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RM4HEALTH

Remote Monitoring in Health and sports

Deliverable 7.3

Public report of projects' results and updating the state of the art

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Management Summary

The RM4Health project demonstrates how remote monitoring can be advanced from isolated measurements towards integrated, data-driven ecosystems for healthcare, elderly care, rehabilitation, and sports. Across six active use cases, the project developed and validated technologies that combine wearable and ambient sensing, connected devices, cloud-based data platforms, artificial intelligence, digital biomarkers, dashboards, and user-facing applications. Together, the results support a shift from reactive, episodic follow-up towards more proactive, continuous, and personalised monitoring in real-world environments.

The project results cover a broad but coherent set of application areas. In UC1, the Philips Remote Monitoring system was applied to heart failure and peri-operative care, enabling sensor-based data acquisition, secure data transfer, cloud storage, near-real-time processing, algorithm execution, and web-based clinical monitoring. The work supports earlier detection of deterioration in high-risk patients, including chronic heart failure patients and patients recovering from major surgery. In UC2, an AI-assisted respiratory analysis platform was developed for digital stethoscope recordings, using signal processing and machine learning to detect abnormal breath sounds such as wheezes and crackles, with reported precision close to 90% under project validation conditions.

In UC4, the project explored early detection of heart failure decompensation through multimodal, non-invasive monitoring, including PPG, ECG, activity sensing, and advanced analytics. This use case delivered a proof-of-concept monitoring and analysis pipeline for long-term home monitoring after hospital discharge, while also advancing work on continuous blood pressure estimation and future digital twin applications. In UC5, an elderly-care monitoring ecosystem was developed, combining wearable sensing, medication-routine monitoring, hub-based connectivity, structured questionnaire data, REDCap dashboards, and caregiver-facing interfaces. This use case addresses the need for interoperable, usable, and longitudinal monitoring solutions in home and assisted-living contexts.

The sports and prevention-oriented use cases extend the project's relevance beyond traditional clinical care. UC6 demonstrated an immersive sports monitoring workflow that combines biometric data from athletes with synchronized 360° and conventional video, visualized in an XR environment for post-training analysis. This enables coaches and athletes to interpret physiological responses in their spatial and tactical context. UC7 demonstrated a Patient Journey App-based solution for physical fitness assessment and personalized lifestyle guidance, using structured lifestyle questionnaires, optional consumer device data, and AI-based lifestyle profiling to tailor health and wellbeing recommendations over time.

Across the use cases, RM4Health contributes to the state of the art in three main ways. First, it advances multimodal remote monitoring, combining physiological, behavioural, audio, activity, medication, questionnaire, and video data. Second, it strengthens AI-enabled interpretation, including anomaly detection, respiratory sound classification, heart failure risk monitoring, signal quality analysis, lifestyle profiling, and future digital twin development. Third, it emphasizes practical deployment, with attention to cloud infrastructure, interoperability, dashboards, role-based access, user experience, and integration into clinical, care, coaching, and self-management workflows.

The project also highlights important remaining challenges. These include the need for larger and more diverse validation datasets, stronger evidence of clinical and service-level impact, robust handling of real-world data quality, prevention of alarm fatigue, explainability of AI outputs, privacy

and regulatory compliance, and sustained adoption by professionals, patients, older adults, athletes, and caregivers. The next phase should therefore focus on further validation, integration into operational workflows, refinement of AI models, and preparation for scalable deployment and commercialization where appropriate.

Overall, RM4Health has delivered a portfolio of promising remote monitoring technologies that can support earlier detection, better follow-up, personalized guidance, and more context-aware decision-making. The results provide a strong basis for continued development towards trusted, interoperable, and user-centred monitoring solutions for future health, care, rehabilitation, and sports ecosystems.

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1. Introduction

1.1. Purpose of the document

Remote monitoring is becoming an essential component of future healthcare, elderly care, rehabilitation, and sports performance support. By enabling continuous or repeated measurements outside traditional clinical and laboratory environments, remote monitoring can provide earlier insight into changes in health status, functional capacity, and physiological performance. The RM4Health project was established to accelerate this transition by developing and demonstrating technologies that connect wearable and ambient sensing, secure data platforms, artificial intelligence, digital biomarkers, and user-facing applications into practical remote monitoring solutions for health and sports. The project builds on the need for solutions that go beyond isolated devices or single-point measurements, towards interoperable ecosystems that can collect, process, interpret, and present data in ways that support healthcare professionals, patients, athletes, and coaches.

This final project results deliverable provides a concise overview of the main technological outcomes developed and demonstrated within RM4Health. The results are structured around the six active use cases of the project: UC1, UC2, UC4, UC5, UC6 and UC7. Although the original project plan included eight use cases, UC3 and UC8 were discontinued; the original numbering has therefore been retained for traceability. Together, the remaining use cases cover remote patient monitoring for clinical care, AI-supported respiratory assessment, early detection of heart failure decompensation, remote monitoring of elderly daily activities, sports monitoring, and physical fitness and performance assessment.

The deliverable focuses on the technologies that emerged from these use cases. These include a scalable Philips remote monitoring platform for sensor-based data acquisition, near-real-time processing, cloud storage and clinical user interfaces in UC1; an AI-based digital stethoscope signal analysis solution for early recognition of abnormal breath sounds in UC2; the UC4 sensor and system setup for heart failure decompensation monitoring; an elderly monitoring ecosystem combining wearable sensing, medication intake monitoring, HL7/FHIR-based data management, AI models and caregiver interfaces in UC5; an AR/VR-supported sports monitoring concept combining biometric data with video streams in UC6; and a Patient Journey Application for preventive healthcare and recreational sport performance assessment in UC7.

For each project result, this deliverable also includes a dedicated state-of-the-art section. These sections position the RM4Health outcomes against current technological and market practice, clarifying the gap addressed by each result and the specific innovation achieved. In this way, the deliverable not only documents what has been developed, but also explains why these results are relevant for the evolution of remote monitoring ecosystems in healthcare, elderly care, rehabilitation, and sports.

1.2. Related documents

As this document captures an overview of the project results it has a direct or indirect relation to all the deliverables that have been generated within the context of the RM4Health project as well as with the full project proposal.

2. UC1: Remote monitoring in heart failure and peri-operative care

Below we provide an overview of the technologies resulting from the project in the context of use case 1. Partners involved were Philips, Maxima Medical Center, Catharina Ziekenhuis, Eindhoven University of Technology, Evalan and Polar.

2.1. Technologies resulting from the project

2.1.1. Short description of the use case

UC1 focuses on remote patient monitoring for two clinical contexts in which early detection of deterioration is highly relevant: chronic heart failure and peri-operative care. The use case includes studies with chronic heart failure patients, both after recent hospitalization for acute decompensated heart failure and during in-hospital recompensation, as well as a peri-operative cohort study with patients undergoing high-risk cardiac or major abdominal surgery. The overall aim is to investigate whether non-invasive wearable sensors can generate clinically useful data for detecting deterioration, predicting complications, and supporting follow-up in hospital and home settings.

For heart failure, the use case explores how continuous and repeated measurements can provide insight into the utility of non-invasive sensors for predicting deterioration after hospitalization, and for monitoring patients during clinical recompensation. For peri-operative care, the use case investigates to what extent wearable devices can support detection of post-operative complications in patients undergoing high-risk surgery.

2.1.2. Overview of the technology

Description: The core technology used in UC1 is the Philips Remote Monitoring system. This system enables sensor-based data acquisition from wearables, secure data transfer, cloud-based storage, near-real-time processing, algorithm execution, and web-based monitoring through a user interface. It is designed to scale across monitoring devices, algorithms, and applications, and supports near-real-time data uploading through a data hub, large-scale cloud storage, cloud processing, open APIs, secure authentication, role-based access, and user interfaces that can support patient monitoring and early warnings.

Type: New service, with commercial release planned for H1 2027.

Customers: The intended customers include clinical care providers seeking cost-effective remote patient monitoring solutions, remote patient monitoring service providers that want to use consumer wearables in care pathways, and consumer wearable device manufacturers aiming to enter the medical domain.

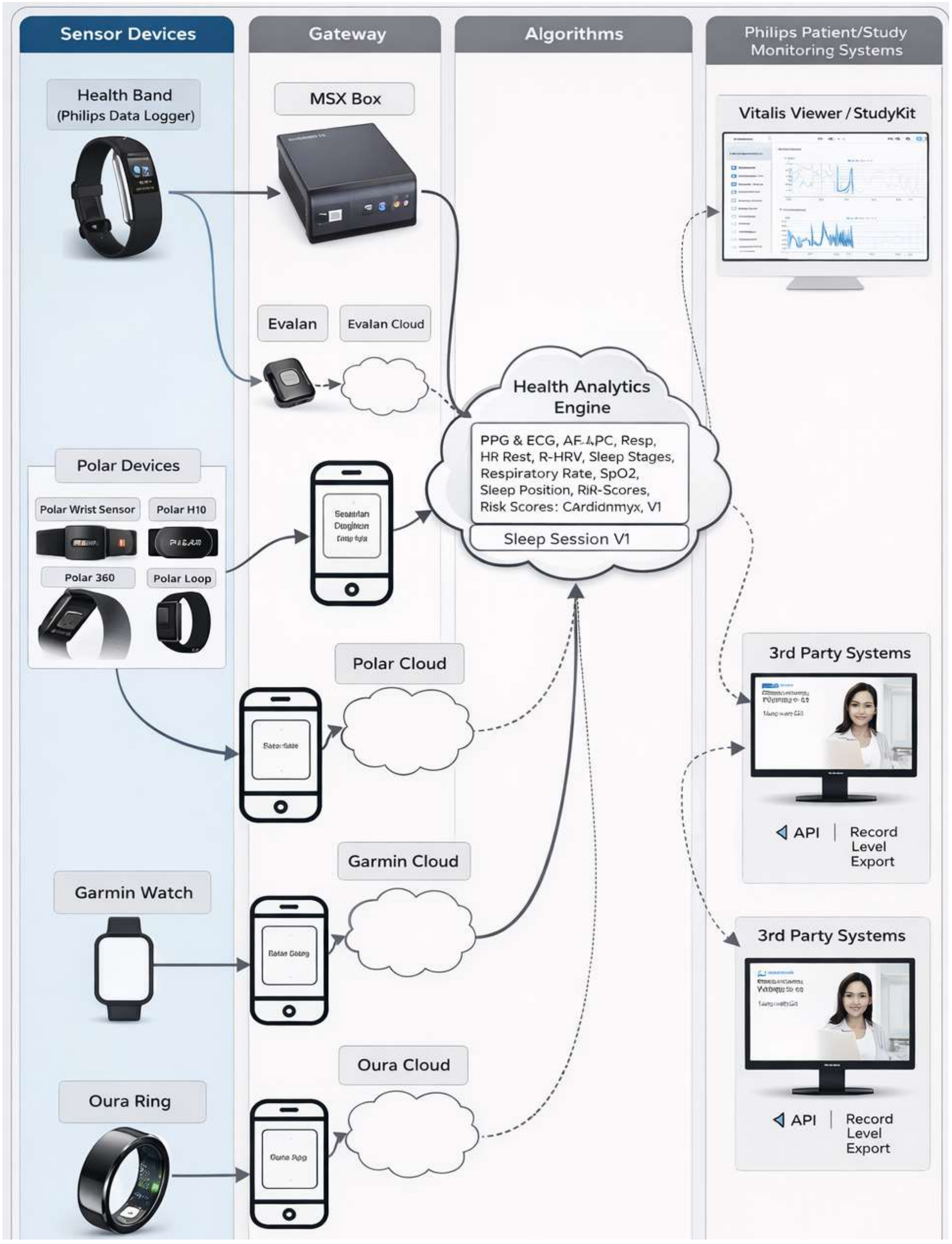


Figure 1: Philips Remote Monitoring Solution

Technical features: The Philips Remote Monitoring solution (Figure 1) is designed as a scalable platform that can support multiple monitoring devices, algorithms, and applications. It enables near-real-time data uploading through a data hub, large-scale cloud-based storage, near-real-time, time-based and event-based cloud processing, and open APIs for uploading and downloading data and algorithm stores. The system also includes secure two-way authentication, role-based access to functionality and data, and interfaces that support patient or study subject monitoring. Withing the RM4Health project, the focus was also on advancing the algorithms for early detection of deterioration. The algorithm store that is part of the remote monitoring solution can be extended to include the algorithms resulting from applying advanced AI techniques to the data collected in the clinical studies in UC1 and similar data collected in an earlier stage (see Figure 2).

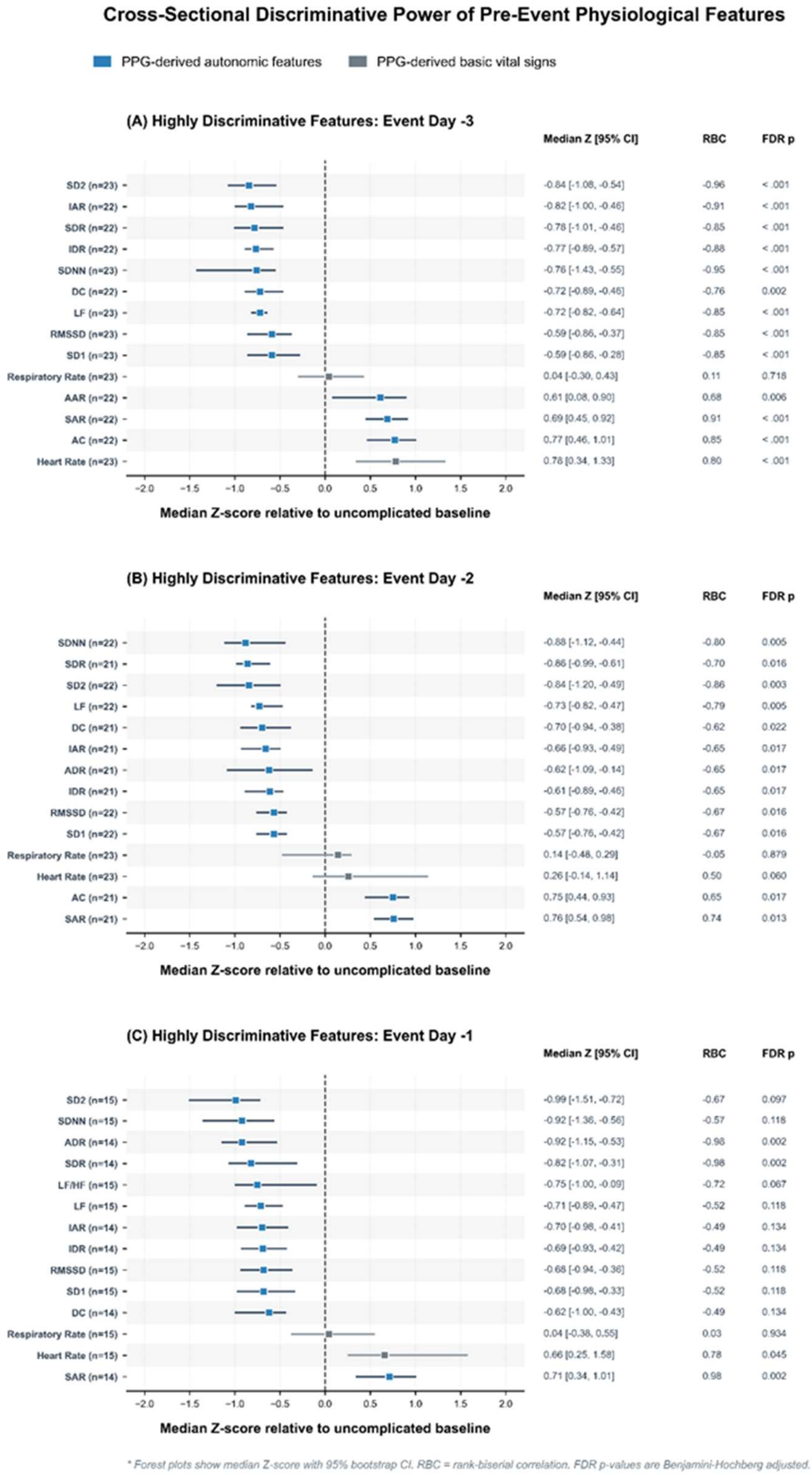


Figure 2: Discriminative power of physiological features

How the technology is used in clinical studies: Within UC1, the technology is applied in studies on chronic heart failure patients, in-hospital recompensation, and peri-operative monitoring for patients undergoing high-risk cardiac or major abdominal surgery. In the chronic heart failure study, the Philips Remote Monitoring system is used with a Philips Data Logger that collects physiological and

behavioural signals such as PPG and accelerometry, from which parameters including heart rate, heart rate variability, breathing rate, energy expenditure, and sleep can be derived. These data are complemented by manually entered measurements such as weight, blood pressure, and symptoms that are collected as part of standard care RPM program. For the peri-operative care study, wearable technologies include devices such as Philips Data Logger, ViQtor and Healthdot.
In addition to the setup that is used in the clinical studies, UC1 also explored alternative data collection routes. UC1 included technical collaboration between Evalan, Polar, and Philips. One proof of concept connects the Polar Verity Sense Band to the Evalan BACE Go gateway using Bluetooth Low Energy to collect PPG and accelerometry data and store these in the Evalan cloud. Another exploration focuses on connecting the Philips Data Logger with the Evalan BACE Go gateway with the Philips Remote Monitoring system receiving (acceleration) data from an Evalan device via an AWS backend.

Research areas: The main research areas are data acquisition, scaling of processing and storage capacity, and data security. In the clinical studies, these areas are applied to remote monitoring for chronic heart failure patients, in-hospital monitoring during recompensation, and peri-operative monitoring for surgery patients.

2.2. State-of-the-art

Patients with chronic heart failure and patients recovering from major surgery are at increased risk of deterioration during transitions between hospital and home. In current standard care, physiological monitoring outside the hospital is still limited. Follow-up often relies on scheduled consultations, patient-initiated contact, intermittent spot measurements, and manual reporting of symptoms, weight or blood pressure. This means that subtle changes in physiological status may remain undetected until symptoms worsen or hospital readmission becomes necessary. UC1 addresses this gap by investigating continuous and repeated monitoring before, during and after hospital care, with the aim of supporting earlier intervention, safer discharge and prevention of avoidable admissions or readmissions.

Globally, remote patient monitoring is moving from isolated home measurements towards integrated models that combine wearable sensors, connected home devices, symptom reporting, cloud-based platforms and clinical dashboards. In heart failure, non-invasive remote monitoring is increasingly explored as a way to detect deterioration earlier, reduce hospitalizations, improve quality of life and support self-care. Wearable-based heart failure monitoring is considered promising because it can capture parameters such as heart rate, rhythm, activity, sleep, respiration and other cardiovascular signals in daily life; however, clinical integration remains challenging because many wearable solutions still require stronger validation, robust data quality handling and integration into clinical workflows.

The state of the art in post-operative and peri-operative monitoring shows a similar shift. Traditional ward and post-discharge monitoring typically depends on periodic vital-sign checks, which may miss early physiological changes preceding complications. Recent work highlights the potential of wearable sensors and digital biomarkers for peri-operative care, including prehabilitation, post-operative recovery monitoring and early detection of complications. At the same time, important barriers remain, including accuracy of measurements, reliability during movement, data security, clinical usability and adoption in routine care.

A major development in the field is the use of artificial intelligence and advanced analytics to move beyond threshold-based alerts. Earlier remote monitoring approaches typically used simple rules, for example triggering alerts when weight, blood pressure or heart rate crossed a predefined value. Current research increasingly focuses on predictive models that combine continuous physiological signals with contextual information and patient-reported outcomes. These models aim to identify patterns of deterioration earlier than conventional monitoring and to generate actionable, personalized alerts for clinicians. In cardiovascular care, the large volume and variability of wearable data make AI methods increasingly relevant for real-time analysis and clinical decision support.
Despite this progress, the field has not yet reached a mature, widely implemented standard of care for continuous remote monitoring of heart failure and peri-operative patients. Key unresolved challenges include selection of clinically meaningful sensor-derived parameters, reliable signal processing in real-world conditions, avoidance of alarm fatigue, explainability of AI-generated predictions, evidence of clinical benefit, and seamless embedding of alerts into care pathways. The most advanced direction is therefore not simply to collect more data, but to transform multimodal wearable and patient-reported data into trustworthy, interpretable and workflow-compatible insights.

Within this context, UC1 contributes to the state of the art by combining non-invasive wearable measurements, cloud-based data acquisition, algorithm execution and clinical monitoring interfaces in the Philips Remote Monitoring system. The use case focuses on parameters relevant to heart failure and post-operative deterioration, including heart rate, heart rate variability, respiratory information, activity, sleep, blood pressure, symptoms and, in the heart failure recompensation setting, thoracic fluid overload. By studying these technologies in heart failure and peri-operative clinical contexts, UC1 supports the broader transition from reactive, episodic follow-up towards proactive, data-driven remote patient management

3. UC2: Detection and monitoring of respiratory diseases using a digital stethoscope

3.1. Technologies resulting from the project

3.1.1. Short description of the use case

Within the RM4Health project, HI-Iberia has developed a digital health solution focused on the detection and monitoring of respiratory diseases through the analysis of lung sounds acquired using a digital stethoscope. The use case addresses one of the major challenges in respiratory healthcare: enabling continuous and remote monitoring of patients outside traditional clinical environments while maintaining reliable and clinically relevant information for healthcare professionals.

The proposed solution combines digital auscultation technologies, cloud computing, mobile applications, biomedical signal processing, and Artificial Intelligence techniques to support early detection of respiratory anomalies and remote follow-up of patients with chronic or acute respiratory conditions.

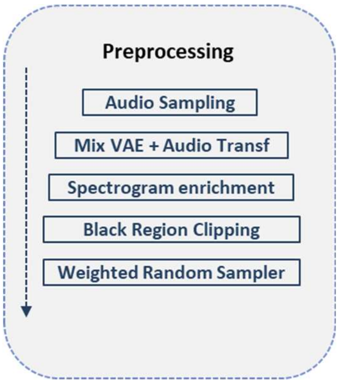
HI-Iberia has been responsible for the design and implementation of the technological platform, including the backend infrastructure, cloud services, AI algorithms, signal processing pipeline, mobile application integration, and healthcare professional dashboard. Clinical stakeholders and healthcare professionals (external to RM4Health project) have supported HI-Iberia in the definition of requirements, validation of respiratory sound recordings and evaluation of the usability of the platform in realistic healthcare scenarios.

The main goal of the solution is to facilitate the identification of abnormal respiratory patterns such as wheezes and crackles, enabling healthcare professionals to remotely assess respiratory conditions and potentially detect early signs of diseases such as COPD, asthma, respiratory infections, or pneumonia.

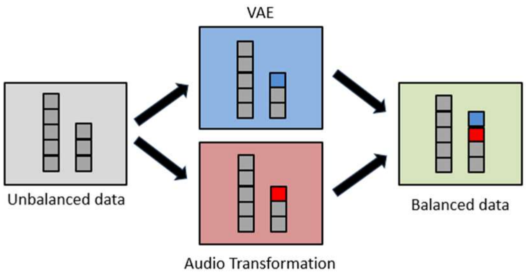
3.1.2. Overview of the technology

Description: The main result of the project is an AI-assisted respiratory analysis platform capable of detecting abnormal respiratory sounds from digital stethoscope recordings and supporting early recognition of respiratory diseases.
The developed technology combines digital auscultation, cloud-based processing, biomedical signal analysis, and Artificial Intelligence algorithms within a single integrated platform.
The system captures respiratory sounds through a digital stethoscope and processes the audio signals using a dedicated AI pipeline capable of detecting abnormal respiratory sounds associated with respiratory diseases.
The technological workflow includes several stages:

1. Acquisition of respiratory audio signals using a digital stethoscope.
2. Signal preprocessing and normalization.
3. Feature extraction from respiratory audio.
4. Application of AI models for anomaly detection.
5. Visualization of results through remote healthcare platforms.



A major innovation of the solution is the incorporation of advanced data augmentation techniques to improve the robustness and accuracy of the AI models. In particular, the platform combines Variational Autoencoder (VAE)-based augmentation with additional audio transformation techniques in order to compensate for the limited availability of clinically annotated respiratory datasets.



The implemented AI models achieved precision values close to 90% in abnormal respiratory sound detection tasks, demonstrating the feasibility of AI-assisted respiratory analysis for telemonitoring applications.
The overall solution has been conceived as a scalable cloud-based digital health platform that can evolve toward broader remote patient monitoring and digital healthcare ecosystems.

Type: New health service

Customers: The platform is particularly relevant for healthcare environments requiring remote monitoring and early respiratory disease detection. The primary customers are hospitals, clinics and telemedicine providers interested in improving respiratory disease monitoring and early diagnosis capabilities. In addition, the solution is suitable for home-care environments and chronic respiratory patients requiring continuous monitoring outside traditional hospital settings.

Technical Features: The developed platform integrates several technical innovations and functionalities specifically adapted to respiratory sound analysis and remote healthcare scenarios.
The core functionality of the system is the detection of abnormal respiratory sounds from breath audio recordings acquired using a digital stethoscope.
The solution incorporates a complete AI pipeline including signal acquisition, preprocessing, feature extraction, classification, and cloud-based result visualization.
One of the key technological innovations developed during the project is the implementation of an advanced data augmentation strategy combining:

- Variational Autoencoder (VAE)-based augmentation
- Audio transformation techniques
- Synthetic respiratory audio generation
- Robust training enhancement methods

These techniques were specifically designed to improve AI robustness and mitigate the scarcity of annotated respiratory datasets.
Additional technical features include:

- Respiratory sound anomaly detection
- AI-based classification of respiratory audio
- Cloud-based processing architecture
- Support for remote and unassisted diagnosis
- Integration with telemonitoring applications
- Scalable infrastructure for healthcare environments
- Audio preprocessing and filtering mechanisms
- Secure data management and remote access

The implemented AI models achieved precision levels close to 90% in respiratory anomaly detection tasks under project validation conditions.

How the technology is used in clinical studies: The technology is used by capturing respiratory sounds through a digital stethoscope connected to a mobile application. The acquired audio recordings are securely uploaded to the cloud platform, where AI-based algorithms automatically process and analyze the respiratory signals to detect abnormal patterns such as wheezes or crackles. The resulting analysis is then made available to healthcare professionals through a remote monitoring interface, enabling clinicians to review recordings, assess respiratory conditions, and support early diagnosis and continuous patient monitoring without requiring the patient to be physically present at the healthcare facility.

Research areas: The project contributes to several research and innovation areas related to Artificial Intelligence, biomedical signal processing, and digital health technologies. More specifically, the work focuses on AI-based anomaly detection in respiratory sounds, deep learning techniques for audio classification, and remote diagnosis support through telemedicine and remote patient monitoring solutions. The use case combines expertise from healthcare, cloud computing, and biomedical engineering to develop scalable AI-assisted respiratory monitoring systems for real-world healthcare environments.

3.2. State-of-the-art

The application of Artificial Intelligence to respiratory sound analysis has become a rapidly growing research field due to the increasing demand for remote healthcare solutions, telemedicine services, and AI-assisted diagnosis systems.

Traditionally, respiratory assessment has relied on manual auscultation performed by healthcare professionals using acoustic stethoscopes. Although this approach remains widely used in clinical practice, it is highly dependent on clinician expertise and subjective interpretation, which can lead to variability in diagnosis quality and limited reproducibility.

The emergence of digital stethoscopes has enabled high-quality recording and storage of respiratory sounds, opening the possibility of applying advanced biomedical signal processing and machine learning techniques to automated respiratory analysis.

Current state-of-the-art approaches in respiratory sound classification commonly rely on deep learning models trained on spectrogram representations of respiratory audio. Convolutional Neural Networks (CNNs) are among the most widely adopted architectures due to their ability to automatically extract discriminative features from time-frequency representations.

Recent research trends include:

- AI-based anomaly detection in respiratory sounds
- Deep learning classification of wheezes and crackles
- Transfer learning techniques using pretrained models
- Audio data augmentation for small medical datasets
- Integration of respiratory AI into telemedicine systems
- Cloud-based remote respiratory monitoring platforms

One of the major challenges in the field is the limited availability of large clinically annotated respiratory datasets. This limitation significantly affects model generalization and robustness in real-world conditions.

To address this issue, recent state-of-the-art research increasingly incorporates synthetic data generation and advanced augmentation techniques. In this context, the RM4Health UC2 approach contributes an innovative augmentation strategy based on the combination of Variational Autoencoders (VAE) and audio transformation methods to improve model robustness and classification precision.

Another major challenge in current respiratory AI systems is deployment in realistic remote healthcare environments. Many existing approaches remain limited to laboratory validation scenarios and lack integration into operational telemonitoring ecosystems.

The RM4Health solution advances beyond traditional experimental approaches by integrating:

- AI-based respiratory anomaly detection
- Cloud-based telemonitoring infrastructure
- Remote and unassisted diagnosis support
- Advanced augmentation techniques
- Scalable healthcare-oriented architecture
- Integration with digital health ecosystems

The achieved precision values close to 90% demonstrate the feasibility and clinical potential of AI-assisted respiratory monitoring using digital stethoscope signals.

Overall, the project contributes to the evolution of digital auscultation technologies toward scalable, intelligent, and remotely deployable respiratory healthcare solutions.

4. UC4: Early detection of heart failure decompensation

4.1. Technologies resulting from the project

4.1.1. Short description of the use case

Use Case 4 (UC4) focused on early detection of heart failure (HF) decompensation through remote monitoring technologies. By leveraging feature engineering based on traditional parameters such as heart rate (HR), heart rate variability (HRV) and respiration rate (RR) combined with more advanced features and activity we approach the detection of HF in a novel way. We utilize modalities like ballistocardiography (BCG, EmFit bed sensor), photoplethysmography (PPG, Polar watch and VTT sensor), ECG (VTT sensor) and activity (accelerometer, Polar watch), as well as other novel modalities and advanced AI modelling to predict and prevent acute heart failure event.

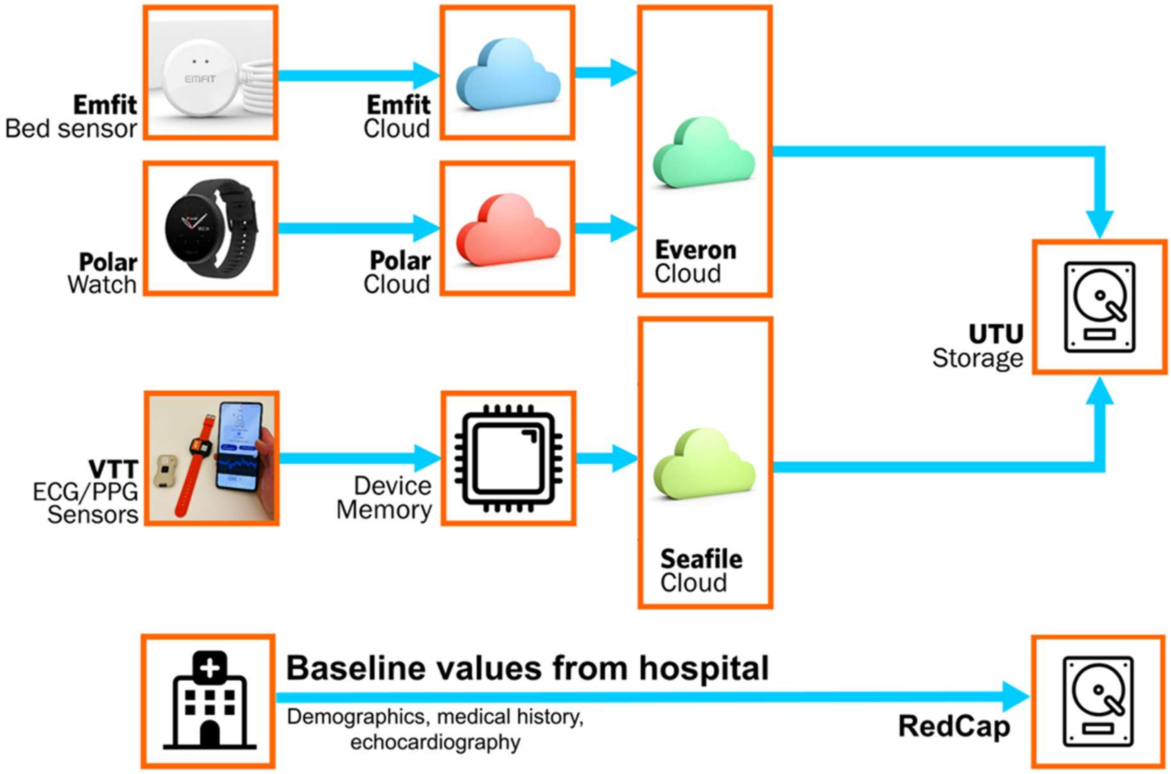


Figure 3: Monitoring solution in UC4 for University of Turku (UTU) trial.

HF patients participating in UC4 are monitored at Turku university hospital, Turku, Finland for up to three months in their home environment, ensuring continuous data collection in real-life settings. Additionally, information about new decompensation will be obtained and a short in-hospital monitoring period is included to gather baseline information and validate the remote monitoring systems' accuracy. This comprehensive approach aims to improve patient outcomes and facilitate a more proactive approach to heart failure management. In addition, spot measurements with dataloggers are made three times for each patient, once at baseline (when patient comes to hospital), once at discharge (when patient is discharged from hospital) and follow-up (after 3 months follow-up) with echocardiography as reference modality. As a part of the use case, methods for continuous and unobtrusive monitoring the pulse arival time (PAT) and derived blood pressure are developed using VTT sensors. In addition, VTT has developed a prototype of a PMUT ultrasound sensor, which can be also be used to estimate the continuous blood pressure by measuring the artery distension. This maturity of this sensor does not yet allow for use in real-life pilots, and was therefore tested in the lab with volunteers.

4.1.2. Overview of the technology

Description: The monitoring system is able to carry out data acquisition, data transfer, intermediate storage and final storage of clinical data as pointed out in Fig. 1. Interactive Power BI dashboard allows the daily monitoring of patients at UTU side and giving feedback to hospital nurses if needed regarding the availability and quality of acquired data. The acquired data is finally analyzed and illustrations related to parameters like HR, HRV and RR are made across the follow-up period are made to illustrate the change in parameters according to the condition of the HF patient. Although the data monitoring system is important, the most relevant part of the project is the data analysis, which finds indicative parameters as well as ML approaches for the prediction of HF decompensation.
Type: New service in the future.
Customers: The results of the project provide a proof-of-concept solution for HF monitoring which can be later supplemented with additional means for product development and additional validation study of the service.
Technical features: Following initial validation, the EmFit and Polar sensors were deployed in the homes of HF patients immediately after hospital discharge, capturing continuous nocturnal data for up to 103 days per patient. To establish clinical ground truth, discharge echocardiograms were compared to a 3-month follow-up. The patients were evaluated also using stroke volume and the E/e' ratio. Nightly aggregated parameters were smoothed using a Kalman filter to isolate underlying physiological trajectories from day-to-day variance. The system combined with statistical analyses provides a proof-of-concept evidence of the method. In addition, we provided and reported an extensive comparison between the signal quality of bed sensor solution between hospital and home in a longitudinal manner and performed ML experiments with various PPG data for SQA (signal quality analysis) and rhythm detection.
The data from the pilot is being used for the training of a ML model for blood pressure and other cardiac or HF disease related parameter estimation (e.g. NYHA). The model will in turn be used in the digital twin (DT) aiming to provide real-time information to patients and doctors on HF related trends. The current number of patients are not yet sufficient for the proper training and evaluation of the DT.
Research areas: Research areas in UC4 include remote monitoring of HF patients including the development data monitoring pipeline ETL (Extract, Transform, Load) process and signal processing and ML methods development for patient monitoring. From a technical perspective, integrating the algorithms into a continuously operating digital twin for HF patients raises its own challenges.

4.2. State-of-the-art

Early detection of HF decompensation with non-invasive sensors is an active area of research, but not yet fully solved. Beyond invasive sensors different proposed approaches include BCG, non-contact radar methods, PPG, ultrasound and various other modalities. One potential way is also to combine different modalities and utilize sensor fusion to this task. Many of the proposed modalities allow extraction of HR, HRV, RR potentially combined with other markers such as activity or step-count and more elaborated features. Beyond engineered features more advanced machine learning (ML) methods are to be seen in the future such as deep learning (DL). Also, traditional ECG, especially wearable and portable approaches can be used to track changes in heart health. Traditional ML algorithms like logistic regression and random forest are common baseline methods due to their interpretability and robustness.

Deep learning, particularly CNNs, has shown remarkable success in recognizing complex patterns in BCG, radar, PPG and ECG signals. These techniques allow deeper analysis of raw data, uncovering subtleties that simpler models might miss. CNNs can automatically extract features, reducing the need for manual feature engineering. UC4 employs non-invasive sensors like BCG, ECG, and Photoplethysmography (PPG) combined with ML methods and physical activity measurements. These approaches aim to improve early detection while minimizing the risks associated with invasive procedures, promoting greater patient comfort and longer-term monitoring capabilities.

The VTT sensors are used to measure pulse arrival time (PAT) which is a class of pulse transition features derived from portable ECG and PPG signals and one of the most promising candidates for implementing continuous blood pressure monitoring solutions in wearable devices because of their simplicity and interpretable nature. PAT is inversely proportional to blood pressure and hence the blood pressure at a given time can be modelled as a linear (simpler models) or non-linear (complex models) combination of PAT features and some model parameters. Traditionally, model parameters are estimated using empirical methods such as least squares. Recently, ML-based algorithms such as gradient descent are also used to estimate the model parameters. There are various other approaches reported in the literature such as adopting DL -based models and using a combination of waveform-based features and PAT features. Although research efforts for developing continuous blood pressure estimation models using pulse transition models have been around for a few decades already, no work extensively addresses the challenges associated with developing and deploying pulse-transition-based models in resource-constrained wearable devices, which one of our targets in this UC.

The PMUT ultrasound sensor array developed by VTT brings in one more modality for observing arterial distension caused by blood pressure variations. The lab tests on volunteers in this project has meant a step forward from previous phantom-based tests towards utilisation in real pilots like this one. Current research challenges focus mostly on making the technology more robust – easy positioning of the sensor and automatic location and tracking of the artery – as well as algorithm development for feature extraction. After the technology is mature enough for daily wearable use, research can move to deploying the sensor data for continuous unobtrusive blood pressure assessment, either by means of a single sensor or as part of a multi-sensor set-up.

5. UC5: Remote Monitoring 4 Elderly Daily Activities

5.1. Technologies resulting from the project

5.1.1. Short description of the use case

Use case 5 focuses on remote monitoring and support for elderly people in home and assisted living environments, with the objective of exploring how wearable and connected technologies can support medication routines, daily activity monitoring and communication with caregivers. The use case combines wearable devices, an intelligent medication dispenser, a pocket hub acting as a gateway/HUB, and remote monitoring applications to support caregivers and elderly users in assisted living scenarios. The overall aim is to investigate how interoperable smart sensing technologies and data analysis approaches can contribute to remote elderly care and assisted living support, as shown in Figure 1.

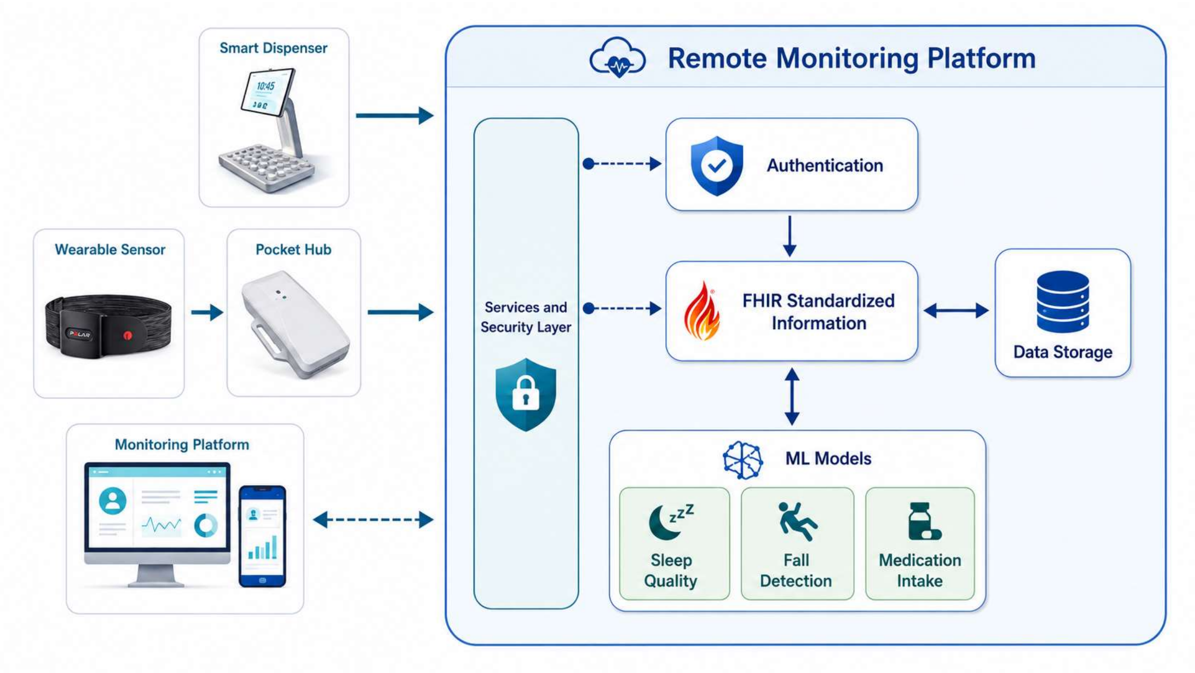


Figure 1. System architecture overview.

The use case explores the integration of wearable devices for monitoring physiological parameters and daily activities, together with medication management, communication functionalities and a pocket hub responsible for supporting communication and data exchange between the monitoring components. The use case also analyses interoperability between sensors, mobile applications, pocket hub components and monitoring interfaces, supporting the development of integrated demonstrators adapted to elderly care contexts. Additionally, UC5 includes pilot and integration activities focused on usability, communication between devices and monitoring components, sensor interoperability, and the exploration of AI-supported approaches for tasks such as medication-related monitoring and behavioural pattern analysis in elderly care environments.

In the Portuguese pilot, the demonstrator is applied in the context of Santa Casa da Misericórdia de Vagos and addresses both institutional and home-based elderly care scenarios. The pilot considers older adults living in residential care facilities, older adults living at home, and formal or informal caregivers, allowing the use case to evaluate the ecosystem from the perspectives of monitoring, care support, usability and longitudinal follow-up.

5.1.2. Overview of the technology

Description: The UC5 technology consists of an integrated elderly monitoring ecosystem combining wearable sensing, medication-routine monitoring, connectivity components, structured questionnaire-based data collection, dashboard-based visualization and caregiver-facing interfaces. The wearable component supports the collection of physiological and activity-related information, while the smart medication dispenser supports medication-routine monitoring in home-based scenarios. The gateway or hub layer provides communication between monitoring components and the broader platform, supporting data exchange and integration between devices, applications, and monitoring interfaces.

Type: New product/service

Customers/users: The potential users include elderly care institutions, home-care providers, healthcare and social-care organisations, caregivers and elderly users involved in assisted living or remote care scenarios.

Technical features: The UC5 demonstrator includes a wearable sensing component, a smart medication dispenser, connectivity mechanisms for data transmission, the RM4Health Portal, and REDCap-based dashboards for questionnaire-derived monitoring data.

The wearable component supports the collection of physiological and activity-related information. In this stream, the wearable sensor communicates with a local hub or control board, which supports data transmission to the broader digital environment. The smart medication dispenser supports medication-routine monitoring in home-based scenarios and acts as the hub for its own data stream, transmitting medication-related information through an internet connection.

The RM4Health Portal acts as the general dashboard and operational interface of the UC5 demonstrator. It supports user, participant, and device management, the introduction of participant information, upload of paper-based questionnaires, and visualization of monitoring parameters and analytical outputs.

In parallel, REDCap is used as the structured data collection platform for questionnaire-based follow-up. REDCap-derived data are visualized through two complementary dashboards: an aggregated and anonymized dashboard for group-level monitoring, and a participant-specific dashboard for individualized longitudinal follow-up. These dashboards support descriptive monitoring of the study population, visualization of questionnaire-derived indicators, review of repeated follow-up records, and data-completeness checks.

How the technology is used in pilot activities: Within UC5, pilot activities focus on the Portuguese elderly-care setting and combine technical integration with the analysis of questionnaire-based follow-up data. The demonstrator integrates REDCap data collected by Santa Casa da Misericórdia de Vagos with sensor-derived and medication-dispenser-derived data streams, consolidating them within the pilot's monitoring and dashboard environment.

The integrated system supports aggregated, individualized and data-quality dashboard views, enabling descriptive monitoring of the study population, longitudinal inspection of participant profiles, and verification of data completeness across instruments, participant groups and connected data sources. Wearable-derived data and smart medication-dispenser data are incorporated into the broader monitoring workflow, allowing questionnaire-based information to be complemented with continuous or event-based digital data.

Research areas: The main research areas include wearable sensing, medication-routine monitoring, gateway and hub architectures, sensor and platform interoperability, structured longitudinal data collection, REDCap-based dashboards, participant-level follow-up, data-quality assessment, caregiver-facing monitoring interfaces, usability in elderly-care settings, and AI-supported analysis of elderly monitoring data.

5.2. State-of-the-art

Remote monitoring technologies are increasingly important for supporting older adults to live independently and safely for longer. Recent advances in wearable devices, mobile sensing, telemedicine, eHealth and Internet of Things technologies have enabled repeated or continuous monitoring of activity levels, mobility patterns, physiological parameters, sleep, medication routines and daily behaviours outside traditional care settings.

Commercially available devices such as smartwatches, smart bands, smartphones, activity trackers and electronic medication dispensers already provide useful functionalities for health monitoring and medication management. However, many current solutions still operate as standalone systems, with limited interoperability, restricted integration of heterogeneous data streams, and incomplete communication between older users, caregivers, and healthcare providers.

Recent evidence on consumer-grade wearable and mobile sensing technologies combined with machine learning shows increasing interest in domains directly relevant to elderly care, including activities of daily living monitoring, gait and mobility assessment, fall detection or fall-risk assessment, frailty assessment, cognitive-related monitoring and Parkinson-related functional monitoring. Across this literature, inertial sensing remains the dominant technical approach, especially accelerometry and related motion signals collected from wrist-, waist-, trunk- or hip-worn devices. These data are commonly used for activity recognition, mobility characterization, and fall-related applications. In some studies, inertial data are complemented by physiological signals such as photoplethysmography, heart rate, skin conductance, or temperature, which may help contextualize activity, exertion, sleep, or changes in health status.

Machine learning approaches in this field range from classical models, such as support vector machines, decision trees, random forests and k-nearest neighbours, to deep learning architectures, including convolutional and recurrent neural networks. These models are mainly used for classification tasks, including activity recognition, mobility-pattern identification, fall detection, and functional-status estimation. However, the evidence base remains methodologically heterogeneous. Studies differ substantially in participant characteristics, care settings, sensor placement, data-collection protocols, outcome definitions, validation strategies, and reporting quality. Therefore, strong technical performance in one study cannot be assumed to generalize automatically to other older-adult populations, care environments, or device configurations. This reinforces the importance of transparent reporting and validation practices for AI-supported models used in health-related contexts.

A central limitation of the current state of the art is the gap between technical model performance and practical clinical or care relevance. Many studies report accuracy, sensitivity, specificity, F1-score, area under the curve or similar model-level metrics, but fewer report outcomes that are directly meaningful for older adults, caregivers or care organizations, such as functional decline, fall incidence, quality of life, medication adherence, caregiver workload, usability, acceptability or service-level impact. External validation, long-term follow-up and evaluation in free-living conditions remain limited. As a result, wearable- and AI-based elderly monitoring should currently be understood as technically promising, but not yet as a mature or routinely validated standard of care.

Implementation also depends on ethical, regulatory, and usability-related factors. Continuous monitoring raises issues related to privacy, data protection, consent, data governance and user trust, particularly when systems collect longitudinal behavioural and physiological data in home or assisted-living environments (European Parliament and Council of the European Union, 2016). Depending on the intended use and claims made about the system, medical-device regulation may also become relevant for monitoring technologies and AI-supported outputs used in care contexts (European Parliament and Council of the European Union, 2017). Digital health literacy, comfort, perceived usefulness, accessibility and co-design with older adults, caregivers and care professionals are also critical for sustained adoption. These factors are especially relevant in elderly care, where cognitive, sensory, motor or social limitations may affect the ability to use and maintain digital monitoring technologies over time.

Within this context, UC5 contributes to the state of the art by investigating an integrated remote monitoring ecosystem for elderly care. The demonstrator combines wearable sensing, medication-routine monitoring, smart medication dispenser, hub-based connectivity, structured questionnaire data, dashboard-based visualization, data-management components, and caregiver-facing interfaces. This approach addresses several limitations identified in the current field by moving beyond isolated device-based monitoring toward an interoperable system focused on longitudinal follow-up, medication routines, communication reliability, caregiver support, usability and suitability for real home and assisted-living contexts. AI-supported outputs should therefore be interpreted as supportive monitoring information rather than diagnostic or fully automated clinical decision-making.

Overall, the state of the art indicates that remote elderly monitoring is moving from single-device measurement toward integrated, multimodal, and caregiver-oriented ecosystems. The key innovation challenge is no longer only the development of accurate algorithms, but the creation of trustworthy, usable, interoperable and validated monitoring systems that can operate in everyday elderly-care environments.

6. UC6: Exercise monitoring for sports and rehabilitation

6.1. Technologies resulting from the project

6.1.1. Short description of the use case

The UC6 demonstrator shows a novel sport monitoring workflow that integrates biometric sensor data (heart rate) with synchronized video recordings, visualized in an immersive XR environment for post-training analysis.

During real training sessions, athletes were equipped with Polar Team Pro sensors while activities were recorded using both 360° and conventional cameras. Data from all sources was timestamped, enabling accurate offline synchronization. Sensor data was retrieved via API into the Everon data platform and combined with processed video streams.

A custom Unity-based XR application running on a PICO 4 headset enabled immersive playback, where biometric data was overlaid directly onto 360° video. Users could interactively control playback, switch players, and explore physiological responses in context. The demonstrator successfully shows that XR-enhanced visualization provides clear added value over traditional 2D dashboards by linking physiological responses with spatial and situational context.

Partners in this use case are Polar Electro Oy, Everon, and Nokia Oyj.

6.1.2. Overview of the technology

Description: UC6 demonstrates a sport use case where HR data of the player is combined with a video stream. AR/VR technologies are used to improve user experience and help the coach in getting the situational information from the training session.

Type: New product/service

Customers: Coaches, athletes

Purpose of use:

- Produce video coaching material for the players, where certain situations can be viewed from several different perspectives on the field
- Players technical and tactical guidance at field
- Physical deficiencies in performance situations are demonstrated
- Encourage the development of specific capabilities for special situations

- Measurement of biometric information of players in a team
  - Calculate advanced metrics from the collected data
  - Visualize the data with AR/VR tools (Panning the Field View During Operation)

Research areas:

- AR/VR technologies
- Bio signal measurements

Integration constraints: The use case is strongly dependent on location data and its accuracy. GPS is limited to outdoor applications, whereas e.g. UWB technology is needed for indoor applications.

Use case demonstrated:

- Reliable data acquisition and transfer
- Accurate timestamp-based offline synchronization
- Stable XR playback and overlay rendering
- Meaningful user experience for coaching and analysis

6.2. State-of-the-art

The state of the art in this area combines multimodal data integration, advanced analytics, and immersive visualization technologies to support sports performance analysis. Modern systems typically fuse wearable sensor data, such as heart rate, GPS, and motion signals, with synchronized video recordings from multiple camera sources.

This integration enables a more comprehensive understanding of athlete performance by linking physiological responses to movement and tactical context. A key component of current solutions is precise synchronization between heterogeneous data streams. While timestamp-based alignment remains widely used, advanced systems increasingly apply AI-based synchronization methods that automatically correct timing offsets. This allows more accurate matching between sensor signals and visual observations, especially in dynamic environments.

Another important trend is the use of computer vision and pose estimation techniques. These enable automatic extraction of biomechanical and positional data directly from video, complementing wearable sensor measurements. Such approaches allow deeper insights into movement efficiency, workload, and injury risks.

In terms of visualization, immersive technologies such as virtual reality (VR) and extended reality (XR) represent a rapidly emerging frontier. Instead of traditional 2D dashboards, analysts and coaches can explore training situations in a spatial and interactive way. Overlaying biometric data onto 360° video in XR environments enhances situational awareness and improves understanding of cause-and-effect relationships.

User interaction and experience design are also central to state-of-the-art systems. Modern platforms emphasize intuitive controls, interactive timelines, and the ability to compare players or scenarios seamlessly. This supports more effective coaching and decision-making processes.

Finally, leading solutions are increasingly incorporating AI-driven analytics. These systems can automatically detect key events, identify performance patterns, and generate actionable insights.

Overall, the state of the art is moving toward real-time, intelligent, and immersive sports analytics ecosystems.

7. UC7: Physical fitness assessment and personalized guidance

7.1. Technologies resulting from the project

7.1.1. Short description of the use case

Use Case 7 focuses on improving lifestyle and health by translating knowledge and best practices from the Olympic and elite sports sector into guidance for the general population. The use case addresses key lifestyle domains, including physical activity, strength development, cardiovascular fitness, nutrition, and mental wellbeing.

The guidance is delivered through an interactive app that supports users over time through a personalised timeline. This timeline provides tailored recommendations, activities, and information based on the user's preferences and collected data. As the user continues to interact with the app, the timeline is dynamically adapted to better match the individual's needs, behaviour, and progress.

Smart data collection and artificial intelligence/machine learning techniques are used to support this personalisation process. In this way, UC7 aims to provide an evolving, user-centred lifestyle intervention that helps individuals adopt healthier behaviours based on insights from high-performance sport.

7.1.2. Overview of the technology

Description: Use Case 7 demonstrates the smartphone/tablet application that uses AI-based lifestyle profiling to deliver personalised health and well-being advice. The demonstrator is built around the Patient Journey App (PJA) platform (Interactive Studios, the Netherlands), which serves both as the data-collection channel and as the delivery channel for personalised advice. Users complete structured lifestyle questionnaires within the app — covering physical activity, nutrition, sleep, stress, mental well-being, social participation, substance use and quality-of-life indicators — and optionally connect commercially available biometric devices (e.g. Apple Watch, step counters, blood-pressure meters) via Apple HealthKit or Google Health Connect. Responses are transmitted in near real-time to a cloud-based backend. https://www.patientjourneyapp.com/

Type: New product

Industrialization: This patient journey app is unique and already running in many hospitals and patients/doctors are using it.

Deploy the Patient Journey app to insurance companies, industry, ministry.

Customers: Hospitals, Care centers, fitness people, patients, Healthy people

Technical features: The AI component is a Latent Class Analysis (LCA) clustering model that has been trained on a synthetic dataset representative of the target population and that assigns each user to one of five to six lifestyle profiles. Classification results are returned to PJA via a RESTful JSON API, after which the platform automatically configures the educational content and health modules shown

to the user. No new hardware is developed in UC7; the demonstrator runs on commercial off-the-shelf consumer devices.
Testing of the demonstrator is performed in two phases. In Phase 1, the trained LCA model is validated on the synthetic dataset to confirm statistical fit, class stability and the correct functioning of the PJA-API integration. In Phase 2, a live cohort of 25 participants (employees at Interactive Studios) — varied in age, gender, educational level and health status — was recruited to validate the demonstrator end-to-end under realistic conditions.
The application is available on iOS and Android platforms for patients. Various devices (weight scale, smart watch, smart phone, etc.) are linked to the smartphone through Apple Health Kit or Google Health Connect. An internet connection is mandatory for both the PJA app and the PJA platform.

How the technology is used: Monitoring of participants takes place through the Patient Journey App (PJA). The app collects manual or device-delivered data (e.g. weight, blood pressure, quality of sleep, stress scores). This data is processed. Every time a quick-scan or vitality check-up is performed the data is processed and outliers are communicated through the app for self-management purposes and/or to an external coach.
The app is available and easy to use and allows participants to share their data. The app sends participants a reminder to share their data, especially when the data does not come from automated source (e.g. Bluetooth weight scale). The PJA platform will allow health/lifestyle professionals to monitor the data, receive alerts and communicate with participants via the app.

Research areas: preventive health

7.2. State-of-the-art

Digital lifestyle and health applications increasingly combine user-facing coaching with data-driven personalisation. Current solutions typically support behaviour change in domains such as physical activity, fitness, nutrition, sleep, stress management, and mental wellbeing. They often use a combination of device-generated data, such as steps, heart rate, activity intensity, sleep patterns or wearable sensor data, and subjective user input, such as goals, preferences, symptoms, perceived exertion, mood, stress, dietary habits or self-reported barriers. Based on these inputs, apps can provide tailored feedback, recommended activities, educational content, reminders, progress visualisations, and goal-setting support.

A major development in this field is the move from static, one-size-fits-all recommendations towards adaptive and personalised interventions. Reviews of personalised mobile technologies suggest that tailoring content to an individual's goals, behaviour and context can support lifestyle change, although effectiveness varies across studies and intervention designs. Digital and mobile health interventions are therefore increasingly seen as useful adjuncts to existing health and wellbeing services, provided that they are matched to the user's goals, preferences, motivation, literacy and context.

Wearables and connected devices have strengthened this trend by enabling continuous or repeated measurements in daily life. Activity trackers and smartwatches can capture behavioural and physiological signals outside clinical or laboratory settings, allowing apps to monitor progress and provide feedback close to the moment of behaviour. Evidence indicates that wearable activity trackers can contribute to improvements in physical activity and related outcomes, but their impact depends on how the data are translated into meaningful guidance and sustained engagement.

The most advanced approaches are moving towards just-in-time adaptive interventions. These interventions aim to provide the right type and amount of support at the right moment by adapting to a user's changing internal state and external context. In practice, this may mean using sensor data, smartphone data and self-reports to identify when a user is receptive to a prompt, at risk of inactivity, or likely to benefit from a specific recommendation. Machine learning and other adaptive methods are increasingly explored to support this form of hyper-personalisation, although the development and validation of such interventions remain complex.

At the same time, the state of the art shows several limitations. Many apps still rely on relatively simple rules, generic goals or manual user input, and evidence of effectiveness is variable. Sustained engagement remains a challenge, especially when feedback is not perceived as relevant or actionable. There is also a need for stronger integration of objective device data with subjective user data, so that recommendations reflect not only what users do, but also how they feel, what they prefer, and what barriers they experience. For UC7, the opportunity lies in combining elite-sport knowledge with adaptive digital coaching, using both sensor-based and self-reported data to provide personalised recommendations, proposed activities and information that evolve over time.