by increased life expectancy and declining birth rates (United Nations, n.d.). In Europe, over 20% of the EU population is currently aged 65 and over, a figure projected to exceed 30% by 2100, with significant growth also expected in the 80+ demographic (Eurostat, 2023). Similar ageing patterns are evident in North America, Japan, South Korea, and China, illustrating a widespread demographic shift affecting developed economies worldwide (European Commission, 2021).

Health and Economic Impacts of Ageing

Population ageing imposes substantial economic burdens, increasing demand for healthcare services, pensions, and long-term care. Age-related public spending already exceeds 25% of the EU's GDP and is projected to rise significantly (European Commission, 2021). Additionally, the declining working-age population will further stress pension systems, potentially threatening economic stability and requiring innovative economic and social policy solutions (European Commission, 2021).

Ageing, Chronic Disease, and Health Outcomes

Ageing strongly correlates with increased prevalence of chronic diseases, notably cardiovascular disease (CVD), diabetes, osteoporosis, sarcopenia, and dementia (European Commission, 2021). Cardiovascular disease remains Europe's leading cause of mortality, responsible for approximately 4 million deaths annually (World Health Organization, 2024). Over 50 million Europeans live with CVD, costing more than €280 billion per year, highlighting a critical area for targeted intervention and prevention strategies (European Society of Cardiology, 2021).

Obesity Trends and Associated Health Risks

Obesity prevalence has risen sharply in recent decades, affecting approximately two billion people globally. In the EU alone, obesity rates have tripled since 1980, with 59% of adults now overweight and nearly 23% classified as obese — with rates reaching 70% in the 65–74 age group (European Commission, 2021). Obesity significantly increases the risks of diabetes, cardiovascular diseases, certain cancers, reduced mobility, and cognitive

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[1] **Footnote:**
Data presented are based on Eurostat, UN, WHO, and European Commission reports unless otherwise indicated.

impairment, compounding health burdens associated with ageing populations (World Health Organization, 2024).

The importance of metabolic fitness

Poor metabolic fitness and impaired glycemic control are the hidden drivers of the world's most deadly diseases — and the root cause of type 2 diabetes, obesity, and cardiovascular disease. We now know that metabolic dysfunction plays a major role in Alzheimer's, often called '*type 3 diabetes*,' and even fuels the development of many cancers through chronic inflammation, insulin resistance, and disrupted cell metabolism. Recent literature highlights the importance of considering metabolic flexibility — the ability to shift between fat and carbohydrate oxidation during exercise and feeding — as a key determinant of health and disease risk (Maunder et al., 2018; San-Millán & Brooks, 2018).

Social Determinants and Health Inequalities

Health inequalities exacerbate ageing- and obesity-related challenges, driven by socioeconomic status, education level, geographic disparities, and access to healthcare (European Commission, 2021). Populations in lower socioeconomic groups often experience higher rates of obesity, chronic disease, and premature mortality, emphasizing the need for targeted public health policies to address these disparities.

Preventive Strategies and Policy Interventions

Recognizing these challenges, the European Union and global organizations have launched major initiatives such as the EU4Health program (€5 billion, 2021–2027) and the Healthy Lifestyle 4 All (HL4A) campaign to promote physical activity, healthy nutrition, and age-friendly environments (European Commission, n.d.). Globally, the World Health Organization (WHO) supports active ageing frameworks and obesity prevention strategies that emphasize evidence-based approaches to promoting public health (World Health Organization, 2024).

Technological Innovation and Market Opportunities

The rapid expansion of the Silver Economy — already representing about 28% of Europe's total spending power — is driving strong demand for innovative health technologies (World Data Lab, 2023). Developments in wearable devices, digital therapeutics, telemedicine, and personalized health analytics present substantial economic opportunities. Despite significant progress, existing fitness and health tracking solutions still face limitations, especially in accurately estimating energy expenditure and food intake. This highlights important market potential for next-generation products, such as continuous metabolic monitoring, heart rate-based calorie tracking, and advanced fitness assessment tools

State of the art

Human Metabolism

Total energy expenditure (TEE) comprises resting metabolic rate (RMR), physical activity energy expenditure (PAEE), and diet-induced thermogenesis (DIT), often referred to as the thermic effect of food (TEF). TEF typically accounts for approximately 10% of TEE but varies based on meal composition, size, and individual physiological responses (Calcagno et al., 2019; Tzeravini et al., 2024). Protein-rich meals produce the highest TEF, while fat-rich meals induce the lowest, with variations also influenced by factors such as age, physical fitness, insulin sensitivity, and obesity (Kinabo & Durnin, 1990; Aita et al., 2022).

Postprandial Thermogenesis

Recent research emphasizes the role of brown adipose tissue (BAT) in postprandial thermogenesis, particularly after carbohydrate ingestion, pointing to potential new strategies for obesity prevention and management (Aita et al., 2022). Meal composition, meal timing, and individual metabolic characteristics, such as mitochondrial efficiency and insulin sensitivity, are significant determinants of postprandial thermogenesis (Brun et al., 2022; Calcagno et al., 2019). Furthermore, TEF has been shown to decline with ageing, likely due to decreases in lean body mass and impaired sympathetic nervous system activation (Tzeravini et al., 2024).

Challenges in Human Energetics Monitoring

Despite technological advances, accurately monitoring energy balance remains challenging. Gold-standard methods like doubly labeled water and indirect calorimetry are costly and impractical for daily use (Levine, 2005). Fitness trackers are popular but often inaccurate in estimating energy expenditure and lack validated methods for tracking energy intake. Self-logging apps for food intake are also limited by underreporting and recall bias (Calcagno et al., 2019). The FITSILVER project introduces heart rate–based metabolic models that estimate both energy expenditure and intake from heart rate alone, offering a promising alternative.

Limitations of Traditional Fitness Testing and Wearables

Traditional fitness testing methods like VO_2max testing and gas exchange analysis, while considered reference standards, are often impractical for mass application, especially in older adults. Wearable devices offer significant promise but face challenges in measurement accuracy, particularly regarding energy intake tracking. Driftline's TrueZone framework addresses these gaps by integrating individualized heart rate kinetics, muscle fiber recruitment modeling, and real-time endurance assessment, offering a physiologically grounded alternative (Steinarsson & Agnarsson, 2020; Plotkin et al., 2021).

FITSILVER

The FITSILVER project

FITSILVER (*Fitness and calorie tracking for the Silver generation*) is a two-year collaborative project (March 2023 – April 2025) between the Icelandic software company Driftline and the Swiss technology company CSEM. The project is funded by the Icelandic Technology Development Fund and InnoSuisse through the EUROSTARS program of the European Union (EUROSTARS-3 project nr. 2671).

The project has three main goals:

1. To develop and validate Driftline's heart rate analysis software.
2. To create new solutions and applications for fitness assessments in older adults.
3. To develop, manufacture, and test a prototype calorie-tracking device capable of estimating energy expenditure and food intake based on heart rate analysis.

The solutions and measurement devices will be tested through scientific studies conducted at Reykjavík University, the University of Iceland, and CSEM's research laboratories in Switzerland. The project is expected to deliver scientific and technological advancements in fitness and health monitoring for older adults.

The project manager is Agnar Steinarsson (Driftline CEO), and the project is also part of his PhD research (METFIT) at the University of Iceland. CSEM's project leader was Alia Lemkaddem and Mathieu Lemay, CSEM Head of Signal Processing, sat on the project board.

Consortium

Driftline

Driftline is an Icelandic health-tech company specializing in advanced heart rate analytics, recently patented by the European Patent Office. The analytics are based upon new and disruptive physiological theories developed by Driftline and pending scientific verification through the METFIT PhD study. These theories include a physiological breakthrough, linking muscle fiber recruitment, gas exchange, substrate oxidation and heart rate analytics in one universal metabolic system. Driftline is also presenting the first scientifically valid direct measure of aerobic endurance. Endurance is a reflection of fat oxidation capacity and a crucial prerequisite for metabolic health.

Driftline developed TrueZone (www.truezone.app), an innovative smartphone application originally designed for athlete performance analysis but now evolving into a comprehensive health monitoring tool. By analyzing heart rate data from submaximal walking tests using smartwatches and heart rate monitors, Driftline's methodology could replace traditional laboratory-based cardiovascular fitness testing, making scientific fitness tracking accessible to the general population, including the Silver Generation. Future innovations include the assessment of metabolic parameters and fully automated calorie tracking based on heart rate analytics (www.driftline.io).

CSEM

CSEM (Centre Suisse d'Électronique et de Microtechnique) is a leading Swiss research and development center specializing in microtechnology, nanotechnology, microelectronics, system engineering, and communication technologies. Founded in 1983, CSEM provides customized, cutting-edge solutions to industry partners, leveraging its expertise in applied research.

CSEM has played a key role in Switzerland's industrial innovation, founding 29 start-ups employing over 500 people. With an international presence in the UAE (since 2005) and Brazil (since 2007), CSEM fosters global technology transfer and local economic growth. CSEM employs approximately 500 highly skilled specialists across multiple disciplines and holds ISO 13485 certification, ensuring excellence in medical and wearable technology development. It is recognized as one of Europe's premier research institutions in MedTech and wearable sensors, with an extensive IP portfolio covering heart rate, blood pressure, SpO_2, arrhythmia monitoring, and more.

CSEM technology is applied across various body locations, including the ear, thorax, upper arm, and wrist, and has been licensed or transferred to companies such as AKTIIA, AVA, Biospectal, Body Connect, DECATHLON, Icon Health & Fitness, PulseON, and Vexatec.

Work structure

Work Package 1 (WP1) - Software development and analysis

Task 1.1 - Development of DRIFTLINE ANALYTICS Software (DA)

Driftline is developing DA software to analyze heart rate data for institutions like companies, universities, and hospitals. This cloud-based, API-accessible platform will process large-scale data and may replace traditional cardiovascular tests. Driftline will hire software engineers and collaborate with the University of Iceland to validate fitness and metabolic parameters. The first version will launch on the Driftline website.

Task 1.2 - Development of the LONGEVITY App

Driftline is developing the LONGEVITY app for middle-aged and elderly users to track fitness, heart rate, and metabolism. The app will analyze submaximal activity (e.g., walking) and integrate with major smartwatches. It will assess endurance, muscle typology, body composition, and energy balance.

Task 1.3 - Development of the CALO Smartphone App

The CALO app will integrate with the CALO calorie tracker, classifying activities (e.g., walking, running) and estimating daily energy expenditure based on heart rate data. The app will use Driftline's metabolic profiling to compute calorie intake and balance.

Work Package 2 (WP2) – Development of Metabolic Fitness Tracker

Tasks 2.1-2.3 - Design, development and production of CALO Fitness Tracker

CSEM will lead the development of the CALO fitness tracker, designed to collect heart rate and activity data for Driftline's metabolic models. The device will feature optical heart rate sensors and inertial motion tracking to ensure accuracy in elderly users.

Tasks 2.4-2.5 – Application Library & Algorithm Optimization

Multiple prototype fitness trackers will be produced, with embedded algorithms customized for elderly populations. The system will include APIs and libraries to integrate with mobile apps.

Work Package 3 (WP3) - Validation studies

Task 3.1 - Elderly Citizen Fitness Study

This study validates the Driftline Walking Test (DWT) by comparing it to the six-minute walking test (6MWT) in a group of at least 40 elderly participants (ages 70–90). Conducted at Reykjavik University, the study will track heart rate, fitness parameters, and metabolic data. Participants will perform both tests and the results will help refine Driftline's walking test and improve 6MWT analysis.

Task 3.2 - Calorie Tracking Validation Study

A validation study for the CALO prototype tracker will compare Driftline's calorie tracking and metabolic assessments against measured single-meal feed intake and measurements of gas exchange and glucose responses. Ethical approvals will be obtained, and the study will involve participants from a wide demographic in terms of age and physical fitness (50:50 male/female). The metabolic responses to exercise and food intake will be assessed with indirect calorimetry and metabolic testing at the University of Iceland.

Task 3.3 – Validation and improvements of CALO tracking in clinical trials

A clinical study will validate the CALO tracker's accuracy in energy tracking. Conducted at CSEM's laboratories, the study will compare tracker data against gold-standard metabolic tests. The study will be divided into three major phases, i.e. 1) work phase, 2) exercise phase and 3) VO2max test with walking, running and recovery. Ethical approvals will be obtained, and the study will involve healthy volunteers from CSEM personnel.

Task 3.4 – Knowledge base and key opinion leaders

The partners will prepare a specific validation report, compiling the methodology and results from the validation studies. This report will include a detailed scientific literature review. The final report from the FITSILVER project will include a section with comments and evaluations from selected key opinion leaders.

Work Package 4 (WP4) - Project Management

Task 4.1 – Project management, risks and mitigation measures

The FITSILVER project will be managed by Driftline and CSEM, with regular meetings and consortium-wide gatherings in Switzerland. Driftline will oversee budgeting, reporting, and communication. Agnar Steinarsson is project manager, and Alia Lemkaddem is the project manager on behalf of CSEM. The project team meets online biweekly, and a monthly progress report (MPR) is prepared. The final deliverable is a comprehensive project report.

Task 4.2 – IP rights and regulations

The final report will include a section on IP rights and regulations.

Deliverables

Deliverables 1 – 9

- D1.1 DRIFTLINE ANALYTICS software launched on website (PM4).
- D1.2 A masters study report from the RU Elderly fitness study (PM6).
- D1.3 A functional version of the LONGEVITY smartphone app (PM9).
- D1.4 A scientific paper from the Driftline Calorie tracking study (PM16).
- D1.5 A functional version of the CALO smartphone application (PM17).
- D1.6 A final project report for the FITSILVER project (PM24).
- D2.1 Functional prototype of the CALO fitness tracker (PM12).
- D2.2 Library, API and samples to interface tracker from app (PM12).
- D2.3 Report from CSEM validation study (PM24).

This project aims to revolutionize metabolic and fitness tracking, particularly for aging populations, by integrating cutting-edge heart rate analytics and metabolic profiling into wearable technology.

Methods

Driftline Analytics software

Advanced heart rate analytics

The core of Driftline's analytics is TrueZone, a novel framework linking heart rate kinetics to muscle fiber recruitment, redefining exercise thresholds, aerobic endurance, and training zones. TrueZone presents the first direct measure of aerobic endurance (0–100%), reflecting threshold alignment and fat oxidation capacity. A novel heart rate kinetics model predicts heart rate responses to activity and recovery, offering a more physiologically grounded alternative to conventional methods.

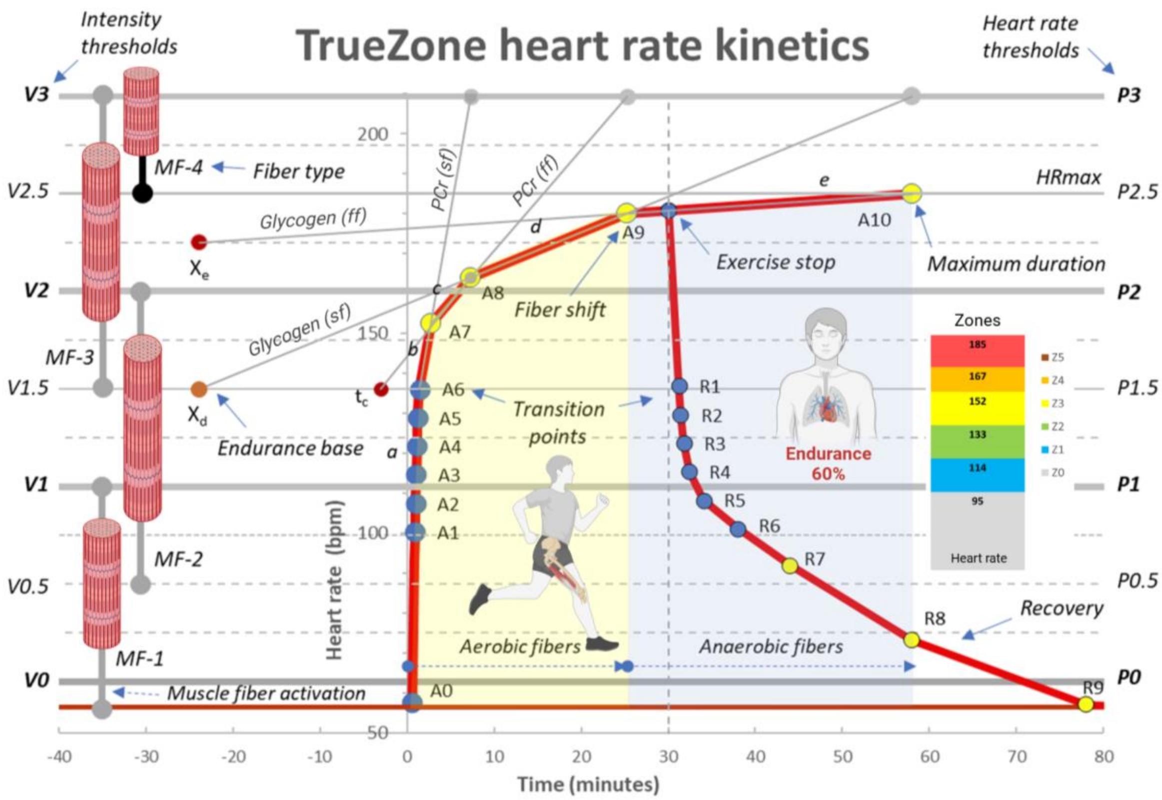


Figure 1. *The TrueZone heart rate kinetics developed and patented by Driftline.*
The TrueZone heart rate kinetics model illustrated through a heart rate response (red curve) to a 30-minute treadmill run at steady speed by an individual with 60% endurance (E), followed by 50 minutes of passive recovery. The HR curve is divided into an activity curve and a recovery curve with corresponding metabolic transition points (A1-10 and R1-10). The diagram maps heart rate thresholds (P) and intensity thresholds (V), while muscle fiber activation is shown as vertical lines, reflecting the progressive recruitment of fiber types (MF). The A9 transition point (fiber shift) marks glycogen depletion in oxidative fibers and transition to anaerobic fiber dominance.

DA software

The DA (Driftline Analytics) software includes Driftline's proprietary heart rate analytics, providing fitness testing and metabolic tracking, along with a commercial RESTful API and an embeddable SDK (Software Development Kit) for seamless integration and access. The SDK is a set of pre-built tools, libraries, and APIs that developers can integrate into their own applications or devices without needing to build the functionality from scratch. This means that the DA software can be integrated into third-party fitness apps or smartwatches to provide instant fitness and metabolic assessments.

The Metabolic Model

Calibration and metabolic coefficients

The Driftline Metabolic model must be calibrated for each individual to calculate correct individualized metabolic coefficients. This can be done with a sub-maximal calibration test, i.e., a sub-maximal tri-phased fitness test, including a 5-min warmup, 20-min run and a 10-min passive recovery.

The individualized metabolic coefficients include a base factor (BF), an activity factor (AF) and a food factor (FF), each describing the relationship between heart rate and energy expenditure in each specified heart rate category.

Function

The Metabolic Model categorizes heartbeats into base (resting metabolism), activity (movement/exercise), and food (post-meal response) to estimate total energy expenditure (TEE) and energy intake (EI) without user input. By analyzing post-meal heart rate elevation (diet-induced thermogenesis) through mathematical modeling, it isolates food-related heartbeats to determine calorie intake.

Thermogenic food wave fitting

Metabolic calculations incorporate food factor (FF), activity factor (AF), and base factor (BF), adapting to individual metabolism and fitness levels. Energy expenditure (EE) is estimated by fitting minimum heart rate values with thermogenic food waves, which can follow right-skewed unimodal functions, such as exponential decay, logarithmic growth/decay, Gamma distributions (α>1), or Weibull distributions ($k > 1$).

Figure 2 illustrates food waves induced by meals of varying sizes—larger meals generate greater heart rate responses, with higher amplitude, longer duration, and increased area under the curve, corresponding to total food beats contributing to EE.

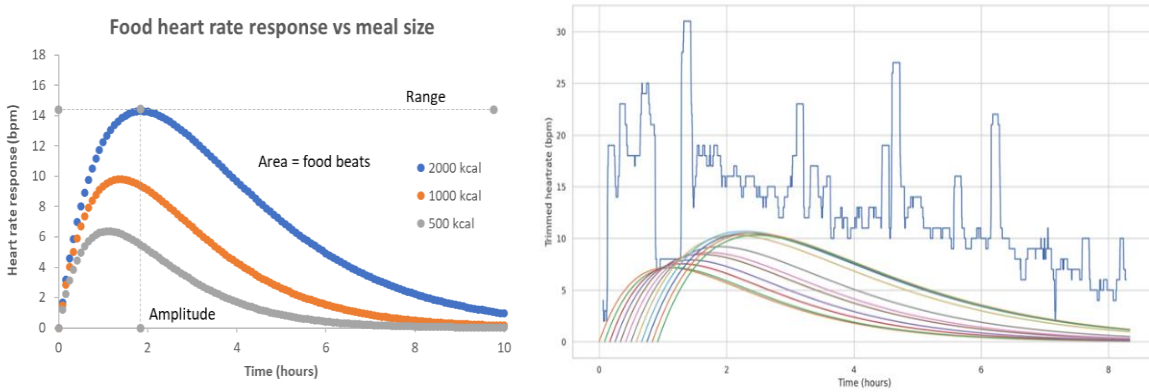


Figure 2. *Food heart rate response vs. meal size in the Driftline metabolic model.*
A) Thermogenic food waves for meals of different caloric sizes (500, 1000, and 2000 kcal). B) The fitting of a single-meal heart rate response with overlapping, multiple thermogenic food waves.

The overlapping multiple food waves combine to create a combined food response, i.e. the area under the combined curve can be integrated to quantify the number of food beats. The beats above the food response are classified as activity beats.

Heart Rate-Based Energy Analysis Method

The method processes heart rate data over time to estimate energy intake (EI) and energy expenditure (EE) by integrating individual metabolic parameters. These parameters include:

- Basal heart rate (BHR)
- Food factor (FF)
- Base factor (BF)
- Activity factor (AF) or intensity-adjusted AF

Processing Steps

- Data Input & Preprocessing
  - Provide heart rate data and metabolic parameters to a processing unit.
  - Subtract basal heart rate (BHR) from the heart rate data.
  - Optionally estimate intensity-related elevation of resting heart rate.
- Identification & Adjustment
  - Identify minimum heart rate points in the data.
  - Adjust these points using intensity-related resting heart rate elevation (if applicable).
- Food Wave Fitting & Heartbeat Quantification
  - Fit food waves to minimum heart rate points.
  - Connect food waves to estimate heart rate response to energy intake.
  - Quantify:

        ▪ Food heartbeats (related to EI).
        ▪ Base heartbeats (resting metabolism).
        ▪ Activity heartbeats (exercise/movement).

- Energy Calculation & Output
    - Determine energy parameters:
        - Energy intake (EI) from food heartbeats & FF.
        - EE from food intake using food heartbeats & FF.
        - EE from activity using activity heartbeats & AF.
        - EE from basal metabolism using base heartbeats & BF.
        - Total energy expenditure (TEE).
    - Output results to the individual.

Quantification of the heart rate response

The diagram in Figure 3 shows a screenshot from the Driftline metabolic model.

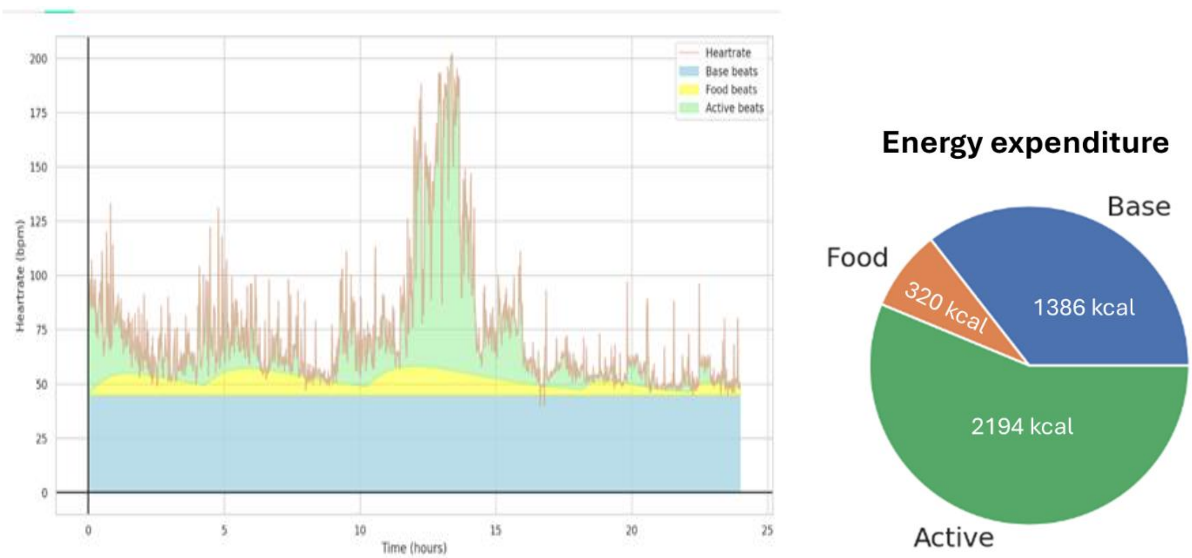


Figure 3. *The Driftline metabolic model.*
(Left) A quantification of heartbeats in a full day study for participant ingesting regular meals throughout the day and performing an exercise session. (Right) A pie chart detailing the division of energy expenditure into three main categories.

The graph in Figure 3 shows an example of a whole day heart response for an individual consuming food with an energy content of 2560 kcal. The diet-induced thermogenesis equals 320 kcal, i.e. the thermic effect of feeding (TEF) equals 12.5%.

Tracking Energy Expenditure

The Driftline Metabolic Model estimates total energy expenditure (TEE) by analyzing continuous heart rate data. The model uses individual metabolic parameters but no activity mode or speed data are required for the calculations. More specifically, the method quantifies the activity-induced heart rate response (Pt) and translates into energy expenditure (EE) using the tri-phasic activity factor (AF).

Figure 4 shows an example comparison of measured (CPET), modeled (TrueZone) and speed-predicted EE across activity modes for one subject in the activity trials, with the model metabolic parameters indicated for each activity phase.

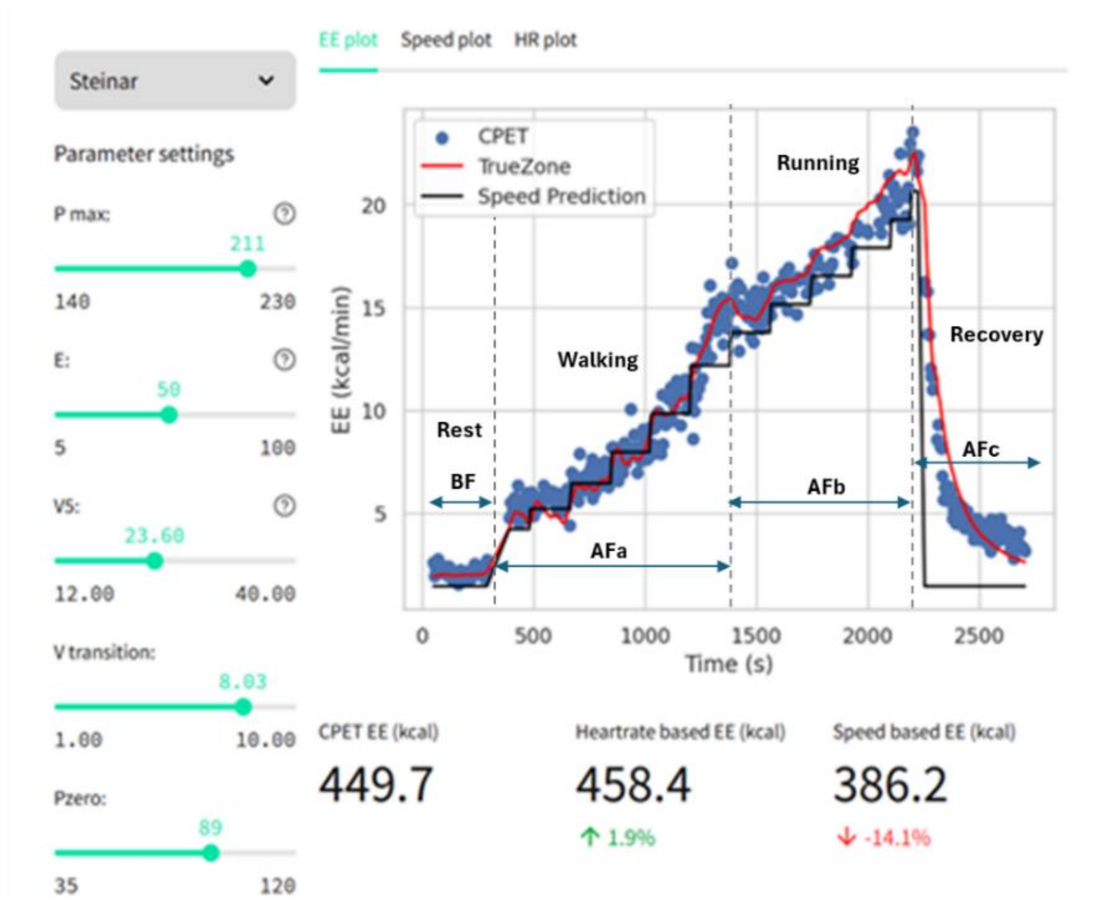


Figure 4. *The dashboard of the Driftline Metabolic model.*
Example comparisons of CPET measured EE (blue dots), TrueZone calculated EE (red line), and speed-predicted EE (black line), across activity phases—rest, walking, running, and recovery—separated by dashed lines. The appropriate metabolic parameters (BF, AFa, AFb, AFc) for EE calculation are indicated for each phase. The dashboard includes adjustable model parameters and total EE estimations, showing deviations between methods.

The Elderly Citizen Fitness Study

Objective

To evaluate the validity and reliability of 6- and 12-minute treadmill walking tests compared to the 6-minute walk test (6MWT) on the floor and to assess whether Driftline's analytics can measure aerobic endurance in older adults through submaximal protocols.

Methods

Participants: 42 older adults (60% female, mean age: 71.9 ± 4.7 years) completed up to four submaximal endurance tests:

- 6MWT on the floor
- 6MWT on a treadmill
- 12MWT on a treadmill
- 6MWT at self-selected speed on a treadmill

A total of 28 participants completed all tests. Heart rate (HR) was monitored throughout, with a 10-minute seated rest period post-test. Repeated measures ANOVA and Pearson correlation were used for analysis.

Figure 5. *The Elderly Citizen Fitness study.*
Master's student (now graduated) Þórey Hákonardóttir poses with one study subject while another performs a walking test on the treadmill.

The TrueZone smartphone app

Driftline has developed and recently launched TrueZone, a dedicated smartphone application for heart rate-based fitness assessment. TrueZone uploads and analyzes heart rate data from commercial fitness trackers and performs a full-scale heart rate analysis, returning individualized fitness- and metabolic parameters for athletes and non-athletes. The app is available on the App Store and the Play Store, for both iPhone and Android users.

TrueZone is capable of analyzing heart rate data from various exercise modes, including walking, so the consortium decided to integrate the Longevity application into the TrueZone app, with a custom-made health-oriented user interface for elderly or non-athletic users. Figure 6 shows the TrueZone treadmill test protocol and a screenshot from the TrueZone smartphone application.

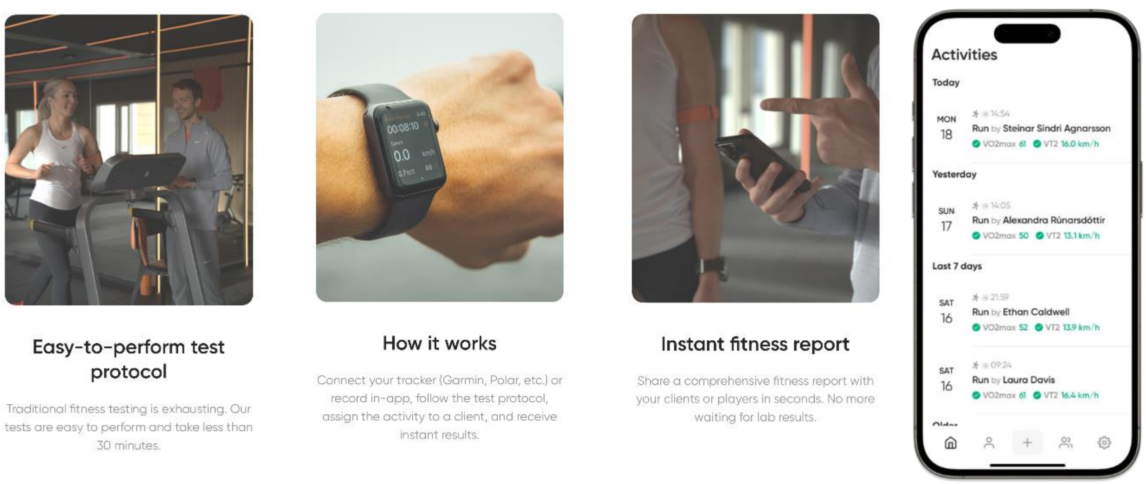


Figure 6. *The TrueZone smartphone application.*
The TrueZone application is currently designed for coaches and instructors to fitness test their clients. The testing protocol is easy, and the results are delivered instantly.

The user can choose to either visit a health Clinique or a personal trainer to get a guided assessment through TrueZone or alternatively, personally perform a fitness assessment with his or her own fitness tracker connected to TrueZone.

The planned Fitsilver deliverable was a custom-made smartphone application, specifically designed for easy fitness testing of elderly citizens. The suggested name (Longevity) was not available, and it was decided to use the FITSILVER name instead. It was also decided to integrate the FITSILVER app with Driftline's **Truezone** app, which is now available on both iOS and Android. The plan is later to release the application as a stand-alone **FITSILVER** app.

The Calo web application

Since it was decided to produce a research-prototype metabolic tracker instead of a commercial-prototype, there was no reason to develop a smartphone application to go with it. Instead, it was decided to develop a CALO web application to interface with the prototype tracker. The CALO web app will receive continuous heart rate and activity data from the prototype tracker and other types of fitness trackers. The web application imports data from the Metabolic Model and presents a visual timeline for the energy balance measurements of individual CALO prototype users. The original aim was to deliver a functional alfa-version no later than by month 17 (PM17) but the work on the CALO web app started in early 2024 and was completed in November 2024 (PM21).

Activity related algorithms

Given the CALO web app's reliance on precise activity data, substantial efforts have been dedicated to refining the existing activity algorithms. A notable improvement is the expansion of activity classifications. Initially, the algorithm grouped all non-rhythmic activities under a single category labeled "OTHER." This category has now been subdivided into three distinct classes, utilizing heart rate data and accelerometer magnitude to ensure that high-intensity exercises are accurately distinguished from low-intensity activities when estimating energy expenditure. Additionally, other parameters such as speed and cadence have been meticulously improved.

The CALO prototype

Requirements analysis and technical specifications

At the project's start, a comprehensive CALO Requirements Specification document was compiled. This document outlines the requirements of the CALO tracker from the PPG perspective, recognizing its critical role within the system. It also details the dependencies of various software libraries and their respective requirements. Additionally, it includes a list of potential requirements for future CALO products. The research-prototype metabolic tracker developed during this project prioritized delivering high-quality raw and accelerometer data, along with an ecosystem for cloud upload, to facilitate its use during the validation study conducted at CSEM.

Technical specifications

The CSEM technical team adapted data collection to meet the requirements for the prototype metabolic tracker. Special attention was also given to factors such as battery life, measurement accuracy, and sensitivity to motion tracking. A data analysis platform was developed for the device, which can interface with a smartphone app. The prototype was given the working name CALO 1. It is a technical prototype assembled from CSEM components and specifically programmed for calorie tracking applications. The CALO 1 prototype includes a PPG sensor for heart rate monitoring and a 3-axis accelerometer for motion tracking. It is important to note that this prototype is not designed for commercial use; its sole purpose is to validate calorie measurements in dedicated research studies.

CALO prototype validation study (CSEM)

Before starting the validation study, the project plan was created and submitted to the Swiss ethics committee for approval.

The aim of the validation study is to investigate a novel method for calorie tracking. This method requires accurate measures of HR heart rate and activity monitoring. To obtain these measurements, the CALO prototype will be used to record high quality raw PPG signal with a high range of accelerometer-based features. These signals will be used for offline analysis of HR estimation and activity monitoring, and furthermore, estimate energy expenditure.

The outcome of this method will help individuals better understand their caloric burn, leading to more effective weight management and fitness plans. By encouraging healthier lifestyles and providing tools to manage energy balance, it can help reduce the prevalence of lifestyle-related diseases and improve population health outcomes.

Over a duration of 4 months, we enrolled 20 individuals (of different age, skin color, gender, fitness level, etc.). The protocol included participation to a normal workday (i.e. office work) protocol and a fitness testing protocol. The validation study was conducted at the Sports Lab within CSEM's premises (Figure 7).

Figure 7. *Sports Lab at CSEM.*
The CSEM Sports Lab is equipped with state-of-the-art equipment for exercise testing.

The participant first took part in the normal workday protocol and later on the same day in the fitness protocol. They wore: 1) CALO tracker, 2) a Polar chest belt and 3) a COSMED K5 to measure the gas exchange (Figure 6).

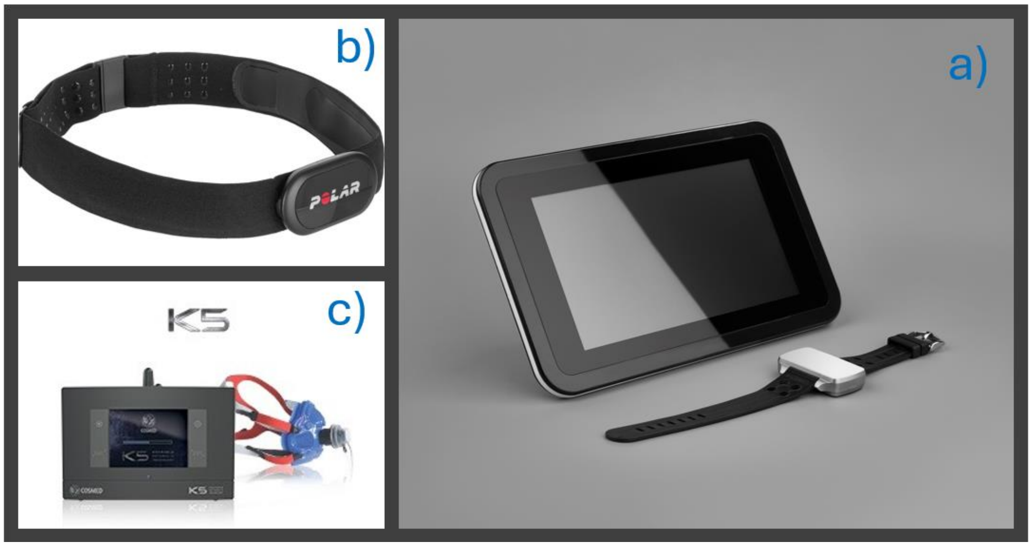


Figure 8. *Devices used in the validation study.*

Panel a) The CALO prototype tracker with XEMWAY console. Panel b) A Polar chest strap heart rate monitor. Panel c) Portable COSMED K5 metabolic device and ventilation mask.

The goal of the CALO validation study was to evaluate and improve the energy expenditure library, which depends on the outputs of the activity and heart rate libraries. To do so we designed an experiment with different classes of activity, corresponding heart rate ranges and resulting energy expenditure. The protocol consisted of three phases:

A. A **working phase**, where the subject is simply working for an hour at their desk, where the aim is to evaluate the performance of the energy expenditure library at rest.
B. A **light exercises** phase, where the subject performs different workout exercises. The aim of this protocol phase is to evaluate the energy expenditure algorithm's performance in cases where the subject is active, has a higher heart rate, but does not have a speed (cycling or running) associated with the activity.
C. A **CPET phase**, where the subject spends 3 minutes lying down, 3 minutes sitting and 3 minutes standing, then walks/runs on a treadmill with a speed which starts at 1.8km/h and increases every 3 minutes by 1.8km/h until they can no longer keep up. Following this, the subject sits down for 20 minutes to recover. The aim of this protocol phase is to evaluate the algorithm's performance at different running speeds and corresponding heart rate ranges and during recovery (during which the heart rate is still high but the energy expenditure is low).

During the protocol, the subjects wore a CALO prototype, a COSMED K5 device used to measure energy expenditure, and a Polar belt used to measure HR. The study included 20 subjects whose demographics are summarized in Table 1.

Table 1. *Demographics of the CALO study population.*

Population	Age (*years*)	Gender	BMI (*SI*)	HRmax (*bpm*)
20 subjects	39.5 ± 7.1	9 females / 11 males	22.8 ± 1.9	183 ± 10

The CALO system calculates energy expenditure using the following inputs: heart rate (HR) with quality index (qi), activity class, speed, and the subject's demographics (age, gender, weight, height). HR can be derived from PPG signals or using Polar reference. When HR qi falls below a certain threshold, the library switches to using accelerometer data only. The EE library can also operate solely with accelerometer data, without any HR or PPG input.

We evaluated the results for energy expenditure estimation by looking at the cumulative percentage error (ref – est) / ref), and absolute error (abs(ref – est) / ref). First, we evaluated energy expenditure accuracy for each of the different activity classes: walk, run, rest and other. Then, we compared energy expenditure errors for each section of the protocol: normal working day, light exercises, and CPET protocol. The CALO approach was also evaluated using different inputs configuration in addition to subject's demographics:

1. Config ECG + ACC: HR (from Polar), activity class, speed.
2. Config PPG + ACC: HR, activity class, speed.
3. Config ACC: activity class, speed.

The data from the CALO validation study was also sent to Driftline for analysis in Driftline's metabolic model, using only heart rate data for the calculation of energy expenditure (EE). The data was divided into the same three phases (A, B and C) for direct comparison with CSEM's results for the same tests. Individualized metabolic parameters were calculated for each subject, based on an analysis of the cardiorespiratory and metabolic data from the VO_2max test (CPET). Exercise thresholds were determined from gas exchange plots (VO_2, VCO_2 and RQ), using the V-slope breakpoint determination method.

The metabolic model uses individual metabolic coefficients (such as base factor and activity factor) to predict EE based on heart rate only. The individual metabolic parameters were then fed into the metabolic model for the direct determination of energy expenditure (EE). The metabolic model predicts the momentary EE and calculates the accumulated EE for each phase as for all the phases combined. The model calculates the deviations from measured values as determined by indirect calorimetry.

The METFIT PhD study – Feeding study

General

Part of the METFIT PhD study at the University of Iceland. Approved by the Icelandic Bioethics Committee.

- Student: Agnar Steinarsson
- Supervisors: Dr. Erlingur Jóhannsson and Dr. Gréta Jakobsdóttir

The aim of the study is to investigate the effects of food intake on various biological factors, such as oxygen uptake, heart rate, and blood sugar levels, while also examining the relationship between these factors and performance indicators, including endurance and exercise thresholds.

Methods

A. Feeding experiments

- Eight participants (four women and four men, aged 31–60).
- Home Economics laboratory at the University of Iceland, School of Education.
- Measurements of metabolism (COSMED K5), blood glucose (iHealth), and body temperature (Withings Thermo) over an 8-hour period (approx. 7:30 – 15:30).
- One large pasta meal at approximately 8:00 AM (Knorr tomato pasta, self-selected portion between 500–1200 g).

Figure 9. *The METFIT feeding study – feeding experiments.*
Single meal intake and gas exchange measurements with the COSMED K5 metabolic system, in cooperation with Sigma Sportslab, Reykjavík University and University of Iceland.

Feeding trials were conducted over two days at the University of Iceland with four participants per day. After an overnight fast, participants underwent baseline metabolic testing, including resting heart rate monitoring and a 15-minute indirect calorimetry session. Standardized pasta meals were then consumed, with energy intake and macronutrient composition carefully recorded. Hourly postprandial metabolic measurements, including energy expenditure, heart rate, blood glucose, and body temperature, were collected over an 8-hour period.

Key indices were calculated:

- **Glycemic Response Index (GRI):** Peak glucose level normalized by glycemic load.
- **Metabolic Fitness Index (MFI):** A novel, dimensionless marker of cardiometabolic efficiency incorporating heart rate kinetics, VT2 speed, and allometric BMI.

Metabolic responses (heart rate and energy expenditure) were modeled using fourth-order polynomials, with total food-induced responses (HR_{total} and EE_{total}) quantified as area under the response curves. The thermic effect of feeding (TEF) and additional derived factors (FF and TF) were computed to assess individual metabolic profiles.

B. Activity experiments

- Conducted at the University of Iceland's research laboratory in Laugardalur.
- Participants sit, walk and run on Woodway treadmill for 30–50 minutes per session.
- Measurements include metabolism (Vyntus metabolic cart), heart rate (Polar and Scosche), and step frequency (Scosche).

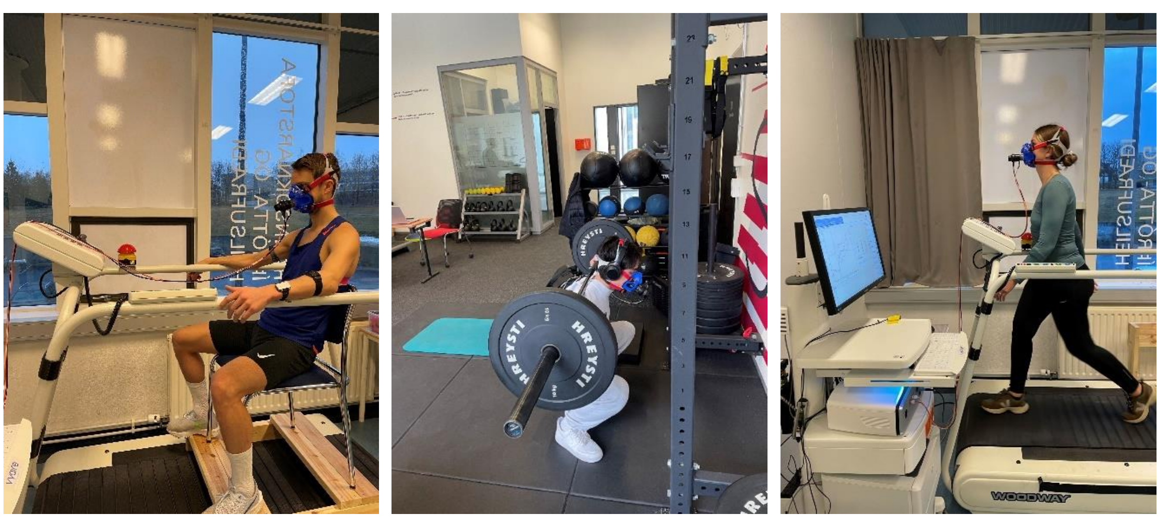


Figure 10. *The METFIT feeding study – activity experiments.*

Activity testing and gas exchange measurements with the COSMED K5 and Vyntus metabolic systems, in cooperation with Sigma Sportslab, Reykjavík University and University of Iceland.

Trials were conducted at the Sports Science Laboratory, University of Iceland. Participants arrived 20 minutes before testing (no fasting required), were weighed, and fitted with a Vyntus ventilation mask and three heart rate monitors (Polar H10, Verity Sense, and Scosche Rhythm). After five minutes of seated rest, they walked and ran on a treadmill, starting at 3 kph with 1 kph increments every three minutes. Running duration varied, ending at submaximal intensity. Metabolic data (VO_2, VCO_2, and energy expenditure) were collected via Vyntus CPX, with heart rate continuously monitored. Exercise thresholds were based on CPX maximal test results (for four participants) or estimated from RER values.

C. Blood Profile Analysis

Participants arrived at the Sameind Medical Laboratory, Ármúli 32, Reykjavík, in a fasting state for blood sample collection. Blood analyses included metabolic and hormonal profiling, measuring blood glucose, blood lipids (total cholesterol, HDL, LDL, triglycerides), insulin, cortisol, estrogen, testosterone, and thyroid-stimulating hormone (TSH).

CALO commercial technology report

As part of FITSILVER, a functional prototype of an electronic wrist-worn fitness tracker, preliminarily called the CALO Tracker, is planned for development. While heart rate alone is sufficient for estimating metabolic parameters, activity tracking improves accuracy. From a hardware perspective, FITSILVER consists of:

1. Hardware (CALO Tracker - TC): A wearable device that provides heart rate and activity data for metabolic calculations. It may also include a display for user feedback.
2. Software: The analytical platform that processes collected data and calculates fitness and metabolic parameters.

This report evaluates the scalability of the CALO Tracker (TC) as a marketable product, focusing on technical feasibility and cost estimation.

Project management

Meetings, reporting and bookkeeping

Agnar Steinarsson is the project manager, and Alia Lemkaddem is the project manager on behalf of CSEM. The project team met online biweekly, and a monthly progress report (MPR) was prepared.

Results

Deliverable 1.1 - Driftline Analytics (DA) software

SDK & API

A highly optimized C++ SDK was developed with built-in security measures, including authentication, ensuring both protection against unauthorized use and a viable revenue model. This SDK is designed for high performance, enabling both real-time and post-processing analytics on-device or in the cloud. Additionally, a commercial RESTful API was built on top of this SDK. Hosted on a Firebase Cloud Function, the API is designed for scalability, efficiently handling varying levels of demand.

The TrueZone heart rate model

The TrueZone heart rate model was constructed by Driftline as a powerful analytical engine, enabling instantaneous analysis and assessment of exercise-induced heart rate data (Figure 11).

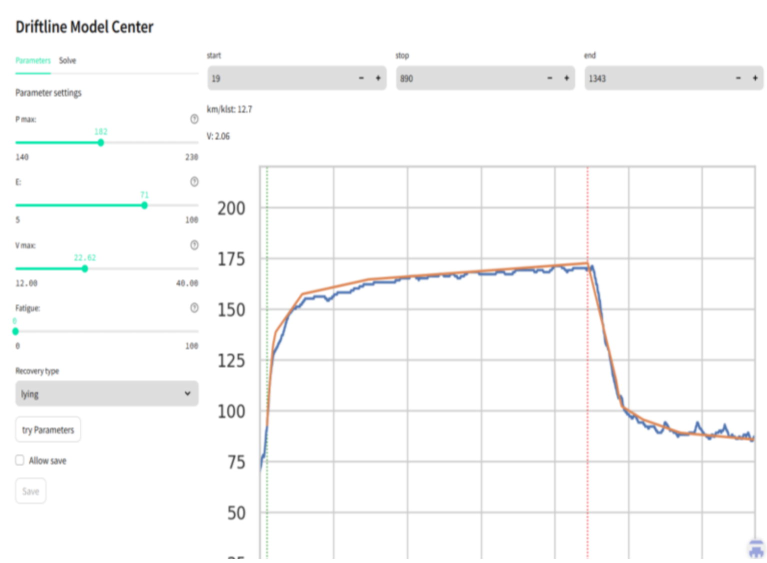


Figure 11. *The Driftline analytical engine for heart rate data*.
The TrueZone heart rate model (developed by Driftline) analyzes exercise-induced heart rate data, including passive recovery analysis. The engine solves for best fit to the data and produces an instantaneous assessment of cardiovascular fitness parameters, including maximum heart rate (HR_{max}), maximum running speed (V_{max}) and aerobic endurance (E).

The TrueZone heart rate model dynamically links heart rate kinetics to muscle fiber recruitment, metabolic transitions, and endurance capacity, providing a physiology-based framework for assessing fitness, performance, and health.

The Driftline metabolic model

The Driftline Metabolic Model is a mathematical model, analyzing heart rate and activity data from commercial or purpose-built fitness trackers and estimates energy expenditure and energy intake for the user. The model is based on currently patent-pending heart rate and activity analytics developed by Driftline. The model was constructed by Driftline as a powerful analytical engine, enabling instantaneous analysis and assessment of exercise-induced heart rate data (Figure 12).

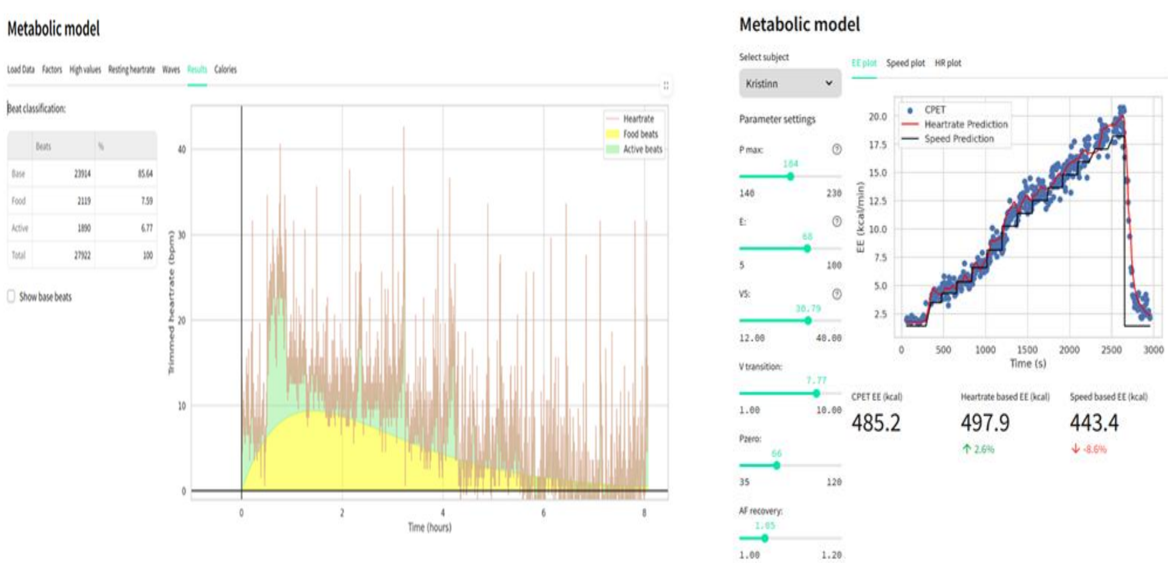


Figure 12. *The Driftline metabolic model.*

(Left) A screenshot from the metabolic model showing thermogenic wave fitting to the resting heart rate measurements of one subject in the feeding study. The meal was ingested at time 0 – 15 minutes and the food wave represented by the yellow area. (Right) Energy expenditure (EE) for one subject during the activity trial, comparing EE_{HR} (orange dots) and EE_{SPEED} (black line) with measured EE_{CPET} (blue dots).

The Driftline metabolic model can also be used to track the metabolic response from multiple meals during the same day. It can also be used to calculate the energy expenditure associated with non-rhythmic movement such as gym exercise or physical work.

The Driftline metabolic model predicts energy expenditure and energy intake by integrating heart rate tracking with individualized metabolic calibration, providing a precise and dynamic assessment of metabolic indicators and energy balance.

Deliverable 1.2 - The Elderly Citizen Fitness study Master's report

This study was an RU Master's study by Þórey Hákonardóttir. The Master's report was delivered online in June 2024 (https://hdl.handle.net/1946/47765).

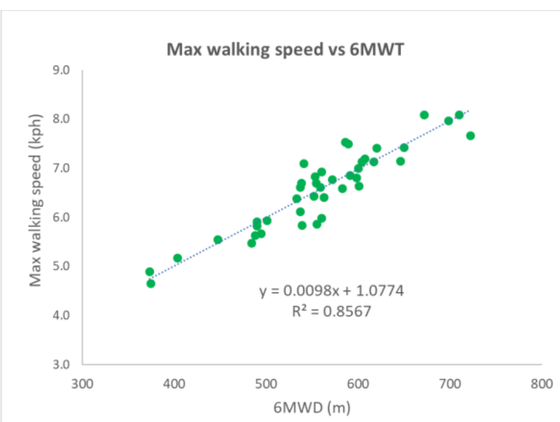
Results

- Strong correlations were observed between 6MWT on the floor and treadmill tests (r = 0.874–0.955).
- Significant differences ($p < 0.001$) were found between treadmill and floor-based 6MWT:
    - Distance walked was 83.4 ± 31.8 m greater on the treadmill.
    - HR response was 14% lower on the treadmill.
    - Step frequency decreased by 5.5–9.4 steps/min on the treadmill.
- Driftline's endurance scale significantly correlated with walking distances in all tests (r = 0.350–0.469).

Conclusions

The 6MWT and 12MWT on a treadmill are valid alternatives to the floor-based 6MWT for assessing aerobic endurance in older adults. U-turns in the 6MWT impact performance metrics. Driftline's heart rate analytics effectively assess aerobic endurance at submaximal intensities.

Retrospective analysis of the study data revealed that measured 6-minute walking distance (6MWD) was highly correlated with Driftline-predicted maximum walking speed.



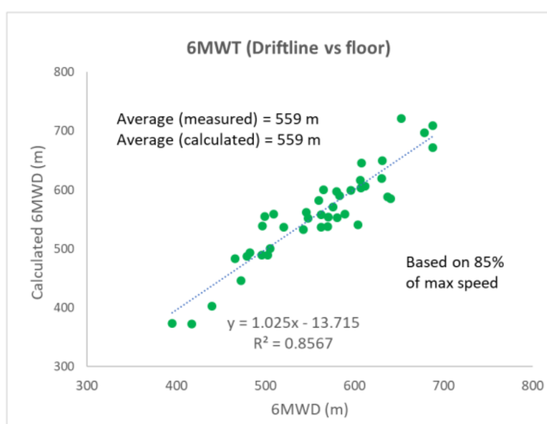


Figure 13. *The Elderly Citizen study – prediction of 6-minute walking distance.*
6-minute walking distance (6MWD) vs Driftline-predicted maximum walking speed vs (Left) and vs Driftline-predicted 6MWD (Right).

Deliverable 1.3 – The FITSILVER smartphone app

This planned deliverable was a custom-made smartphone app, specifically designed for easy fitness testing of elderly citizens (suggested name: Longevity). The suggested name was not available, and it was decided to use the FITSILVER name instead. It was also decided to integrate the FITSILVER app with Driftline's **Truezone** app, which is now available on both iOS and Android. The plan is later to release the application as a stand-alone **FITSILVER** app.

The FITSILVER app provides a user-friendly interface for conducting fitness tests and receiving instant results. It supports both walking and running tests, delivering insights into health and fitness metrics. Its interface is designed to accommodate a wide range of users, from individuals tracking their own progress to coaches managing multiple individuals.

Building on results from the FITSILVER study, a new feature has been integrated into the TrueZone app to enhance fitness assessment for middle-aged and older adults. This addition refines the interpretation of submaximal walking tests with recovery monitoring—a protocol validated during the study—to deliver more accurate, age-appropriate metrics of cardiovascular and metabolic health.

Figure 14. *The FITSILVER smartphone application.*
A screenshot from the FITSILVER smartphone application with dedicated metabolic health and fitness metrics shown.

The app offers an individualized Metabolic Fitness Report, triggered automatically when a user completes a steady-paced walk followed by a short recovery phase. From this data, the app calculates three core indicators:

- **Primescore:** An age-adjusted version of the TrueZone Runscore, adapted for walking, which reflects overall cardiovascular efficiency relative to age norms.
- **Metabolic Fitness Index (MFI):** A novel, dimensionless measure of energy efficiency per heartbeat, scaled by heart rate reserve and body composition.
- **Six-Minute Walk Distance (6MW):** A recognized clinical marker of functional capacity, estimated directly from the recorded walking session.

These metrics are delivered through an intuitive, senior-friendly user interface designed for non-athletic users. FITSILVER continuously syncs with the user's own fitness tracker (e.g., smartwatch or chest strap), automatically detecting qualifying activities and updating fitness trends over time. The system enables users—and potentially healthcare providers—to monitor improvements or early signs of decline in cardiorespiratory and metabolic function without requiring lab-based testing.

This addition positions FITSILVER as a practical tool for preventive health monitoring in aging populations, combining scientific rigor with everyday usability.

Deliverable 1.4 – A scientific paper from the METFIT feeding study

The METFIT feeding study aimed to validate the Driftline Metabolic Model. Eight participants underwent controlled feeding trials, during which EE was measured via indirect calorimetry and compared to model-based predictions. A scientific manuscript (*A Heart Rate-Based Model of Metabolic Fitness: Linking Energy Intake, Expenditure, and Glycemic Response*) has now been delivered and is currently under revision at the University of Iceland. The main results are summarized below:

Activity experiments

The Driftline metabolic model was used to calculate the heart rate-based energy expenditure (EE_{HR}) during the activity trials, based on individually specific metabolic coefficients. Figure 15 shows a comparison of measured and predicted energy expenditure.

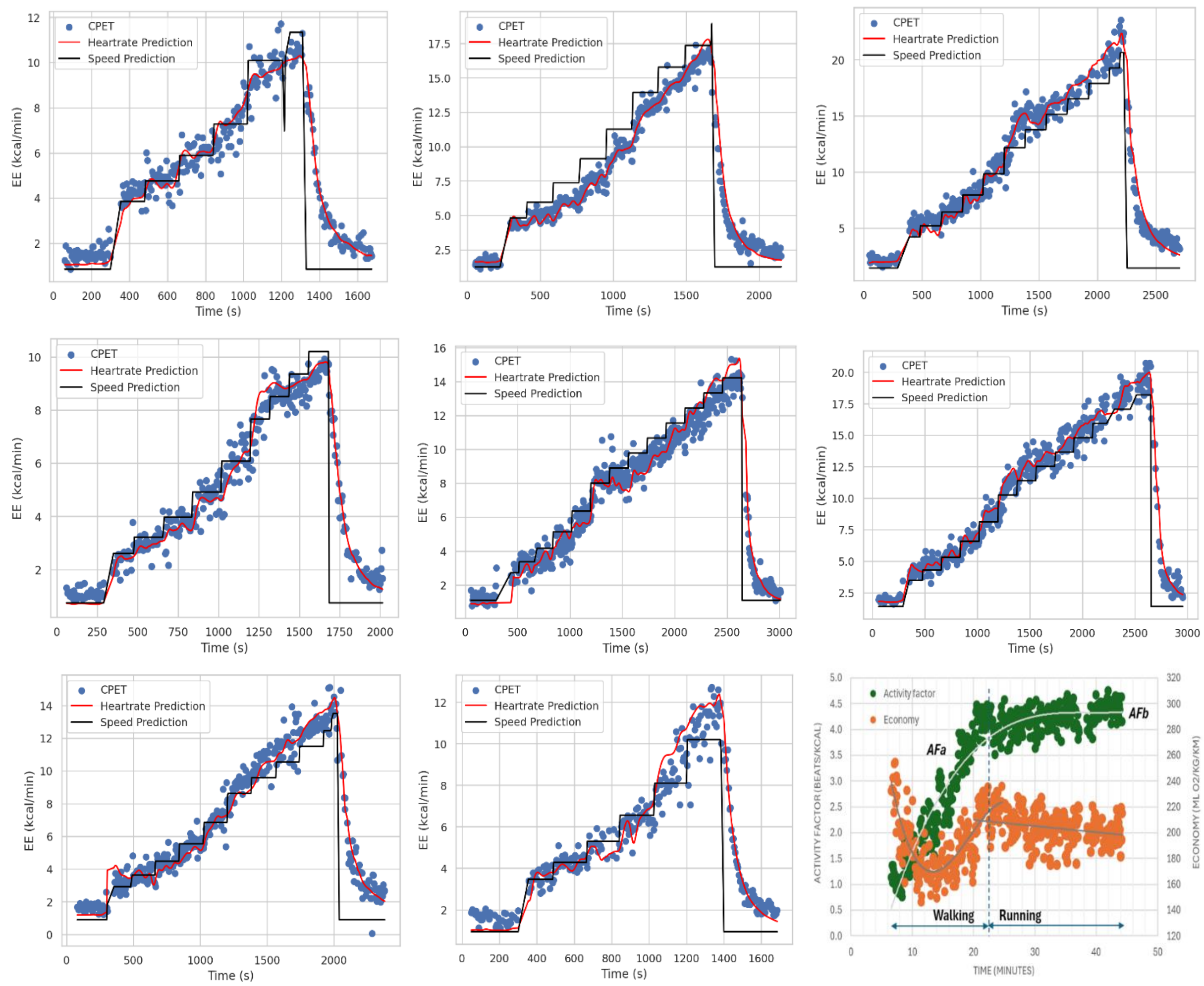


Figure 15. *Comparison of measured and predicted energy expenditure.*
Energy expenditure (EE) over time for different subjects during activity trials, comparing EE_{HR} (orange line) and EE_{SPEED} (black line) with measured EE_{CPET} (blue dots). The last panel shows the activity factor and running economy (RE) over time for one subject during the activity trial.

Figure 15 shows that the deviation in measured and predicted total EE was less than 2.6% for all the 8 participants and averaged only 0.25%. The speed predicted EE, on the other hand, deviated from measured by 6.5% on average, mainly because of the poor fit during recovery.

Single meal experiments

Food-induced heart rate responses were modeled using the Driftline metabolic model, which fitted distinct thermogenic food waves linked to meal-induced thermogenesis (Figure 16).

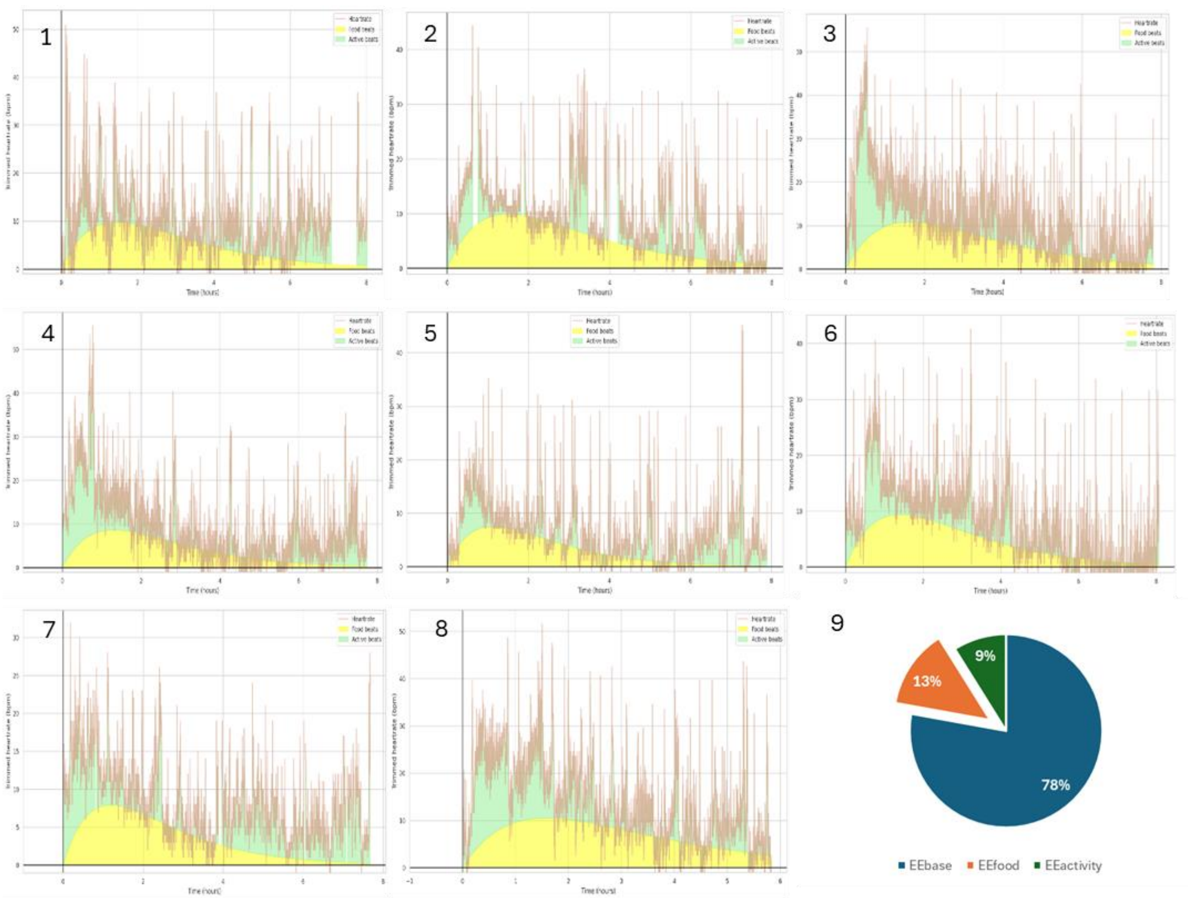


Figure 16. *Fitting of food-induced heart rate responses with thermogenic food waves*.
Panels no. 1 – 8 show the thermogenic food wave fitting of the single-meal resting heart rate response (brown line) of all the eight subjects. Active heartbeats (green area) and food-related heartbeats (yellow food wave area) illustrate the decomposition of heart rate components. Panel no. 9 illustrates the mean relative decomposition of energy expenditure (EE) components (base, food and activity).

The diagrams in Figure 16 show that after the initial meal-related heart rate peak, thermogenic food waves could be fitted quite closely to the single-meal heart rate responses from all the participants in the feeding study. Each food wave is comprised from multiple smaller waves initiated at 5-minute intervals. The size and duration of each food wave are determined by the energy content of the meal and the metabolic parameters.

In general, the food wave durations were longer for men (6–8 hours) compared to women (4–6 hours), correlating with meal size differences. Since all activity was minimized during the feeding trials, the base component accounted for a very large part or about 78% of the metabolism on average, with about 13% being attributed to feeding and only about 9% to activity (Figure 16, panel 9).

Post-prandial physiological responses

The post-prandial physiological responses, measured at hourly intervals before and after meal intake, showed very distinct feeding-related dynamics as shown in Figure 17.

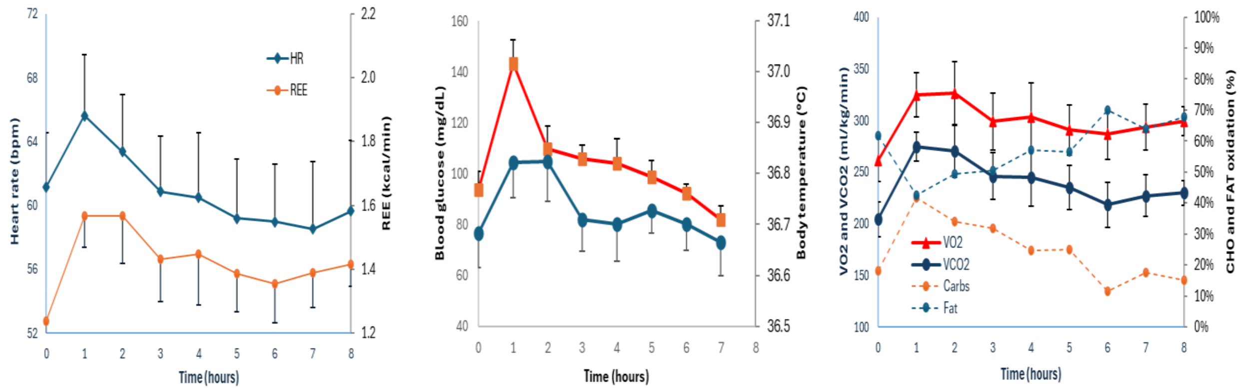


Figure 17. *Average post-prandial physiological responses (±SE) 7-8 hours after meal intake.* (A) Resting heart rate (RHR) and Resting energy expenditure (REE). (B) Blood glucose levels (BG) and Body temperature (BT). (C) Oxygen uptake (VO2) and Carbon dioxide output (VCO2) (whole lines). Carb oxidation (CHO) and Fat oxidation (FAT) (dashed lines).

All panels in Figure 17 display a sharp post-meal increase, early peak, and gradual return to baseline. Resting heart rate peaked around 45 minutes post-meal and normalized within 6–7 hours. Metabolic rate (REE, VO_2, VCO_2) and body temperature showed a biphasic trend, with a secondary rise around 4–5 hours, possibly linked to protein metabolism. Blood glucose mirrored heart rate, peaking at 45 minutes before dropping below baseline by 6–7 hours. Fat oxidation dropped from ~60% to 43% post-meal, then rose back to 60–70%. Carb oxidation peaked at 43% and declined to 10–20% after 6–8 hours.

Blood profile and glycemic control

Fasting blood biomarkers were measured in the eight participants within a few days after the feeding trial. Blood glucose (Glu.), insulin (Ins.), cholesterol (Chol.), high-density lipoproteins (HDL), low-density lipoproteins (LDL), and triglycerides (Trigl.) provided insights into metabolic and cardiovascular health. Thyroid-stimulating hormone (TSH) reflects thyroid function, while estradiol (Estra.) and testosterone (Testo.) represent key sex hormones. Cortisol (Cort.) levels indicate stress and metabolic regulation.

Glycemic control was assessed by calculating a standardized glycemic response index (GRI), reflecting peak glucose levels adjusted by glycemic load per kg body weight. A metabolic fitness index (MFI), based on cardiorespiratory fitness, heart rate capacity (HRmax) and body mass index (BMI), was determined for all participants. Analysis suggests a close relationship between GRI and MFI, demonstrating the correlation between metabolic flexibility and cardiorespiratory fitness. Additionally, a positive correlation was observed between GRI and fasting blood biomarkers (glucose and insulin). These relationships are shown in Figure 18.

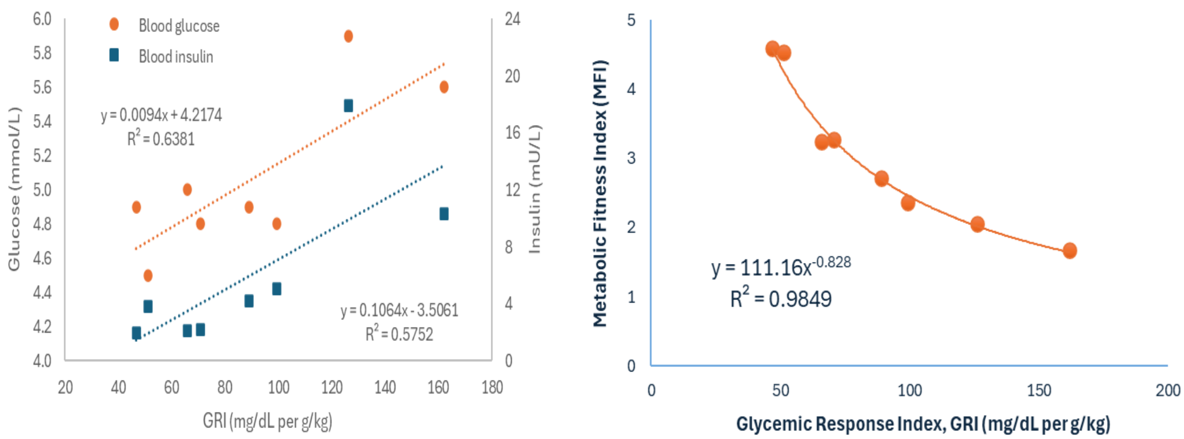


Figure 18. *Glycemic response index and blood biomarkers vs cardiorespiratory fitness.* (Left) The relationship between fasting blood glucose (red circles) and fasting insulin (blue squares) with the glycemic response index (GRI). (Right) The power-based relationship between GRI and MFI for the eight subjects in the feeding study. The regression equations are shown on the graphs.

Fasting blood glucose (GLU) and insulin levels (INS) were shown to be strongly intercorrelated (R_2 = 0.79, p<0.01). GLU was also correlated with BMI (R_2 = 0.63, p<0.01), peak post-prandial glucose (R_2 = 0.49, p<0.01) and fasting triglycerides (R_2 = 0.60, p<0.01). INS was also correlated with BMI (R_2 = 0.67, p<0.01), peak post-prandial glucose (R_2 = 0.58, p<0.01) and fasting triglycerides (R_2 = 0.83, p<0.01).

Overall, the results suggest that lean and aerobically fit individuals exhibit lower fasting blood biomarker values and lower postprandial blood glucose responses. The strong power-based relationship between GRI and MFI suggests that MFI could serve as an indirect indicator or proxy for glycemic control and metabolic flexibility. MFI can be assessed non-invasively through a simple fitness test, such as a walking test.

Deliverable 1.5 - The CALO web application (www.fitsilver.io/calo)

The FITSILVER website

The project has its own specific website, www.fitsilver.io, to present the project, the consortium and the main results from the project. The website is useful for summing up the achievements from the project and presenting the exciting results. The project activities and main results are presented on a timeline from project start (February 2023) to project end (April 2025).

Figure 19. *The FITSILVER website.*

The project has its own specific website, www.fitsilver.io, to present the project, the consortium and the main results from the project.

The FITSILVER website will potentially serve as a platform for continued consortium collaboration beyond the scope of the FITSILVER project.

Driftline has developed a dedicated web application to support the CALO prototype metabolic tracker, available at www.fitsilver.io/calo. The platform is designed to work seamlessly with the Driftline metabolic model, serving as an interface for experimental users to visualize and track their personalized metabolic and cardiovascular data over time.

Each user accesses the system via secure login credentials. Once logged in, users can privately view their daily results, which are automatically imported and analyzed using the proprietary Driftline algorithm. The platform supports both real-time insights and long-term tracking, offering flexible timeframes ranging from single-day views to multi-month summaries.

The application presents three key categories of results:

- **Cardiovascular Metrics:** Categorized heartbeats (e.g., basal, activity, food-related), total accumulated beats, maximum heart rate, and resting heart rate.
- **Metabolic Metrics:** Estimated energy expenditure, energy intake, and resulting energy balance, as derived from heart rate kinetics and personalized calibration.

- **Fitness Metrics:** The Metabolic Fitness Index (MFI), Primescore (age-adjusted Runscore), six-minute walking distance (6WD), and TrueZone endurance score.

Users can explore trends over customizable time ranges (e.g., daily, weekly, monthly), helping them monitor progress, detect changes in metabolic patterns, and assess the impact of lifestyle interventions. Designed with simplicity and clarity in mind, the interface supports non-athletic users and older adults, making metabolic self-monitoring accessible beyond the laboratory.

The CALO web application is a key component of the FITSILVER project's vision to bring advanced, research-grade metabolic tracking into real-world, everyday use.

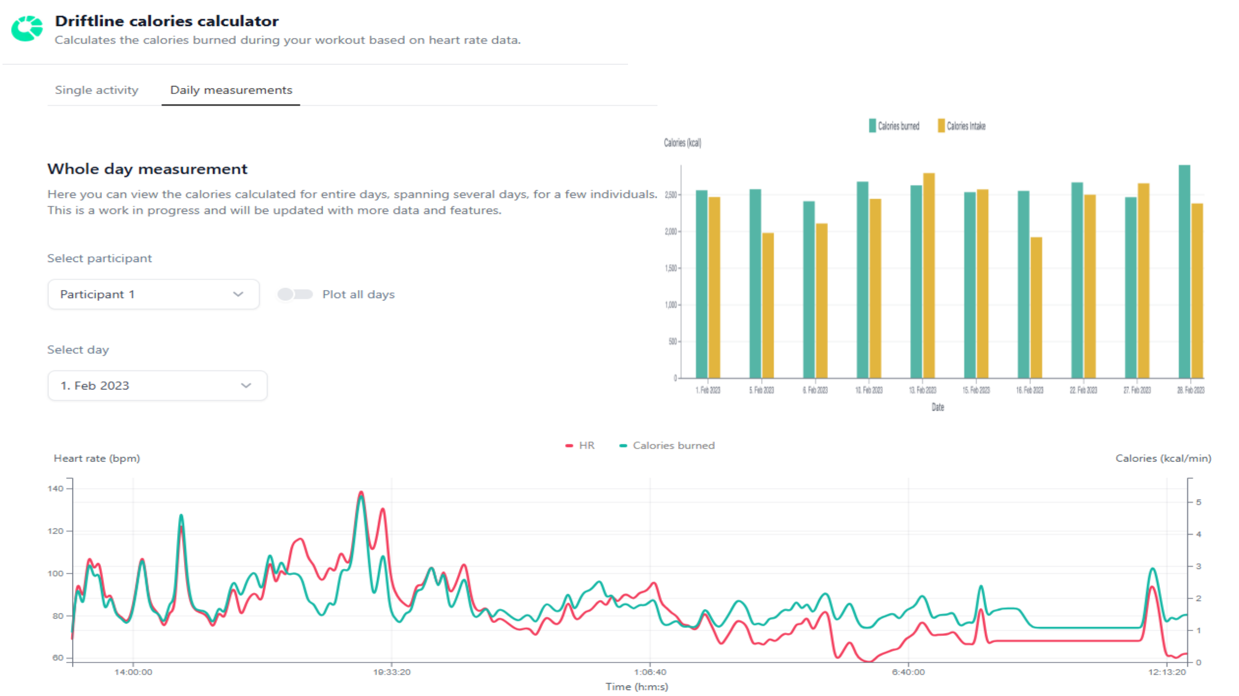


Figure 20. *The CALO web application*.
The CALO web application (www.fitsilver.io/calo) calculates energy expenditure from imported 24-hr HR data from multiple users and plots versus logged calorie intake over extended time periods.

Deliverable 1.6 - The FITSILVER Final Report

The final deliverable from the FITSILVER project is this comprehensive project report. The report summarizes the background for the project (State of the market and State of the art) and outlines the structure of the project with work packages, tasks and deliverables. The report summarizes all methodology and all the major results. The report includes sections about additional deliverables, i.e. the FITSILVER website and the CALO commercial technology report. Also included are sections about risks and mitigation measures, IP rights and regulations, and statements from key opinion leaders.

CALO commercial technology report

A commercial technology report was written by PhD. Baldur Thorgilsson from Reykjavík University and Pi Technology. Pi Technology was sub-contracted in the project as an expert advisor. Below is a summary from the report.

If the FITSILVER project validates the metabolic parameter calculations, there are two possible pathways:

1. Using Existing Fitness Trackers: If the CALO prototype unique characteristics are not required, commercially available fitness trackers can be used to provide the necessary data. This would eliminate the need for proprietary hardware, allowing users to utilize their own preferred smartwatch.

2. Developing a Custom CALO Tracker (TC): If Calo's specialized heart rate and activity signal processing is essential, a dedicated Calo Tracker (TC) could be developed based on TC's technology. In this case:

    - The circuit design can be completed using existing expertise.
    - Most components are readily available off-the-shelf.
    - Fenda, a leading fitness tracker manufacturer, could handle housing and optical mechanics.

For the CALO Tracker (TC) development, we estimate:

- Production feasibility is confirmed.
- Estimated variable cost: $58 per unit.
- Minimum production volume: 200,000 units per year.
- Startup costs: $300,000–$600,000.
- Time to full production: ~1 year after finalizing the design.

The optical design is the most critical factor in replicating TC accuracy, along with advanced activity classification algorithms. While discussions with Fenda have not yet begun, we are confident that these challenges can be addressed with our partners.

Risks and mitigation measures

The FITSILVER project involves the co-development of innovative wearable technologies and metabolic algorithms by CSEM and Driftline. Key risks and mitigation strategies are summarized below, in alignment with Eurostars guidelines for technical feasibility, IP protection, and commercialization readiness.

1. Technical Risks

Device or sensor failure: Malfunction or data loss from prototype wearables could impact data completeness.

- Mitigation: Redundant sensors (e.g., multiple heart rate monitors) and real-time data checks were implemented during testing.
- Algorithmic inaccuracies: Errors in Driftline's metabolic models or CSEM's activity recognition could compromise output validity.
- Mitigation: Algorithms were benchmarked against validated lab instruments (e.g., Cosmed K5), with ongoing cross-verification and version control.

2. Compliance and Participant Risks

Protocol deviations: Participant non-compliance (e.g., diet, activity levels) could introduce variability.

- Mitigation: Clear pre-trial instructions, close supervision, and controlled environments were used to ensure data quality.
- Adverse responses: Although low risk, some discomfort (e.g., fatigue, headaches) was possible during extended testing.
- Mitigation: Safety protocols allowed rest, medical monitoring, and voluntary withdrawal at any time.

3. IP and Data Security Risks

- Confidentiality breaches or IP conflicts: Use of proprietary algorithms and pre-commercial devices requires secure handling.
- Mitigation: IP rights are clearly defined in consortium agreements, with controlled access and pseudonymized data handling in line with GDPR.

4. Regulatory Risks

- Unclear device classification: The wearable system may fall under future medical device regulation.
- Mitigation: Early consultation with regulatory experts ensures development is aligned with EU MDR/FDA pathways for potential clinical applications.

The consortium met regularly to assess emerging risks and ensure all mitigation strategies are effectively implemented throughout the project lifecycle.

IP rights and regulations

The FITSILVER project involves proprietary technologies developed by both CSEM and Driftline. CSEM holds patents on its core activity-detection algorithms and has developed the CALO prototype metabolic tracker used during the trials. This device is currently a research instrument and is not yet commercially available. All data collected via the CALO prototype remains under CSEM's ownership and is subject to confidentiality and IP protection agreements within the FITSILVER consortium.

Driftline has filed a patent-pending application covering its novel heart rate–based metabolic analysis methods, including the segmentation of heart rate kinetics and derived energy expenditure components. These methods are implemented in the TrueZone algorithm, which provides individualized estimates of energy intake and expenditure based solely on heart rate data.

In general, IP regulations for wearable metabolic tracking technologies cover a range of domains, including algorithmic innovation, device design, data processing methods, and user interface functionalities. Patents may be granted for novel and non-obvious solutions to technical problems, including methods for measuring, estimating, or displaying metabolic variables. Regulatory approval for commercialization — particularly in health-related applications — may also require compliance with relevant medical device directives (e.g., EU MDR or FDA Class I/II regulations), depending on the intended use and risk classification.

All technologies developed in the FITSILVER project are used in accordance with applicable IP rights and contractual agreements between project partners. Future deployment of these tools will follow appropriate regulatory pathways for validation and approval where required.

Endorsement of the FITSILVER Project

Willum Þór Þórsson

Former Minister of Health (2021-2024), Chairman of the Budget Committee, and Member of Parliament

"FITSILVER lays the groundwork for next-generation metabolic monitoring solutions that support healthier aging and improved population health."

Alongside rapid global population growth, we have witnessed remarkable technological progress and growing scientific knowledge that have allowed us to tackle numerous diseases and improve both public health and the welfare of nations. Yet, despite these advancements — and in part because of them — ensuring sufficient staffing and sustainable funding for healthcare systems remains a major global challenge.

We are experiencing this firsthand in Iceland and are actively working to address it. Life expectancy in Iceland has increased substantially, now reaching approximately **81 years for**

men and **84 years for women** and is projected to rise further in the coming years. At the same time, the **age pyramid is shifting rapidly**, even though we are still considered a relatively young nation. Currently, older adults (67+) represent about **14% of the Icelandic population**, while this figure is closer to **20% in other Western countries** (Eurostat, 2023). The familiar warning that there are *"fewer working hands behind each older citizen"* has never been more relevant.

As the need for healthcare and long-term care inevitably increases, it is essential to act now. **FITSILVER represents a highly inspiring and promising solution** in this regard — a valuable response to the challenges facing not only Iceland but countries around the world.

What sets FITSILVER apart from other initiatives is its ability to offer **accurate energy expenditure tracking** and **indirect assessments of metabolic health** using biometric data. This enables early detection and long-term prevention strategies that support individuals in maintaining better health and independence as they age.

From a policy perspective, this project strongly supports **key national strategies**:

- The **Icelandic Health Policy to 2030**
  Read policy
- The **Public Health Action Plan (2023–2027)**, which is reviewed annually
  View plan
- The government's **"Good to Grow Old" initiative**, launched in 2022
  Learn more

FITSILVER not only strengthens alignment with these national health goals — particularly those related to **healthy aging**, **digital health innovation**, and **preventative care** — but also plays a crucial role in promoting **health literacy** and **personal responsibility** for well-being.

By empowering individuals to better understand their health data, FITSILVER helps combat lifestyle-related diseases such as **cardiovascular disease, diabetes, and cancer**, and addresses their underlying risk factors (European Commission, 2021). Through such innovation, people are given greater opportunities to **extend the number of healthy, high-quality years in their lives.**

It is therefore especially gratifying that the Technology Development Fund supports innovative solutions like FITSILVER in addressing future health challenges.

May 5th, 2025
Willum Þór Þórsson.

Deliverable 2.1 - CALO prototype metabolic tracker

Design and technical specifications

After several months of work on needs analysis and technical specifications, the CSEM engineering team built a prototype (CALO 1), which was delivered to Driftline in December 2023. The CALO 1 prototype is a wrist-worn tracker that includes a PPG sensor for heart rate monitoring and a 3-axis accelerometer for motion tracking. The CALO 1 prototype was delivered to Driftline as one unit that could be used and validated in the METFIT validation studies. Meanwhile, CSEM produced other units to use and validate in validation studies.

The CALO 1 (Figure 21) is a technical prototype assembled from CSEM components and specifically programmed for calorie tracking applications. It is important to note that this prototype is not designed for commercial use; its sole purpose is to validate calorie measurements in dedicated research studies.

Figure 21. *The CALO-1 prototype calorie tracker.*
The CALO-1 prototype calorie tracker worn on user's wrist.

The specifications are summarized in the *CALO_Requirements_Specification.pdf* file. This document highlights the detailed specifications for both the CALO research prototype and a potential commercial prototype. Additionally, it demonstrates the dependencies between the various libraries, ensuring clarity and coherence in their integration.

Deliverable 2.2 – Libraries and API to interface with CALO tracker

In addition to the requirements specified in Deliverable 2.1, the API details for the various CSEM libraries are presented in the document titled *algo_list_dependencies.pdf*. This document meticulously outlines the essential inputs and outputs for each CSEM library, ensuring a seamless and efficient processing chain. Furthermore, it specifies the calling sequence of the libraries, providing clear guidance for their integration.

Calculations by CSEM

The accuracy of the estimated energy expenditure (EE) was evaluated by calculating the accumulated EE percentage error, and the mean absolute error (MAE) during the three main phases of the protocol and comparing it to the Cosmed K5 reference. EE accuracy was also assessed based on the subject's activity type: walking, running, other activities (which includes non-rhythmic activities), and rest. Figure 22 shows two examples of EE recordings and CALO EE calculations for all three experimental phases.

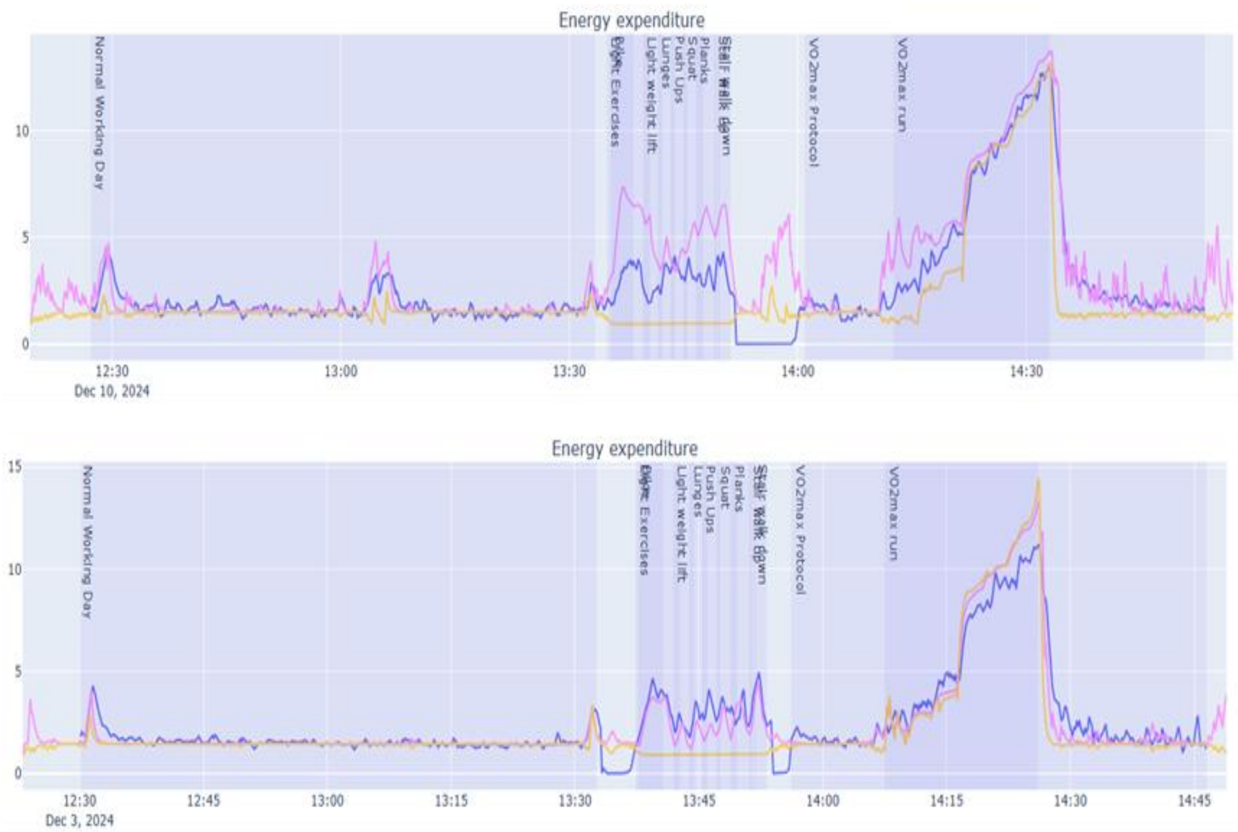


Figure 22. *Example of bad (top) and good (bottom) EE estimations*.
The graph shows the EE reference from Cosmed K5 (blue line), the CALO PPG + accelerometer EE estimation (pink line) and the CALO accelerometer EE estimation (yellow line).

The two examples in Figure 22 show that the CALO calculations were much closer to the reference line (blue line) if the ECG or PPG (heart rate) measurements were also used in the calculations (pink line), in addition to the accelerometry. The correlation was, however, also quite variable between subjects and phases, as seen by comparing the two examples.

The cumulated deviations (errors) from reference values during all three phases were calculated and analyzed to test for systemic bias in the algorithm (Table 2, Figure 23).

Table 2. *Cumulated error per configuration, protocol phase and activity type.*
The mean cumulated deviations (±SD) from reference values (K5) in respective protocol phases for the three CALO input configurations.

	Work	Exercise	Walk/Run	Run	Walk	Rest	Other	Entire protocol
ECG + ACC	-0.94 ± 10.34	-9.33 ± 27.64	0.31 ± 9.48	-0.2 ± 8.41	0.71 ± 16.97	0.48 ± 10.61	-13.32 ± 22.52	-0.2± 10.6
PPG + ACC	0.50 ± 9.40	-11.81 ± 27.57	0.83 ± 9.39	0.62 ± 8.52	1.24 ± 16.44	0.08 ± 9.84	-11.75 ± 20.66	-0.9 ± 9.5
ACC	9.33 ± 9.25	71.98 ± 2.21	2.82 ± 14.66	-4.28 ± 14	26.09 ± 8.93	28.08 ± 4.79	45.70 ± 10.67	18.6 ± 6.6

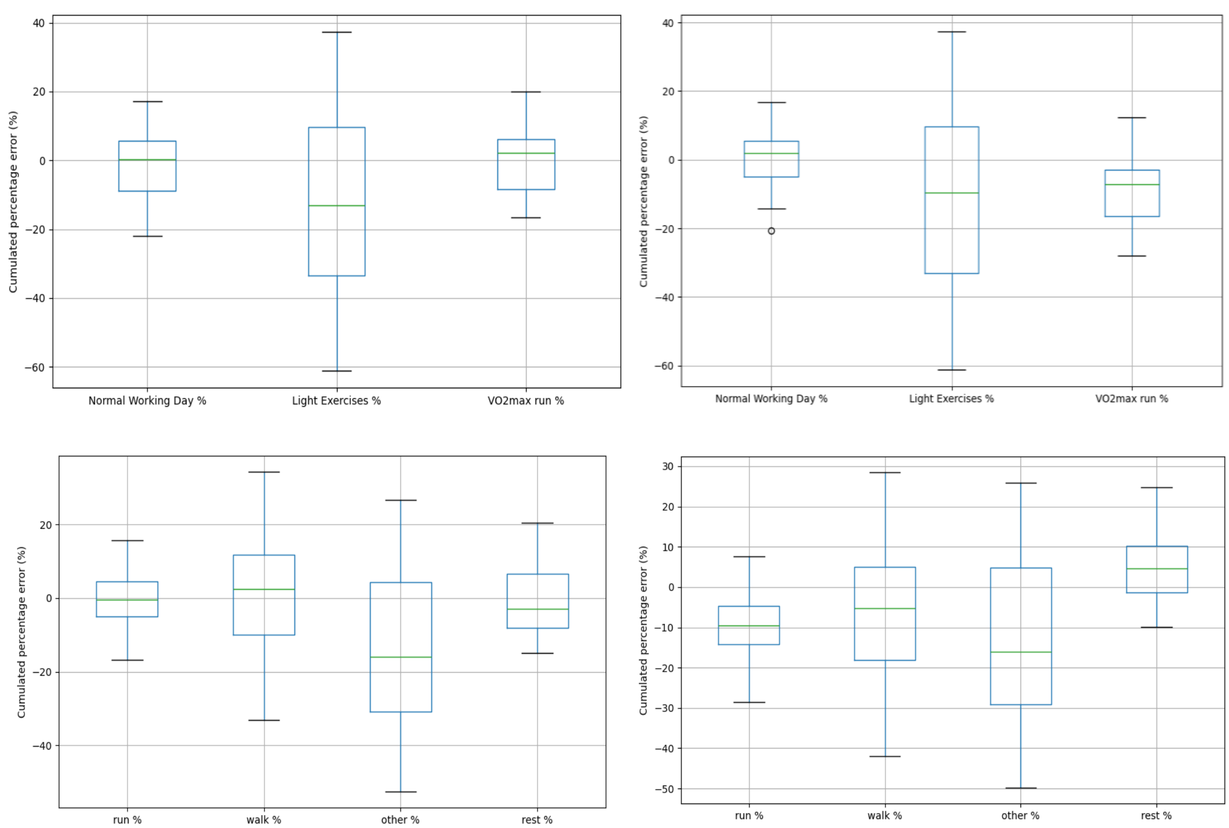


Figure 23. *CALO error boxplots for protocol phases, activity types and configurations.*
Left side: Boxplots for the ECG-ACC configuration in phases and activities. Right side: Boxplots for the PPG-ACC configuration in phases and activities.

The results, summarized in Table 2 and plotted in Figure 23, show that using ECG and accelerometers gives a similar performance than using the PPG and accelerometers but using only the accelerometer gives significantly lower performance except during the run.

The results in Table 2 show indeed an underestimation of the EE using only the accelerometer of almost 20% over the entire protocol. This deviation is particularly high during the exercises phase (+72%), but also during the walking and resting phases (26%, 28% respectively). Table 3 shows that the percentage mean absolute errors (MAE) were almost identical between ECG and PPG configurations and much smaller than for the ACC configuration. The next results focus on the ECG/PPG configurations, and the library behavior and performances on the different phases and based on different activities.

During the work phase and walk/run part of the CPET phase, the percentage mean error was less than ±1%. When considering the entire CPET phase, including rest/walk/run/recovery, the error was slightly higher. The light exercise phase results show an over-estimation of 10% on average but with a high variability between subjects (SD= 30%), which is confirmed with a percentage absolute error of 25%.

Considering the activity type, results show no bias during walk, run and rest but a higher standard deviation of the percentage error during the walk. This is confirmed with a higher percentage mean absolute error for the walk (~14%), than for the run (~7%) and rest (~9%). The resting activity, including working hours and the recovery part, shows higher error rates during recovery (percentage mean absolute error ~12 ± 8%), than during the whole working phase (percentage mean absolute error ~8 ± 5%). During non-rhythmic activity ("other" class) results show an over estimation of ~12%, and a percentage absolute error of ~24%. This high error rate reflects the difficulties in mapping the energy expenditure during short exercises with limited effort using only heart rate.

Table 3. *Cumulated absolute error per configuration, protocol phase and activity type.*
The mean cumulated absolute errors (±SD) from reference values (K5) in respective protocol phases for the three CALO input configurations.

	Work	Exercise	Walk/Run	Run	Walk	Rest	Other	Entire protocol
ECG + ACC	8.40 ± 5.79	24.15 ± 15.55	7.58 ± 5.43	6.50 ± 5.12	13.83 ± 9.33	8.98 ± 5.29	21.56 ± 14.31	8.2 ± 6.0
PPG + ACC	7.81 ± 4.94	24.71 ± 16.27	7.37 ± 5.63	6.68 ± 5.10	13.44 ± 9.06	8.65 ± 4.26	19.43 ± 13.22	7.7 ± 5.5
ACC	10.54 ± 7.75	71.98 ± 2.21	11.55 ± 9.11	12.08 ± 7.85	26.09 ± 8.93	28.08 ± 4.79	45.70 ± 10.67	18.6 ± 6.6

To conclude, these results suggest that the accelerometer input configuration is fairly accurate for walking, running and office work but produces large overestimations during non-rhythmic exercises and resting. The ECG/PPG configurations are very accurate during resting, walking, running or office work but tend to overestimate EE by about 10-12% during light exercise and non-rhythmic exercises.

Calculations by Driftline

The data from the CSEM validation study was also sent to Driftline for analysis using Driftline's metabolic model, which calculates energy expenditure (EE) based solely on heart rate data. The dataset was divided into three distinct phases (A, B, and C) to allow direct comparison with the CALO results for the same tests. Metabolic (base factor and activity factor) and cardiorespiratory (HRmax, lactate threshold, endurance) coefficients were determined individually for each participant based on V-slope and breakpoint analyses from their CPET test data. These coefficients were incorporated into the model to directly estimate EE throughout the testing sessions. Figure 23 illustrates an example of Driftline's heart rate-based energy expenditure calculations for one subject in the study.

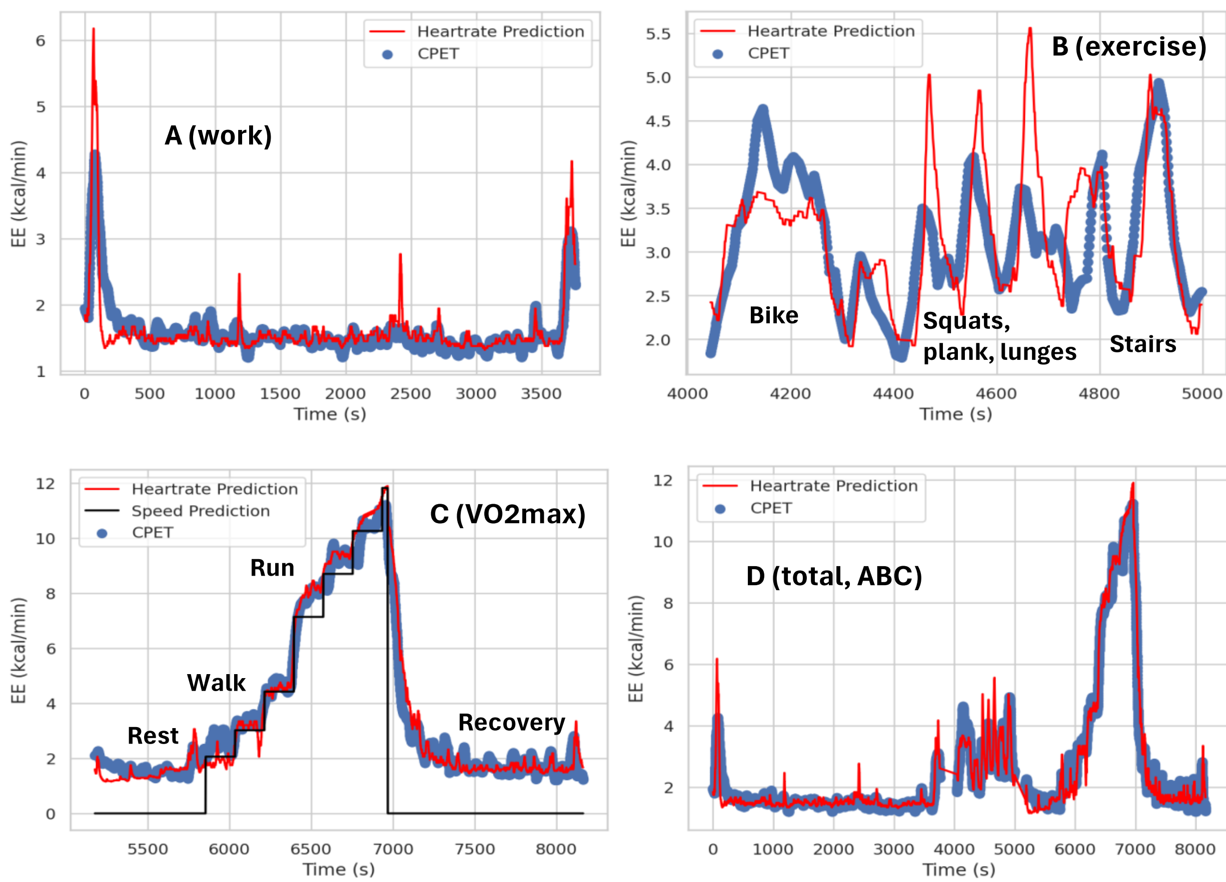


Figure 23. *Driftline's heart rate-based calculation of energy expenditure.*
A screenshot from the Driftline metabolic model showing an example of heart rate-based calculated energy expenditure (EE, red line) and comparison with measured EE (CPET, blue line). Panel A, B, and C show the three different experimental phases, and Panel D shows the full 2-hour experiment.

As shown in Figure 23, the fit between measured and predicted energy expenditure (EE) was very close for this subject using the Driftline method. During the work phase (A), the error was only 1.2%, mainly due to slight overestimations during sudden heart rate spikes. In the exercise phase (B), the model also performed well with a 1.4% error, despite some underestimation during the initial cycling and minor overestimations during squats, push-ups, lunges, and planks; notably, the stair climb exercises showed an especially close fit. While the B phase results were excellent for this subject, variability across subjects was higher. In the CPET test phase (C), which included rest, walking, running, and recovery, the error dropped to just 0.4%. Overall, for this subject the combined ABC phases yielded a low prediction error of 0.8%, highlighting the accuracy of the Driftline heart rate-based method for assessing energy expenditure (Table 4).

Table 4. *Validation of energy expenditure determination in the Calo validation study.* Measured (K5) energy expenditure (kcal) for the 20 study subjects across phases A, B, C, and ABC. Deviations (%) are presented for Driftline (DL) and CALO. Mean error (ME). Mean absolute error (MAE).

Phase	A			B			C			ABC		
	K5	DL	CALO	K5	DL	CALO	K5	DL	CALO	K5	DL	CALO
FS-01	115.2	-1.0%	-13.4%	76.2	-7.3%	-6.1%	372.0	6.4%	-8.4%	563.4	3.0%	-9.0%
FS-02	144.0	-8.5%	-11.9%	69.5	2.3%	-51.2%	361.5	1.4%	1.6%	574.9	-0.9%	-3.8%
FS-04	117.7	4.5%	13.0%	48.7	26.5%	-24.1%	233.2	7.5%	5.1%	399.5	9.0%	2.7%
FS-06	92.4	-18.5%	12.2%	60.8	-18.3%	7.6%	237.0	-5.0%	13.7%	390.2	-10.3%	11.1%
FS-07	126.9	-17.6%	16.8%	58.2	-7.4%	3.6%	258.4	-5.5%	13.5%	443.4	-9.2%	12.4%
FS-09	99.5	1.1%	5.5%	49.7	1.6%	19.1%	184.2	0.4%	3.4%	333.4	0.8%	5.0%
FS-12	93.3	-16.5%	7.6%	52.8	-14.4%	13.3%	189.3	-3.2%	-5.7%	335.4	-8.6%	1.4%
FS-13	115.5	5.3%	0.7%	50.9	11.4%	-67.1%	221.3	6.7%	-9.9%	387.7	6.9%	-15.7%
FS-14	125.2	18.1%	-0.1%	81.7	-11.0%	-13.2%	338.7	1.7%	4.2%	545.6	3.6%	-0.7%
FS-15	126.9	10.3%	-12.3%	73.6	15.1%	-41.1%	374.2	-1.4%	4.2%	574.7	3.3%	-5.6%
FS-16	129.7	-2.6%	3.8%	58.8	-9.5%	44.8%	397.3	-0.7%	20.8%	585.9	-2.0%	19.2%
FS-17	130.2	8.1%	-3.0%	70.0	2.9%	-27.7%	357.9	8.7%	-9.2%	558.1	7.8%	-13.0%
FS-19	128.2	3.4%	6.3%	69.0	-13.9%	10.8%	260.1	-0.1%	2.4%	457.3	-1.2%	4.8%
FS-20	121.2	30.4%	-11.5%	67.4	-4.3%	-30.7%	298.1	2.4%	3.4%	486.7	8.4%	-5.1%
FS-21	138.0	-0.9%	-7.5%	71.9	0.7%	-28.1%	328.1	8.7%	-11.2%	538.0	5.1%	-12.2%
FS-24	122.8	23.0%	-3.7%	63.6	-5.8%	-22.3%	238.8	7.6%	-3.6%	425.2	10.0%	-6.7%
FS-25	132.5	6.8%	-9.9%	62.7	7.0%	-29.0%	348.9	7.7%	4.1%	544.0	7.4%	-3.2%
FS-26	110.2	19.2%	4.8%	60.7	-1.0%	12.9%	246.5	7.7%	16.1%	417.4	9.5%	13.1%
FS-27	114.3	6.7%	0.6%	67.3	0.3%	-24.7%	243.9	12.3%	3.1%	425.5	8.9%	-2.0%
FS-28	114.2	-6.1%	11.8%	50.1	-3.6%	16.8%	204.7	5.6%	4.8%	369.1	0.7%	7.2%
ME	119.9	3.3%	0.5%	63.2	-1.4%	-11.8%	284.7	3.4%	2.6%	467.8	2.6%	0.0%
MAE	**119.9**	**10.4%**	**7.8%**	**63.2**	**8.2%**	**24.7%**	**284.7**	**5.0%**	**7.4%**	**467.8**	**5.8%**	**7.7%**

Table 4 summarizes the accumulated energy expenditure (EE) across the different phases for all study participants, along with deviations from the reference indirect calorimetry measurements.

Figure 24 compares the prediction accuracy between Driftline and CALO across the different experimental phases.

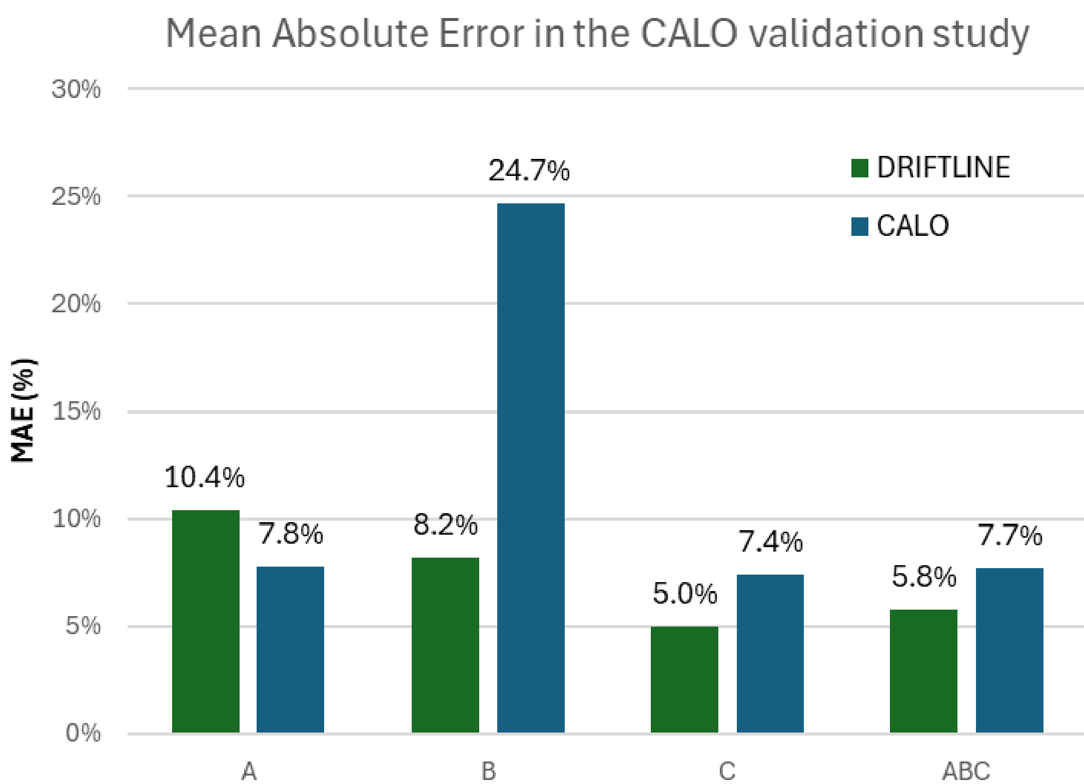


Figure 24. *Energy expenditure prediction accuracy of Driftline and CALO methods.*
Mean absolute error (MAE) for energy expenditure prediction using Driftline (green) and CALO (blue) across three protocol phases: A (work tasks), B (mixed exercise), and C (CPET with recovery).

In the work phase (A), CALO performed better than Driftline (7.8% vs. 10.4%), possibly due to its calibration using demographic variables such as gender, which are not yet implemented in Driftline's modeling. The exercise phase (B) posed the greatest challenge due to its inclusion of non-rhythmic and isometric movements like squats and planks — activities where accelerometer-based systems typically struggle. Driftline still delivered a comparatively low MAE of 8.2%, while CALO's error rose sharply to 24.7%, highlighting the advantage of individualized heart rate–based modeling in complex movement contexts. This may support Driftline's potential as a more accurate and individualized method for real-world energy expenditure estimation

The performance of both methods was especially strong during the CPET phase (C), achieving an MAE of just 5.0% and 7.4%, despite the diverse intensity range, which included rest, walking, running, and a 20-minute passive recovery. This is particularly notable, as energy expenditure during recovery remains a major limitation in most commercial fitness trackers.

When averaged across all phases (ABC), Driftline outperformed CALO with an overall MAE of 5.8% versus 7.7%. This was quite remarkable, since the CALO accuracy was indeed outstanding compared to reported error rates (MAEs of 27–29%) from commercially available fitness trackers during free-living and mixed-activity protocols (O'Driscoll et al., 2020). While further refinements are ongoing, these findings demonstrate that the FITSILVER results may offer substantial improvements over traditional wearable tracking approaches, with implications for integration into next-generation fitness devices.

Integrating Driftline's heart rate–based metabolic analysis into the CALO tracker offers strong potential to enhance real-world accuracy. By using individualized heart rate dynamics instead of relying solely on accelerometry and demographics, CALO could better estimate energy expenditure during non-steady-state activities, static exercises, and recovery — areas where conventional methods often fail. Driftline's performance in these scenarios suggests it could serve as a core engine within CALO, significantly improving analytical precision without altering the user experience. This hybrid model could elevate CALO's capabilities toward clinical-grade accuracy in a consumer device.

Discussion

The FITSILVER project made substantial progress toward addressing the need for more accurate and individualized metabolic and fitness tracking tools, particularly for older adults. Through the development of advanced heart rate analytics, a novel metabolic model, and dedicated wearable solutions, FITSILVER demonstrated that continuous, non-invasive monitoring of energy balance is feasible.

A particularly groundbreaking outcome of the project was the successful modeling of energy intake (EI) through heart rate analysis. By quantifying thermogenic food waves—heart rate elevations induced by meal-related thermogenesis—the Driftline metabolic model was able to estimate caloric intake without relying on self-reported food logs or wearable-based activity tracking alone. This capability represents a major innovation in wearable metabolic monitoring, addressing a long-standing gap in energy balance assessment.

However, while the initial proof-of-concept results for energy intake estimation were promising, further research is needed. Specifically, validation across larger and more diverse populations, different meal types, variable environmental conditions, and free-living (non-laboratory) settings will be necessary to confirm robustness and generalizability. Additionally, continued refinement of the food wave fitting algorithms and integration with multi-sensor approaches (e.g., accelerometry, temperature, or blood glucose) may further enhance accuracy.

The results of the FITSILVER validation study indicate that both the Driftline metabolic model and the CALO prototype substantially outperform currently available commercial wearable devices in estimating energy expenditure (EE). The Driftline model, which uses only heart rate data, achieved a mean absolute error (MAE) of 5.7% across a mixed-activity protocol that included sedentary office work, light resistance exercises, walking, running, and recovery. The CALO prototype, which combines PPG-derived heart rate and accelerometry, performed similarly well with an 7.7% MAE. The CALO prototype used a finer-grained accelerometry system, based on improved activity detection algorithms developed during the project, allowing for more accurate recognition of movement patterns and intensities. These findings represent a significant advancement in wearable EE estimation technology.

When compared to reported error rates from commercially available fitness trackers, the superiority of both systems becomes even clearer. A recent systematic review reported average MAEs of 27–29% across major brands such as Apple, Fitbit, and Garmin during free-living and mixed-activity protocols. Even under controlled walking and running conditions, leading devices typically achieve MAEs between 10–20%, with errors often exceeding 20–40% during light activities, strength exercises, or non-steady-state conditions. In contrast, both the Driftline and CALO models maintained high accuracy not only during steady aerobic activities but also across a wide range of intensities and exercise modalities, where accelerometer-based algorithms usually fail.

Importantly, during the exercise phase of the validation protocol, the Driftline model maintained a MAE of 8.2%, compared to 24.7% for the CALO device. This highlights a key advantage of heart rate-driven metabolic modeling, particularly during resistance or mixed-intensity activities where accelerometry alone tends to misestimate workload and caloric cost. Traditional accelerometer-based models often assume a fixed relationship between movement intensity and energy expenditure, leading to systematic inaccuracies during activities such as strength training, static holds, or low-movement but high-effort tasks like planks. In contrast, heart rate-based modeling captures internal physiological effort more directly, offering a more reliable estimation of metabolic demand under diverse exercise conditions.

Collectively, these findings demonstrate that the Driftline metabolic model not only achieves superior energy expenditure tracking compared to leading commercial wearables but also maintains this accuracy across a broader range of real-world activities. This improvement has important implications for both consumer health applications and clinical or athletic monitoring, where precise energy balance assessments are critical.

Future research should focus on further validating the Driftline metabolic model under free-living conditions and across diverse populations, including older adults and individuals with metabolic disorders. Integration of the model into commercial wearable devices could substantially enhance the accuracy of real-time energy expenditure tracking for consumers and professionals alike.

The project also introduced new non-invasive metabolic health markers, such as the Metabolic Fitness Index (MFI), demonstrating strong correlations with glycemic control and cardiorespiratory fitness. These findings suggest that wearable technology could soon offer meaningful metabolic insights traditionally available only through laboratory testing.

Overall, FITSILVER successfully validated the feasibility of using heart rate analytics for comprehensive metabolic monitoring, including both expenditure and intake components. With further development and validation, the methodology holds the potential to transform how individuals monitor their health, manage weight, and optimize metabolic fitness in everyday life.

In conclusion, the FITSILVER project has laid the groundwork for a new era of individualized, automated metabolic monitoring — bringing the vision of real-time, science-based health optimization closer to everyday reality.

Future work

Building on the promising results of FITSILVER, future work will focus on expanding the validation of heart rate–based energy intake and expenditure models across larger, more diverse populations and real-world conditions. Refinement of food wave fitting algorithms, integration of additional physiological signals (e.g., accelerometry, skin temperature, glucose monitoring), and the development of adaptive AI-based calibration systems will be key priorities. Further technological advances will include optimization of wearable hardware for enhanced signal quality, energy efficiency, and user-friendliness.

Given the positive outcomes of the CALO prototype testing, the project partners — Driftline and CSEM — intend to continue their collaboration and further develop the calorie tracking concept. Following the conclusion of the FITSILVER project, the parties plan to formalize their cooperation through a license agreement. In accordance with the existing consortium agreement, Driftline will compensate CSEM for the use of CSEM's intellectual property if the CALO device or its underlying technology advances to commercial production.

In parallel, efforts will be directed toward scaling the FITSILVER platform, pursuing regulatory approvals, and preparing for commercialization to serve both preventive healthcare markets and the emerging Silver Economy. These steps will be crucial to fully unlock the potential of individualized metabolic monitoring for improving public health, supporting healthy aging, and empowering individuals to manage their metabolic fitness with unprecedented precision.

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