SYMPHONY

Eco-system for disease specific clinical workflow and data integration

DELIVERABLE D6.9

Documentation of the completed demos and pilots

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V0.1	19/01/2026	Starting version, template
V1.0	30/03/2026	Reviewed final version

TABLE OF CONTENTS

1 Introduction

1.1 Aim of the activity

This deliverable D6.9 gives and overview of the demonstrated prototypes and pilot studies completed during the Symphony project and cover all four use cases are: UC1: Prostate Cancer, UC2: Aortic Aneurysm, UC3: Atrial Fibrillation, UC4: Multiple Sclerosis.

This deliverable D6.9, will provide and introduction for each use case, show the Symphony architecture and briefly describe the different prototypes.

1.2 Contributors

Use case	Section	Use case Editors
1	Prostate Cancer (PC)	Karolinska University Hospital
2	Aortic Aneurysm (AA)	Leiden University Medical Center
3	Atrial Fillbrillation	Amsterdam University Medical Center
4	Multiple Sclerosis (MS)	Innova, IntellectiaCS
	Global editor	Leiden University Medical Center

1.3 Glossary

AA	Aortic Aneurysm
AAA	Abdominal Aortic Aneurysm
AF	Atrial Fibrillation
AI	Artificial Intelligence
CNS	Central Nervous System
CSF	Cerebrospinal fluid
CT	Computed Tomography
DRE	Digital Rectum Exam
ECG	Electrocardiogram
EMR	Electronic Medical Record
FDA	Federal Drug Administration
GDPR	General Data Protection Regulation
GP	General Practitioner
HDF	Health Declaration Form
HIS	Hospital Information System
IoT	Internet-of-Things
LA	Left Atrium
LAA	Left Atrial Appendage
LAAC	Left Atrial Appendage Closure
MDT	Multidisciplinary Team
MRI	Magnetic Resonance Imaging
PACS	Picture Archiving and Communication System
PCa	Prostate Cancer
PET	Positron Emission Tomography
PPG	Photoplethysmography
PSA	Prostate Specific Antigen
TAA	Thoracic Aortic Aneurysm
TNM	Tumor Node Metastasis
US	Ultrasound

2 UC1: Prostate Cancer

2.1 Introduction

Prostate cancer (PCa) is the most common cancer among men in Europe. About 450 000 European men are diagnosed with PCa each year. PCa is the number one killer among cancers in men in Sweden. However, only 10% die within 5 years after diagnosis and most men diagnosed with prostate cancer will die due to other causes. Having low case fatality rate, PCa care has a low tolerance for side effects of treatment. Radical prostatectomy – a well-established primary treatment option for localized PCa – comprises trade-offs between complete removal of the tumour and the loss of functions relying on tissue close to the prostate, such as the erectile nerves situated less than 1 mm from the prostate. Very radical treatment leads to incontinence, erectile dysfunction and other, often life-long, sequalae.

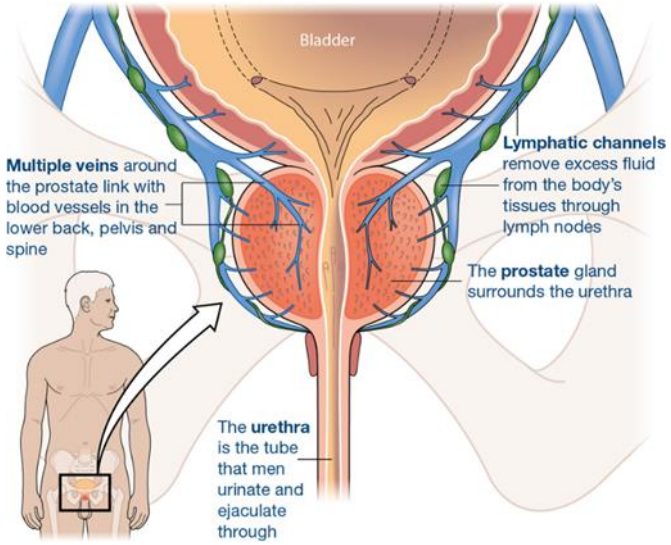
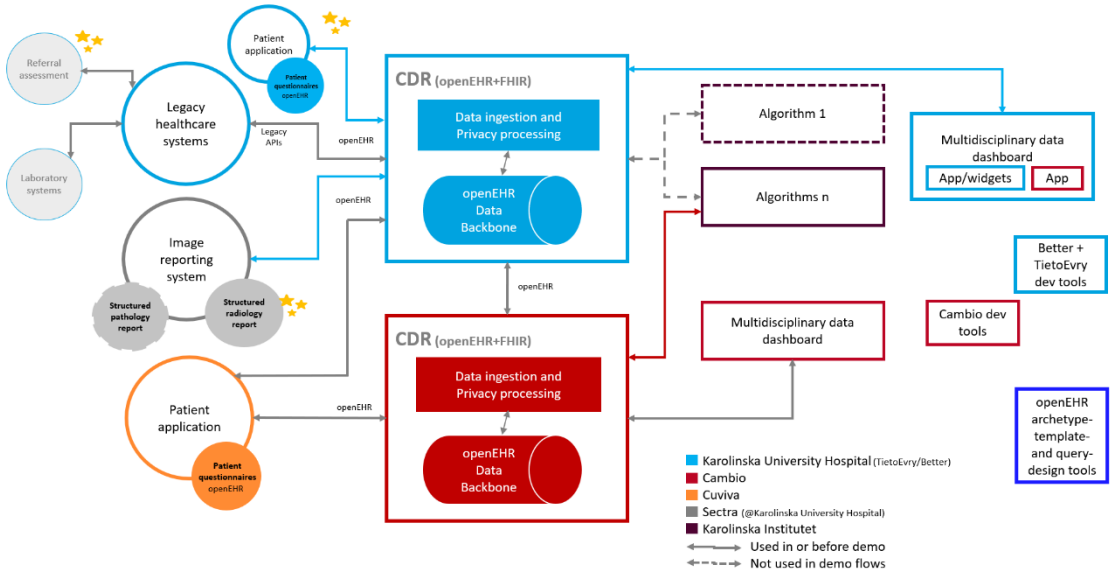


Figure 1 Schematic overview of the prostate and surrounding organs.

Each clinical decision is based on multimodal diagnostics and patient-specific conditions; each treatment and diagnostic modality involves several different clinical professions; the influx of patients is high; the care processes have long duration, and the patients are followed for several years after treatment with respect to oncological and functional outcomes. Therefore, there is a need for a patient-centric, data-driven PCa care approach, focusing on risk stratification, automation, and visualization. Here, we describe how the SYMPHONY reference architecture was employed at Karolinska University Hospital (KAR) to enable compiled visualisation of diagnostic information and data-driven decision-making, ultimately to improve the quality and efficiency of the pre-, peri- and post-prostatectomy care flow.

2.2 Architecture

Here the architecture is listed for the PCa use case.



The UC1 implementation of the SYMPHONY reference architecture incorporates a way of working that ensures semantic interoperability through the creation and use of openEHR archetypes and templates, which are deployed simultaneously in both the source systems and the downstream components (see image 1)

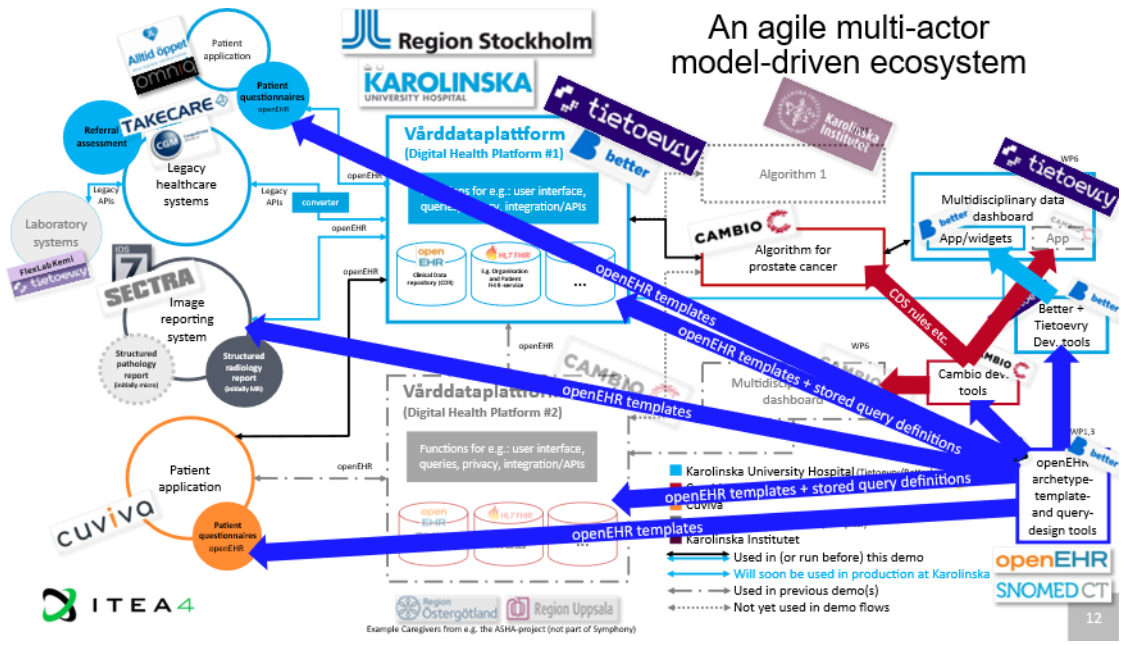


Image 1. An agile, multi-actor, model-driven ecosystem using openEHR

2.3 Demonstrators

The PCa demonstrator in UC1 includes the collection of structured radiology, urology, pathology, and patient-reported data, all modelled in openEHR and sourced from hospital information systems. The data are stored in a central Clinical Data Repository (CDR), then compiled and visualised in a dashboard that also provides automated risk stratification using a third-party Clinical Decision Support (CDS) tool. This process aligns with the clinical pathway models developed within SYMPHONY (WP3).

Access to patient-reported data is essential for treatment selection and for assessing the quality of care. Within the PCa workflow, patients regularly complete sequelae-related questionnaires, from which relevant data are extracted to support treatment decisions, care delivery, and follow-up. In UC1, Cuviva has developed a SaaS-based remote monitoring platform that supports the collection and automated use of patient-reported data (image 2).

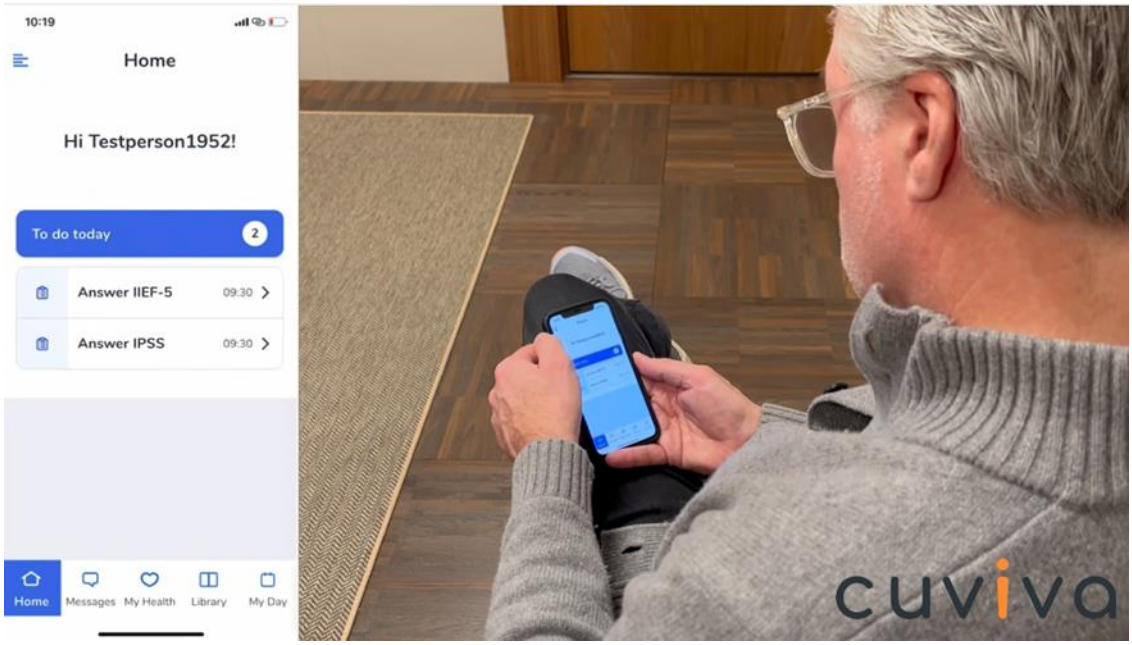


Image 2. Cuviva's patient app

The tools for structured radiology assessment provided by Sectra (a third-party collaborator to Karolinska University Hospital) enable the creation of reporting forms directly from openEHR templates (image 3). Within SYMPHONY, KAR received a mandate from openEHR International to model prostate radiology data in collaboration with clinicians and informaticians from several European countries. The resulting archetypes were then used to capture structured prostate radiology data for downstream use.

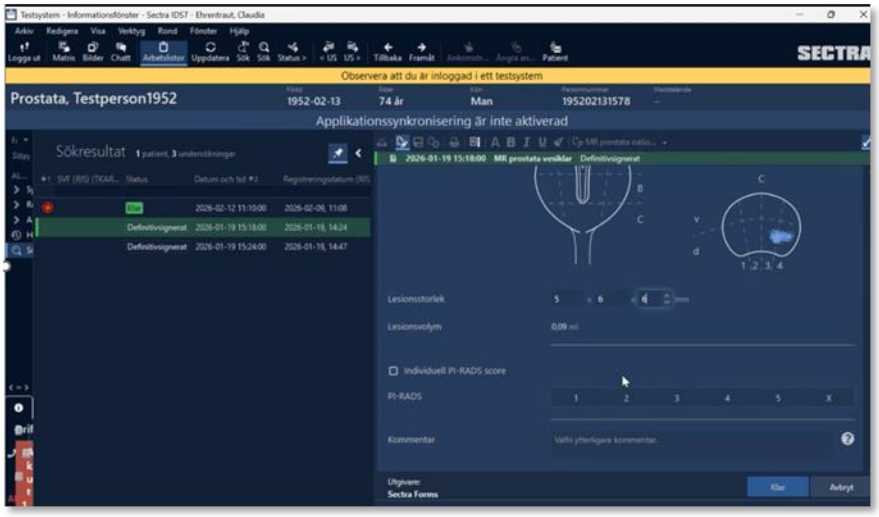


Image 3. Reporting module for prostate radiology assessment

The multidisciplinary team meeting (MDT) is a cornerstone of modern cancer care. During MDTs, healthcare professionals consolidate relevant clinical information and formulate treatment recommendations. Access to integrated, well-structured, and purposefully visualised data has been shown to improve both the quality and efficiency of MDT discussions.

In UC1, Tieto/Better's Care Desktop application (a third-party collaborator to Karolinska University Hospital) was used to retrieve data from the CDR. Using AQL queries, multimodal data can be processed and displayed in configurable widgets, as illustrated in image 4. In addition, risk categorisation according to national guidelines is provided by Cambio's Clinical Decision Support (CDS) system, which uses Guideline Definition Language (GDL)—a formal, machine-readable standard for representing clinical rules and practice guidelines. The CDS works exclusively using openEHR.

Anonymised parameters originating from multiple source systems are automatically transferred from the CDR to the CDS, which then computes and returns a risk assessment score (shown in the bottom right of image 4). In this way, UC1 demonstrates the automated use of multimodal clinical data for predictive modelling in clinical decision-making.

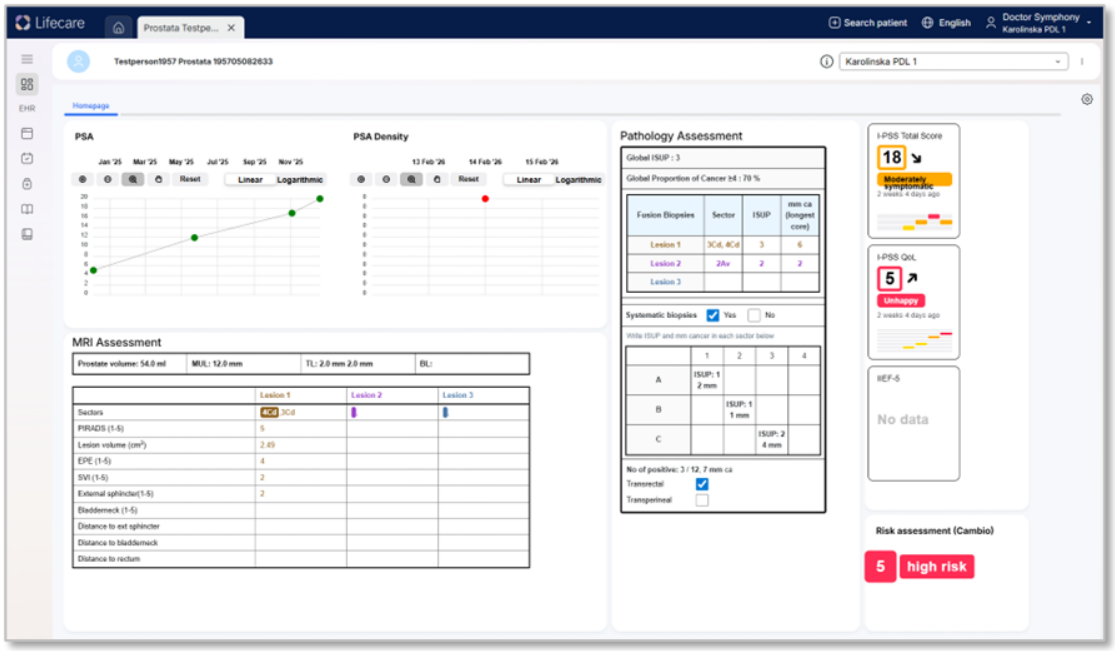


Image 4 Compiled visualisation in Care Desktop for clinical decision-making at multidisciplinary team conferences where prostate cancer patients are being discussed.

2.4 References

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3 UC2: Aortic Aneurysm

3.1 Introduction

The aorta, which is the largest artery in the body, carries oxygenated blood from the heart to the rest of the body, and is susceptible to dilation in certain circumstances. An aortic aneurysm occurs when there is a localized dilation, bulging, or expansion of the aortic wall that exceeds 1.5 times the normal diameter of the artery. This can occur anywhere along the aorta but is most seen at the level of the abdominal aorta (abdominal aortic aneurysm, or AAA) or in the thoracic aorta (thoracic aortic aneurysm, or TAA).

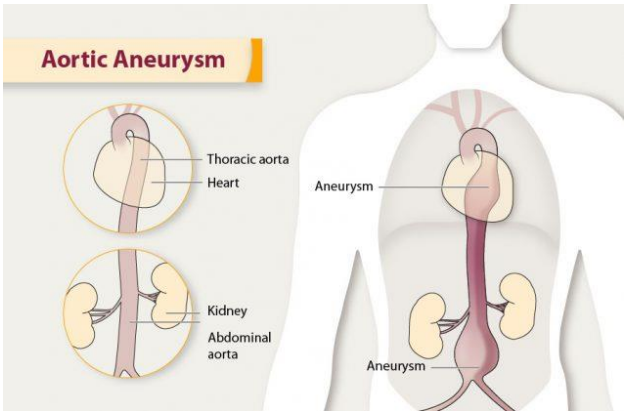


Figure 2 Thoracic and Abdominal aortic aneurysms. Source: [1]

The most common underlying cause of aortic aneurysms consists of weaknesses in the wall of the aorta resulting from degeneration, inflammation, or other chronic medical conditions. For instance, patients with hypertension, atherosclerosis, connective tissue disorders (e.g., Marfan syndrome, Ehlers-Danlos), infections (e.g., syphilis, Lyme disease) are at increased risk of developing aneurysms.

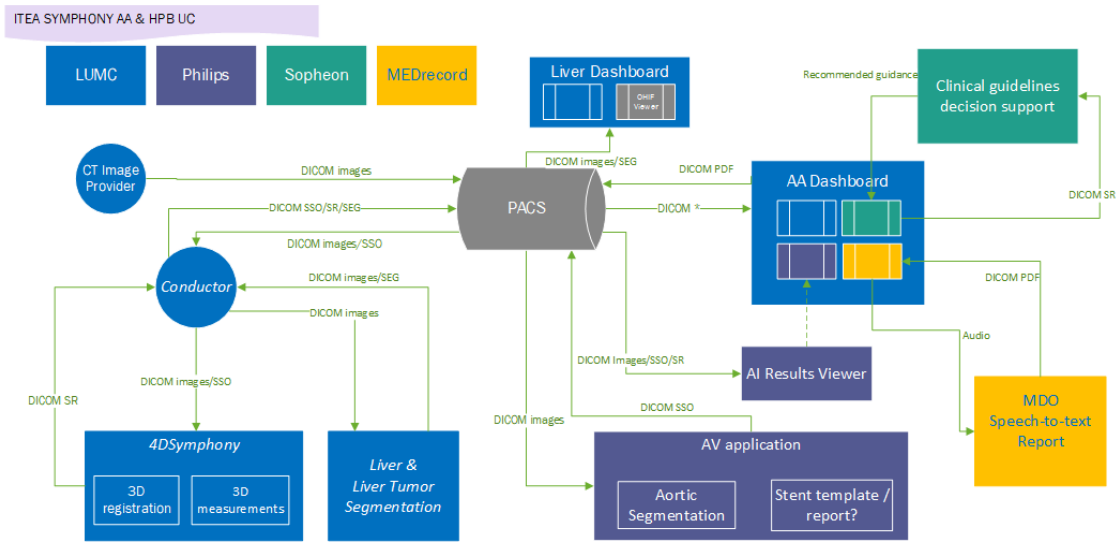
Aortic aneurysms can be asymptomatic, especially at earlier stages. Often, patients are unaware of the condition until an imaging study is performed for another reason. If the aneurysm is discovered at this stage, patients may be monitored closely and undergo routine ultrasound (US), computed tomography (CT) or magnetic resonance imaging (MRI) scans to track the aneurysm over time.

If the aneurysm ruptures, it can cause a life-threatening condition, including massive bleeding that can result in death. Apart from rupturing, another dangerous complication that can arise from aortic aneurysms includes dissection, which is where an abnormal tear occurs in the innermost layer of the aortic wall, causing blood to spread between the layers of the aortic walls, and increasing the chances of aneurysm rupture. Dissections can lead to complications, such as stroke, paralysis, and other organ damage, especially if the aneurysm dissects in or near major aortic branches to key organs, such as the brain or kidneys. Typically, patients with symptomatic or rapidly growing aneurysms, or aneurysms at specific locations, need more aggressive treatment.

The treatment of aortic aneurysms will depend on an individual's overall health, the location and size of the aneurysm, and other factors such as age, lifestyle, and personal preference. The goals of treatment for an aortic aneurysm are to prevent the aneurysm from rupturing, relieve symptoms, prevent enlargement, and avoid complications.

3.2 Architecture

Here the architecture is listed for the aortic aneurysm (AA) and liver cancer (HPB) use case.



The Aortic Aneurysm (AA) use case demonstrator shows the versatility of the DICOM Standard in storing and exchanging (medical) information. It combines applications and algorithms from Philips, MEDRecord, Sopheon and the LUMC.

DICOM (Digital Imaging and Communications in Medicine) is the international standard for transmitting, storing, retrieving, printing, processing and displaying imaging information. DICOM data is typically stored in a PACS (Picture Archiving and Communication System) database system.

As part of the 3rd change request, LUMC has also integrated Liver and Liver tumor segmentation algorithms based on earlier work from the ITEA ASSIST project. The goal of this additional mini use case is to show how easy it is to integrate existing AI-based segmentation algorithms into the Symphony architecture.

3.3 Demonstrators

The final demonstrator consists of 2 parts:
1. Tracking the (Semi-)Automatic analysis of Computed Tomography data for the analysis of Aortic Aneurysms using a dashboard
2. Discussing an AA patient who had a follow-up scan in a multi-disciplinary team (MDT) meeting using the dashboard

The first part demonstrates the analysis workflow of a follow-up scan made for a patient whose aortic aneurysm is tracked pre- or post-intervention. After a patient gets a (CT) scan to track aortic aneurysm changes over time, the scan is sent to and stored in the Hospital PACS. A clinical specialist can track the analysis status on the AA Dashboard of the patient to see if the case is ready to be discussed in an MDT meeting. From the PACS, the data is first sent to the Philips AV application where all relevant parts for aorta aneurysm analysis are segmented and sent back to the PACS system as DICOM SSO (surface segmentation object). Once the DICOM SSO is stored in the PACS this is also indicated on the AA Dashboard. Next the segmented aorta needs to be compared to a previous time point. For this a command is sent to the Conductor, a DICOM Universal Procedure Step (UPS) manager. The Conductor retrieves the DICOM image and SSO from both the current and a previous time point from the PACS and sends them to the 4DSymphony application. The 4DSymhpony application first registers the two segmented aortas onto each other so the 3D aortic aneurysm measurements can be properly compared. The 3D measurements and differences between the two timepoints are sent back to the Conductor as a DICOM Structured Report (SR). The DICOM SR is sent back to the PACS by the Conductor and the AA Dashboard is updated accordingly.

The second part demonstrates a multi-disciplinary team (MDT) meeting where the patient is discussed once both the aortic aneurysm segmentations and 3D measurements are available. At the start of the MDT meeting audio recording using HealthTalk.ai is setup. HealthTalk.ai has a new MDT meeting functionality to create automatic reports which can be generated once the meeting has ended. During the MDT meeting the LUMC AA Dashboard provides a general overview while the Philips AI Results Viewer can be used for a more detailed and integrated view of the DICOM image, SSO and SR data.

The DICOM SR information is also sent to the Sopheon Clinical Guidelines decision support system which uses algorithms created by the clinician to calculate the measurement data/values (the DICOM data are converted), absolute values as well as trend values, and to generate up-to-date treatment advice (notifications) based on the clinician's algorithm, which is based on the latest European guidelines.

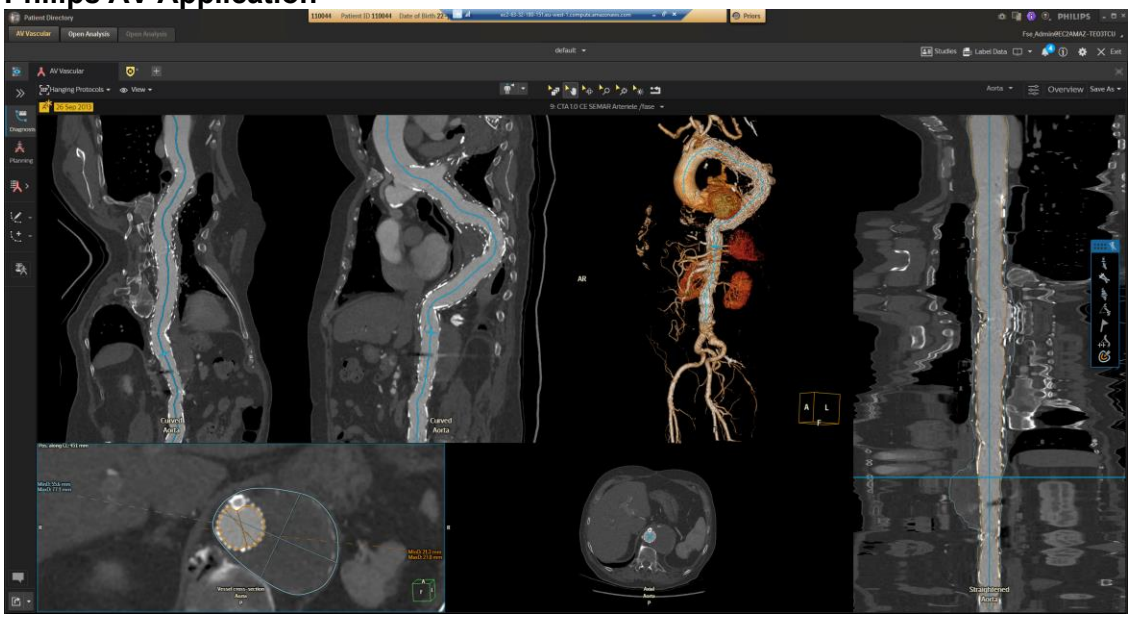
The third part of the demonstrator details the treatment planning in liver oncology. It’s a mini use case to demonstrate the flexibility and extendibility of the AA Symphony architecture. In this mini demonstrator a Liver dashboard can be used to send a DICOM UPS message to the Conductor. The Conductor retrieves the CT scan from the PACS and starts an AI pipeline to segment both liver and liver tumours, computes basic 3D measurements and sends the results back in the form of DICOM Seg (Segmentation Object) and DICOM SR to the Conductor who sends it back to the PACS. The Philips AI Results Viewer can be used for an integrated view of the DICOM Image, SEG and SR data.

The different demonstrator components will be further explained below.

LUMC AA Dashboard

The AA Dashboard is developed by the LUMC. It detects and shows new (CT) scans in the PACS system and shows whether DICOM segmentations and/or DICOM Structured Reports (SR) are available for a scan. If the aorta segmentation or DICOM SR with the relevant measurements is not available, the segmentation of the aorta is requested from the Philips AV application. Once both the segmentation of the Aorta and the 3D measurements of the aortic aneurysm are available, the case can be discussed in a multi-disciplinary team meeting whereby the dashboard with measurements (maximum diameter and largest change compared to a previous scan) can serve as the first overview of relevant results.

Philips AV Application



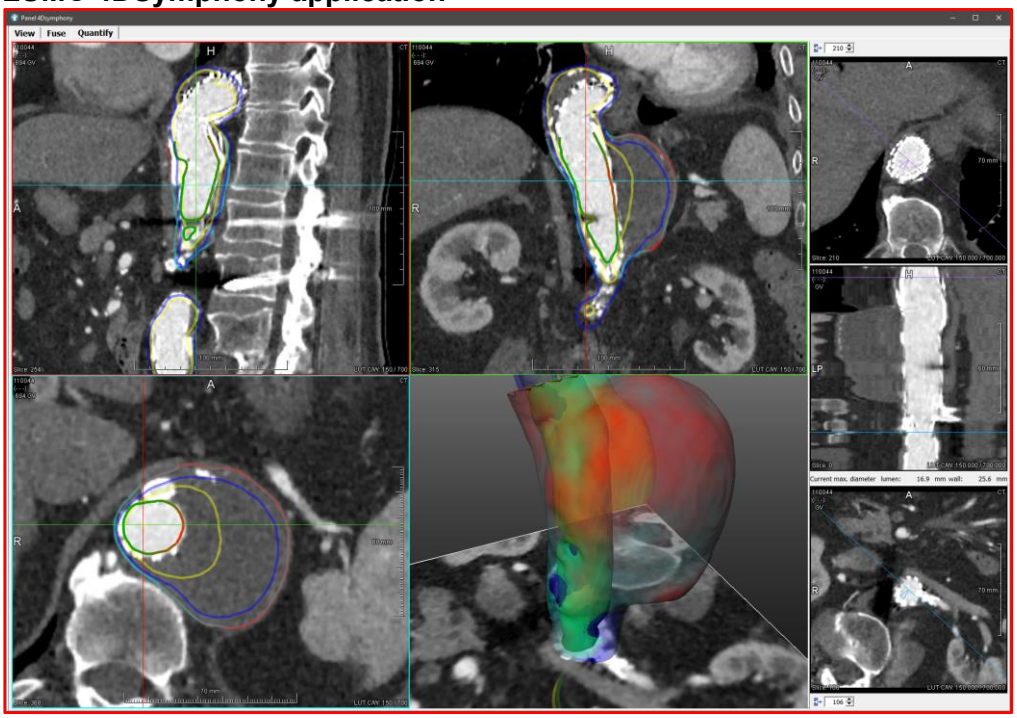
The AV Vascular application has been developed by Philips in collaboration with LUMC and other clinical partners. It provides AI-based aorto-iliac vessel wall segmentation on DICOM CT images and has obtained CE-mark and FDA clearance. A full commercial release is planned for Q3 2026. A key new capability of the AV Vascular application is

the ability to store and export segmentations in DICOM SSO format, allowing the SSO to be shared with external systems. In addition to supporting the diagnosis, surveillance and follow-up of aortic and iliac aneurysms, the AV Vascular application offers standardized templates for pre-procedural measurements. These measurements can be exported to a report, eliminating the need for hand-drawn schematics on paper, and thus aiming to improve the end-to-end clinical workflow and efficiency.

LUMC Conductor

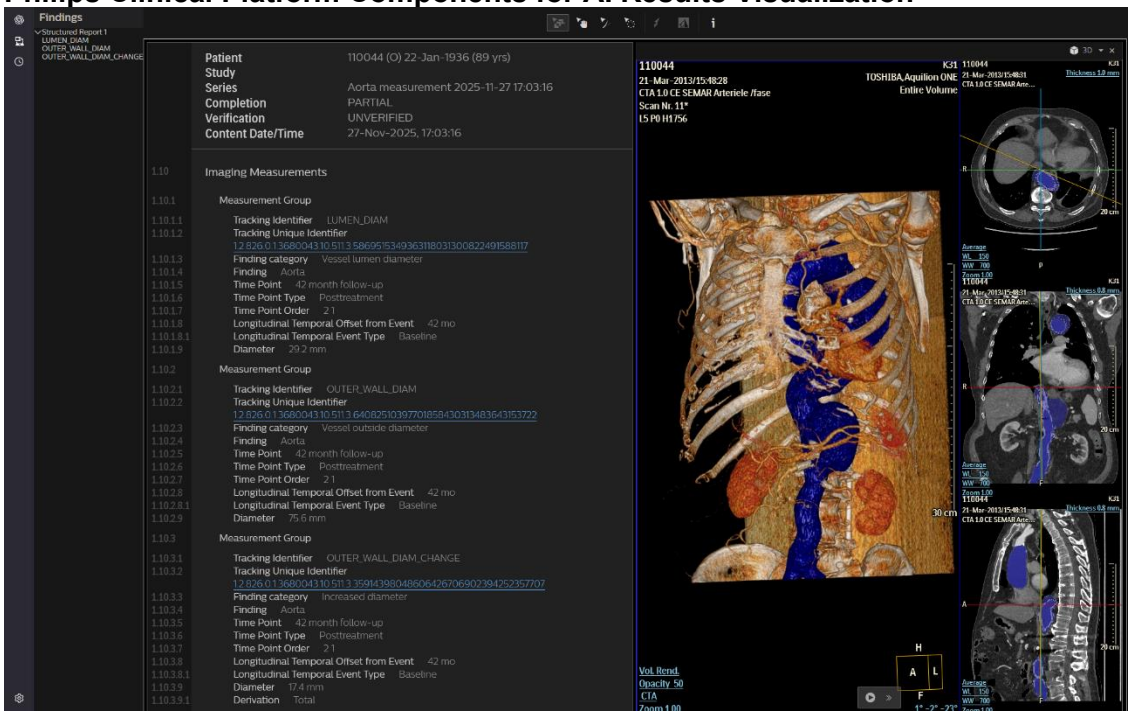
The *Conductor* is a DICOM Universal Procedure Step (UPS) manager developed by the LUMC. When DICOM UPS information is sent to the conductor (e.g. by the AA Dashboard) it will execute the steps outlined in the DICOM UPS command. In the AA use case, it will collect the latest image data and segmentation together with the baseline segmentation data from the PACS and send it to the *4DSymphony* application to register the two cases together and compute the relevant 3D measurements and changes over time.

LUMC 4DSymphony application



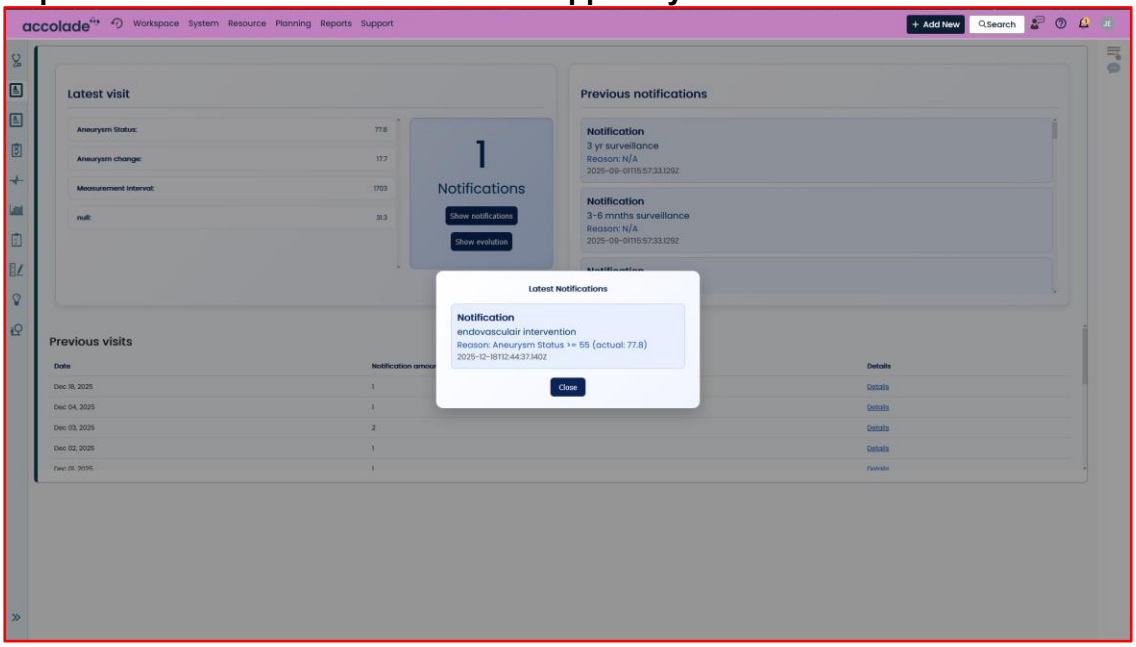
The *4DSymphony* application is a prototype application developed by the LUMC to register 2 aortic aneurysm CT cases to each other, using the aorta centerline(s) exported from the *Philips AV Application.* The application can receive and send data using the DICOM standard. Once the 2 datasets are automatically registered to each other, exact 3D measurements in the follow-up case can be compared with the 3D measurements in the baseline case and the results will be stored in a DICOM Structured Report and sent back to the *Conductor* or other DICOM node.

Philips Clinical Platform Components for AI Results Visualization



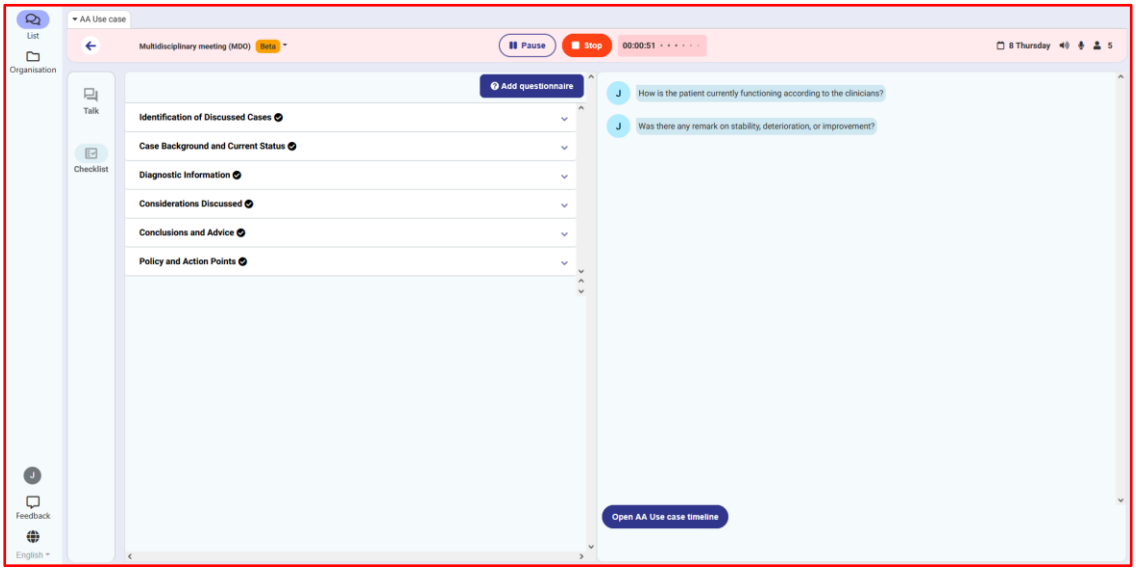
The Philips Clinical Platform Components for AI Results Visualization provide an integrated, linked visualization capability for multiple DICOM object types—including source Images, Structured Reports (SR), and AI-generated segmentation results communicated as DICOM Surface Segmentation Objects (SSO) or DICOM Segmentation (SEG) masks—enabling Philips software products to present image data and corresponding AI findings in a synchronized, interoperable, and clinically coherent manner.

Sopheon Clinical Guidelines decision support system



Sopheon has adapted their Accolade system so it can configure and edit medical guideline compliant algorithms and to generate notification reports based on clinical measurements of the patient. It also shows the historical results of earlier measurements and notifications to build a patient record. This is viewable for the clinician.

HealthTalk.ai



The HealthTalk system, part of the MEDrecord group is a leading platform developed to enhance patient management for mental health professionals, integrating with healthcare providers worldwide. In the AA use case, it is used to record and analyse multi-disciplinary team meetings and provide speech-to-text analysis and summaries thereby reducing the time the primary physician needs to report on the treatment decision made in multi-disciplinary team (MDT) meetings.

3.4 References

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4 UC3: Atrial Fibrillation

4.1 Introduction

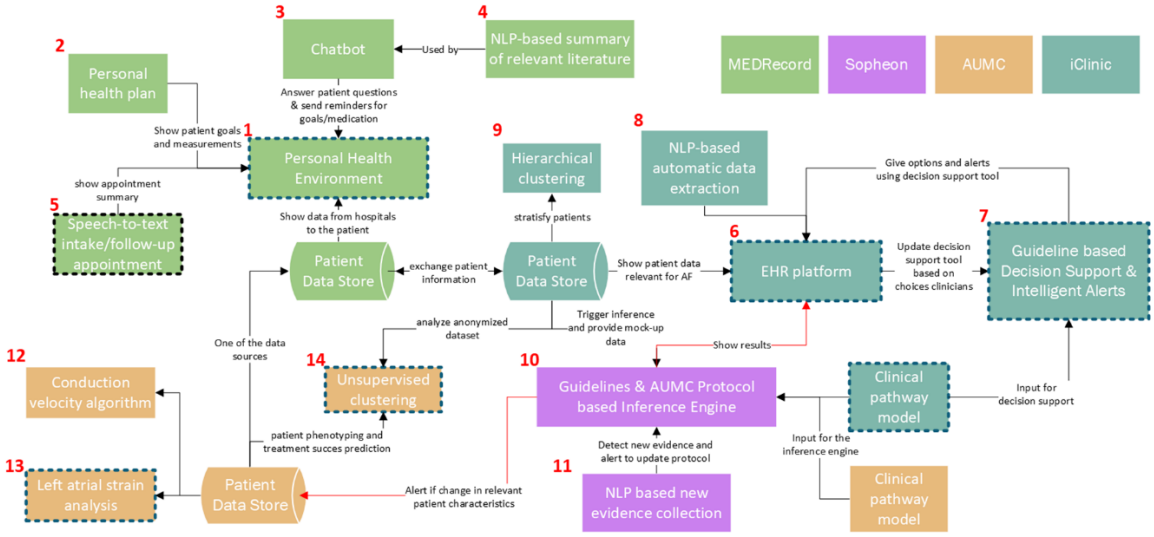
Atrial Fibrillation (AF) is the most common sustained cardiac arrhythmia, originating in the atria and characterized by an irregular and often rapid heartbeat. AF is a chronic disease, affects more than 33 million people worldwide and is associated with increased risks of stroke, heart failure, and mortality. Treatment costs range from $7,000–$14,000 per patient annually. Current AF management faces challenges including fragmented patient data, high numbers of hospital visits for recuring symptoms with considerable manual data entry. The SYMPHONY project addresses these issues through integrated digital tools, predictive analytics, decision-support algorithms, and cross-partner interoperability.

Several opportunities exist to significantly enhance the management of atrial fibrillation, and the SYMPHONY project specifically targets these areas. A key improvement lies in patient education and lifestyle management through a patient-centered personal health environment. Strengthening medication adherence support can help ensure that patients follow prescribed therapies, reducing complications and unscheduled care. Improved lifestyle management, facilitated through digital coaching and remote monitoring, can contribute to better long-term disease control. Ultimately, these changes may result in improved health, and reduced healthcare contacts.

Second, current clinical workflows are hindered by fragmented data across institutions, increasing the risk of incomplete information and suboptimal, non–guideline-adherent decision-making. SYMPHONY addresses this by enabling automatic data extraction and integration across systems, combined with guideline- and data-driven clinical decision support within a user-friendly, clinician-centered electronic health record environment. This reduces manual data entry while improving accessibility of relevant clinical information. Finally, advanced analytics enable more accurate patient stratification, ensuring that individuals are grouped according to relevant clinical characteristics and risk profiles. Integrating predictive models creates the potential for more reliable treatment success prediction, helping clinicians select the most effective interventions for each patient. Together, these improvements lay the foundation for a more personalized, efficient, and data driven AF care pathway.

4.2 Architecture

The architecture of the SYMPHONY AF demonstrator connects personal health environments, specialty EHR systems, algorithm-management platforms, and advanced analytics modules.



The AF architecture illustrates a tightly connected ecosystem in which patient-facing tools, clinical platforms, data-processing modules, and decision-support systems form a continuous workflow. The process begins with the Personal Health Plan, which provides patient goals and measurements to the Personal Health Environment.
Patient-facing elements, including the Personal Health Plan and Personal Health Environment, contribute information on patient goals, measurements, and symptoms.
This environment also receives appointment summaries produced by Speech-to-Text services and is enriched by a Chatbot capable of answering patient questions and providing reminders.

Patient data are stored and exchanged through a Patient Data Store, which aggregates information from hospitals, intake systems, and analytical modules. In addition, NLP-based automatic data extraction enables transformation of unstructured clinical information into structured data, supporting reuse without additional manual workload and facilitating data availability across systems. Clinical professionals access these data through the EHR Platform, where AF-related information is presented in a structured way. The platform combines automatically extracted data with guideline-based decision support and intelligent alerts, supporting clinical decision-making while reducing administrative burden. Underlying this, the Guidelines & Protocol-Based Inference Engine evaluates patient data in relation to clinical pathways and triggers decision-support rules. It also incorporates NLP-based evidence monitoring to identify new insights and support updates in clinical recommendations. Several advanced analytics components, such as Hierarchical Clustering, Unsupervised Clustering, Conduction Velocity Algorithms, and Left Atrial Strain Analysis, feed anonymized or processed data into the Patient Data Store to support patient stratification and phenotyping.

Together, these interconnected elements support a data-driven approach to AF management, in which information is continuously exchanged, made accessible, and used to inform clinical care.

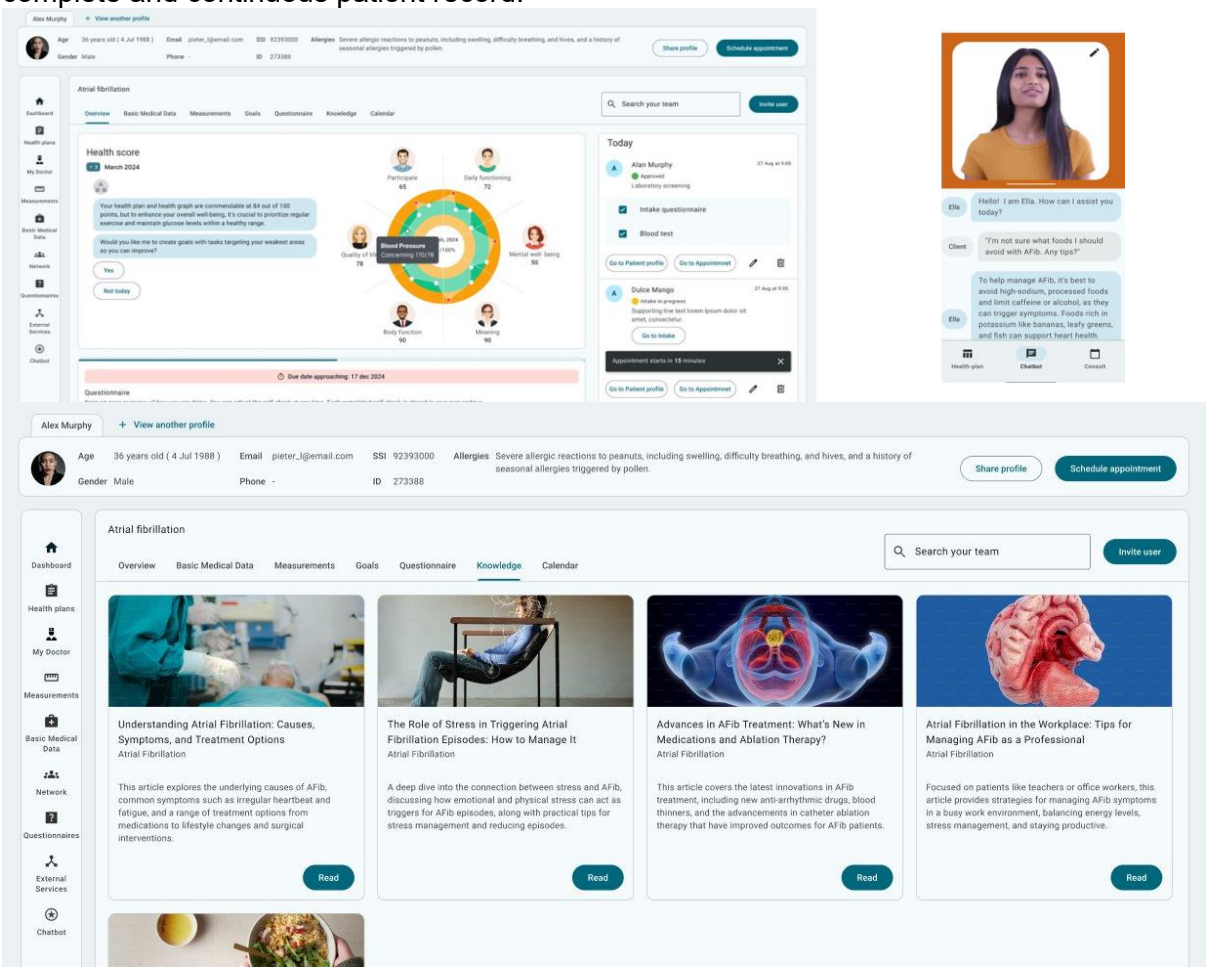
4.3 Demonstration

The AF use case demonstrators highlight workflows across clinicians, patients, and intelligent analytics modules. Demonstrators include:
- Patient-facing digital tools (symptom questionnaires, lifestyle monitoring, chatbot guidance)

- AF specialty EHR workflow enrichment using guideline-based decision support and NLP for data extraction
- Algorithm creation, deployment, and notification generation at Sopheon
- Advanced AF analytics such as conduction velocity mapping and unsupervised clustering at AUMC.

- MEDRecord Personal Health Environment

Enables patients to report symptoms, complete questionnaires, and access relevant health information outside the clinical setting. Supports longitudinal data collection, including clinical history and patient-reported outcomes, contributing to a more complete and continuous patient record.

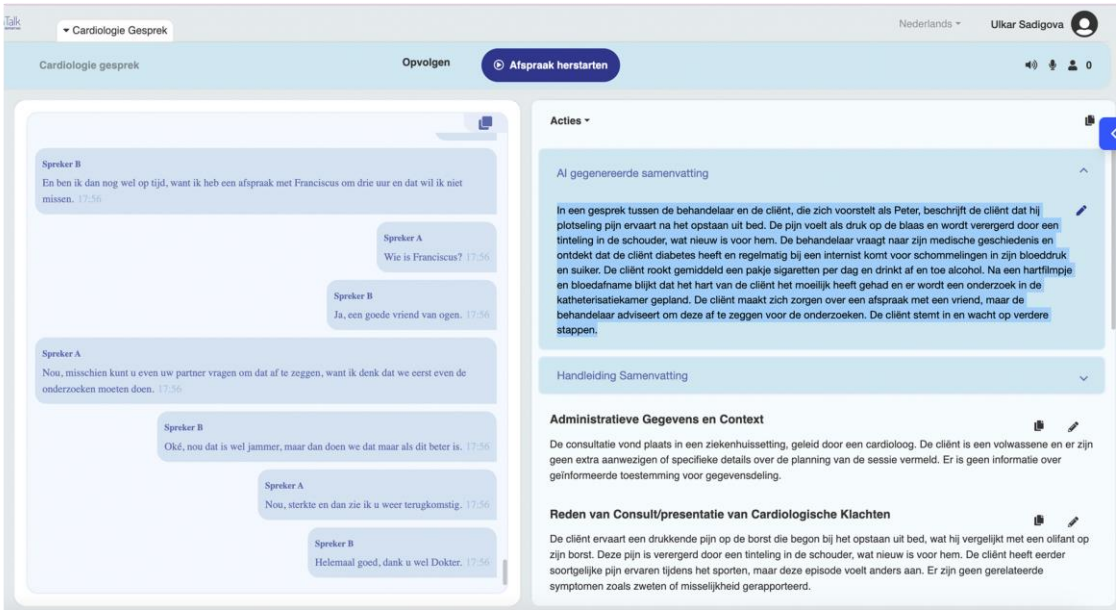


-MEDRecord speech-to-text.

Converts doctor–patient interactions into structured clinical summaries, reducing manual documentation burden. The AI-powered voice-to-text systems improve documentation efficiency by transforming spoken consultations into clinical notes faster than manual typing.

AI voice-to-text tools consistently reduce documentation time and administrative burden, while enhancing patient-provider interaction. Clinicians can speak naturally during the consult while the system extracts symptoms, diagnoses, medications, and key decisions into structured summaries.

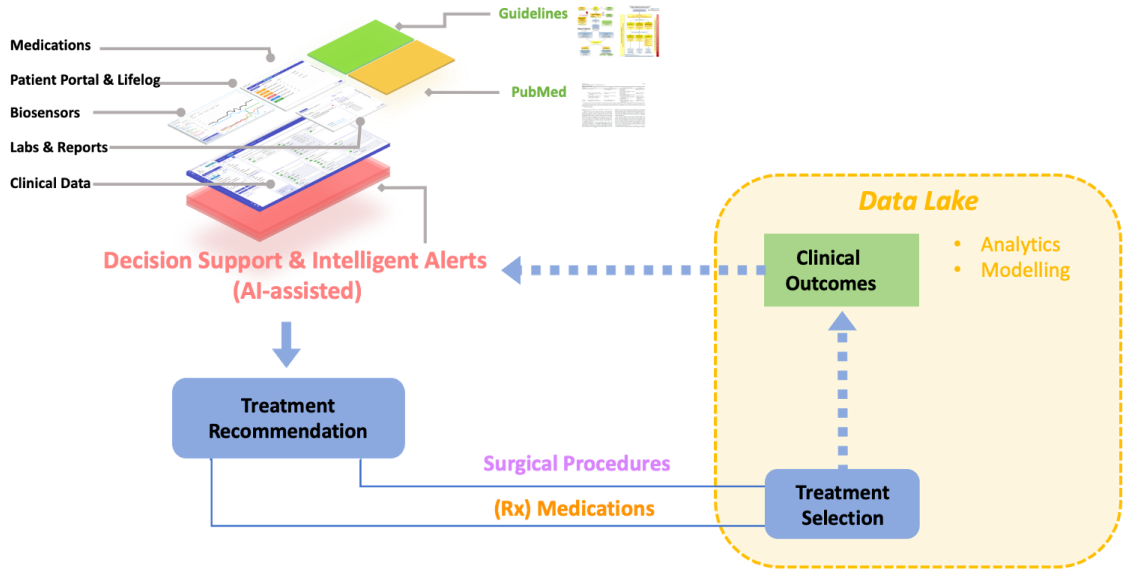
5. MEDRecord – speech-to-text doctors appointment



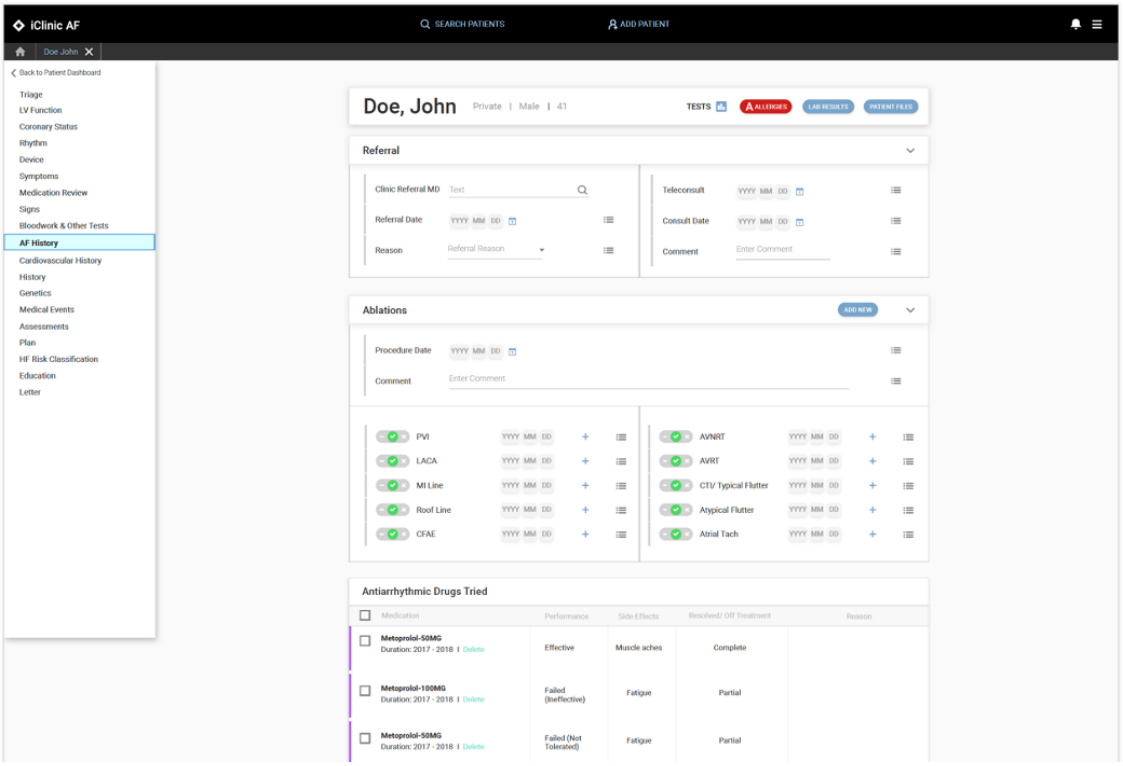
Patient Questionnaire – collection of symptoms and clinical history
Structured questionnaires enable standardized capture of patient-reported data and may be exchanged across partners, supporting data-driven decision support, and more informed clinical decision-making.

Height	cm					
Weight	kg					
Waist	inches					
Premature Family History of Coronary Artery Disease	YES/NO	if YES, which family member				
High Blood pressure	YES/NO					
Smoking - Yes/No	YES/NO					
Smoking Quit Date	Date					
Alcohol	# drinks/week					
Recreational drugs	list					
Physical activity	describe					
Fatigue Level	1 to 5					
Chest Pain Level	1 to 5					
Palpitations Level	1 to 5					
Lighthead/Dizzy	YES/NO	if yes, frequency				
Dyspnea (shortness of breath)	YES/NO	at rest	with exertion			
Edema (swelling)	YES/NO	hands or feet				
Orthopnea (difficulty laying down)	YES/NO	if yes, frequency				
PND - Yes/No	*severe shortness of breath when sleeping				if yes, frequency	
Previous Stroke event	YES/NO	if yes, date(s)				
Previous hospitalization for Atrial Fibrillation	YES/NO	if yes, date(s)				

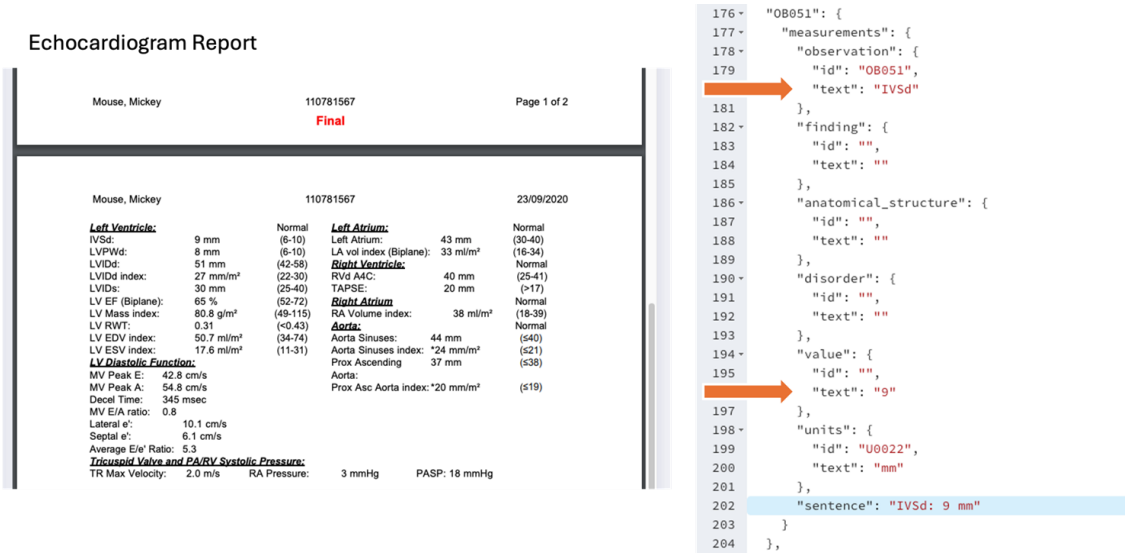
- iClinic specialty AF EHR platform



A specialized EHR platform focused on Atrial Fibrillation - incorporating guideline based clinical data capture and treatment pathway recommendations.
Data ingestion for analytics, modelling, and improving Decision Support tools.



AF-focused data overviews facilitate rapid access to relevant clinical information and reduce administrative burden.

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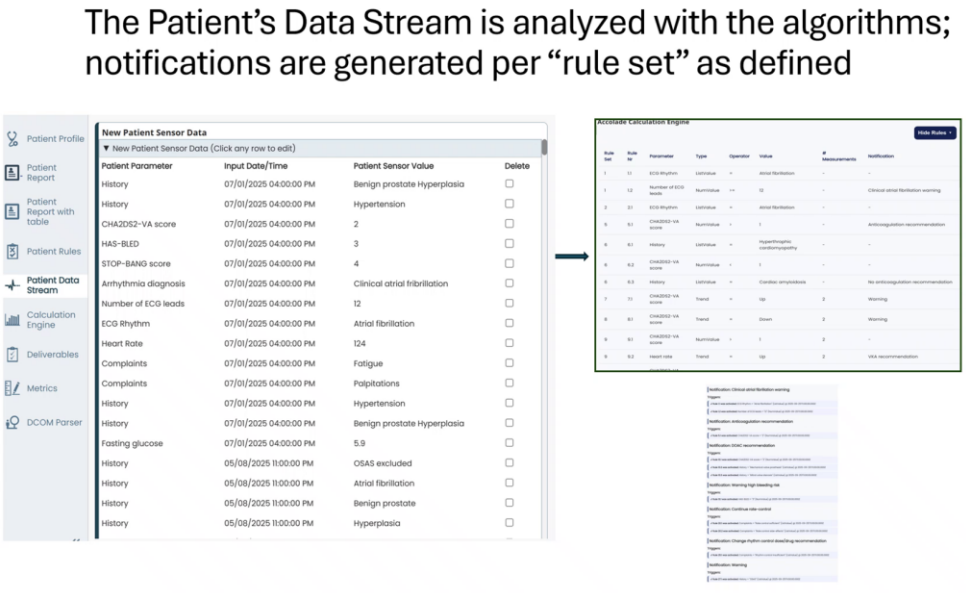
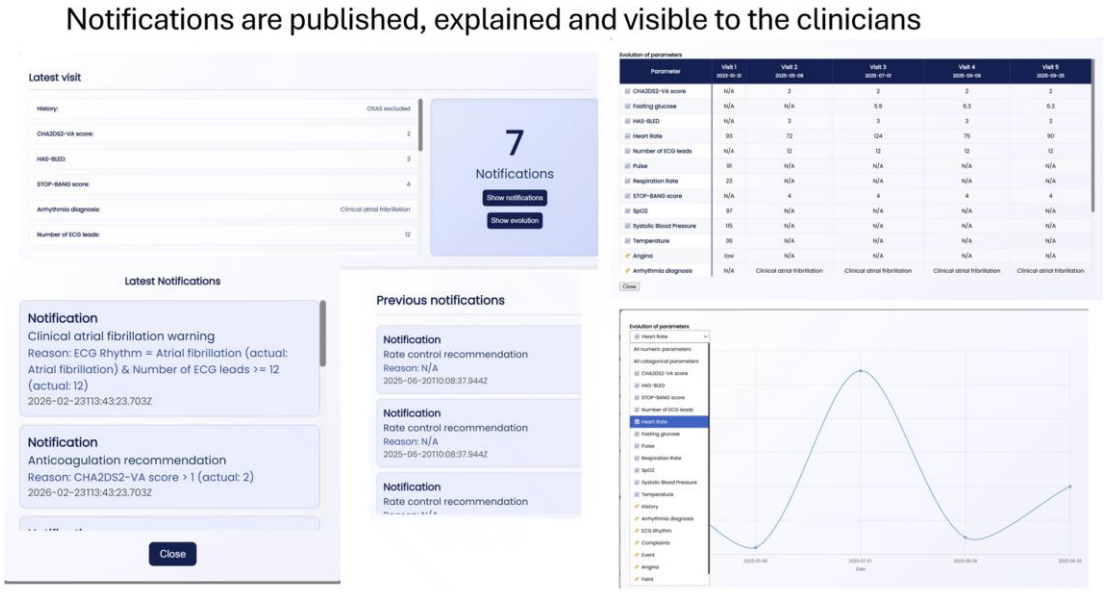
NLP pipelines to extract data to reduce manual entry

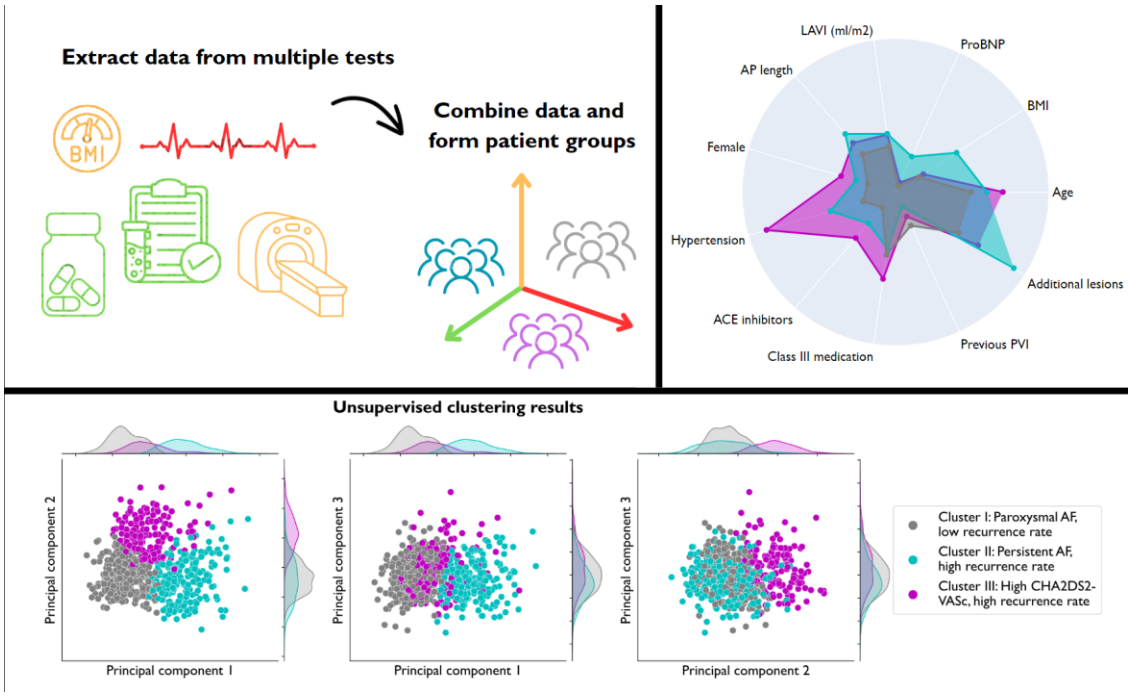
- Sopheon rule-based AI and protocol management system

Clinical algorithms are defined in a structured format and uploaded into the Accolade platform, where they are converted into SQL database format. Patient data are evaluated against these rule sets, generating context-specific notifications. These notifications are presented within the clinical environment, including underlying explanations, supporting transparent and guideline-adherent decision-making.





- AUMC patient stratification and outcome prediction (e.g., conduction velocity mapping, clustering)



Integration of multimodal data (e.g., conduction velocity mapping and clustering approaches) enables patient stratification into distinct groups, supporting prediction of outcomes, and enabling more personalized treatment strategies.

A summary of the Symphony partner interaction for the AF demonstrators

- Clinical pathway models created by **AUMC** and **iClinic** are used by **Sopheon** to create a guidelines and protocol-based inference engine.
- Patient and treatment data stored at the **AUMC** and **iCLinic** (e.g. EHR) can be retrieved by **MEDRecord** for local visualization and evaluation in patient's personal health environments.

5 UC4: Multiple Sclerosis

5.1 Introduction

Multiple sclerosis (MS) is a chronic and often disabling neurological disorder that affects the central nervous system (CNS), which includes the brain, spinal cord, and optic nerves. MS is a result of an immune-mediated attack on the myelin sheath that surrounds and protects nerve fibres in the CNS, causing inflammation, demyelination, and damage to the nerve cells.

The symptoms of MS vary widely depending on the location and extent of the damage, but can include vision problems, muscle weakness, spasticity, numbness or tingling in the limbs, fatigue, difficulty with balance and coordination, and cognitive impairment. Symptoms can come and go and can range from mild to severe.

The underlying aetiology of MS is still not known but is thought to be related to an interplay of genetic susceptibility and environmental factors. Several factors have been investigated, including putative viruses using molecular mimicry, low vitamin D, distance from the equator in early childhood, diet, smoking and toxins. [3,4] Meta-analyses suggest that the strongest evidence of association is related to Epstein-Barr virus biomarker positivity, infectious mononucleosis, and smoking.[5]

Some studies have shown a link between multiple sclerosis (MS) and sarcopenia. Approximately one-fifth of MS patients have sarcopenia [8]. Sarcopenia (age-related muscle loss) is a musculoskeletal disease characterized by decreased muscle mass and muscle function, especially with aging. The symptoms of the Sarcopenia include having one arm or one leg smaller than the other, experiencing weakness in one arm and/or one leg, numbness or tingling in the arms and legs, difficulty with walking or balancing, trouble swallowing or speaking, facial weakness, and gradual memory loss.

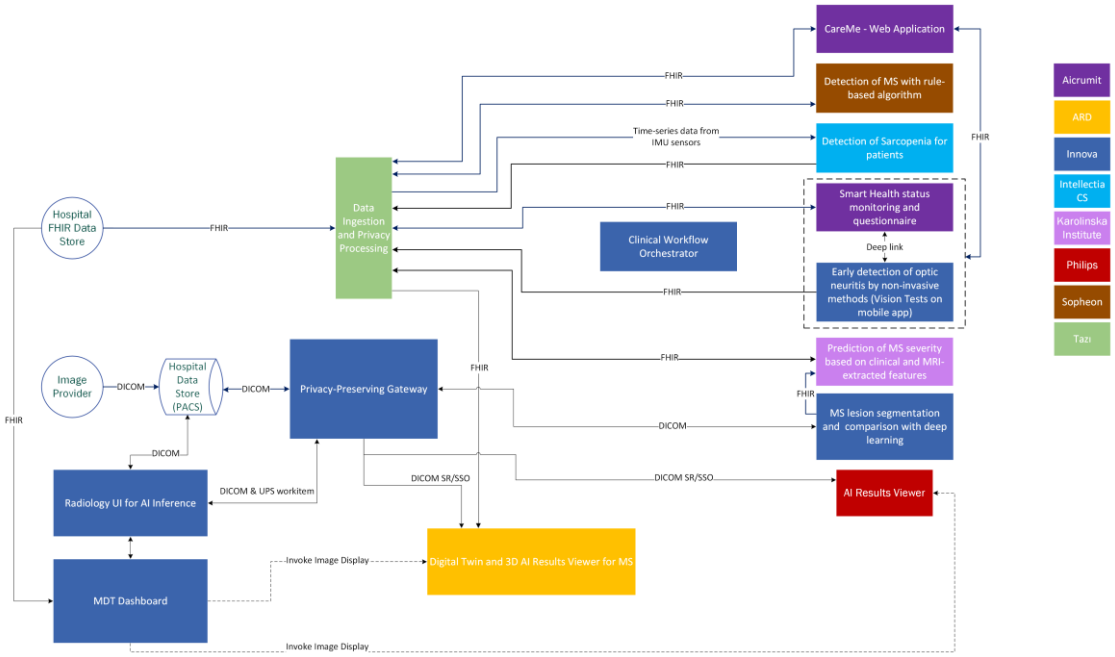
The prevalence of sarcopenia varies between 10% and 40% in the elderly, depending on age, chronic diseases, changes in measurements and differences in diagnostic criteria. Sarcopenia is more common in women, especially after menopause. The World Health Organization predicts that the population aged ≥60 will reach 1.2 billion in 2025, this number will reach 2 billion in 2050, and those with sarcopenia will reach >200 million [6].

A multidisciplinary MS Care Unit approach can be defined as the presence of a group of different specialists, who work together and with the MS neurologists and nurses with a formalized diagnostic workup procedure, protocols for initiation and follow-up of disease modifying therapy (DMT) and management of complications. Spasticity is in generally handled by the neurologists in the MS Care Unit with pharmacological treatment and botulinum toxin injected locally, but when severe spasticity in the legs requires intrathecal baclofen administration, a multidisciplinary approach is needed, including collaboration with neurosurgeons [7].

There is currently no cure for MS, but there are treatments that can help manage symptoms and slow disease progression. Treatment options include disease-modifying drugs, corticosteroids, physical therapy, and symptom management medications.

5.2 Architecture

Here is the architecture diagram for MS use case:



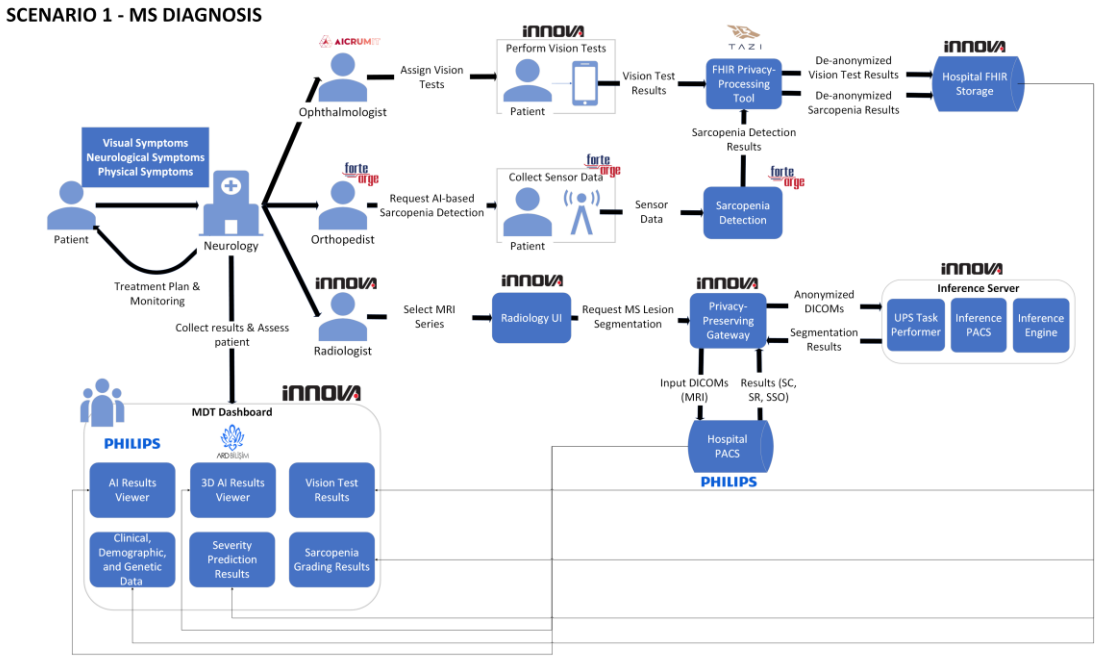
5.3 Demonstrators

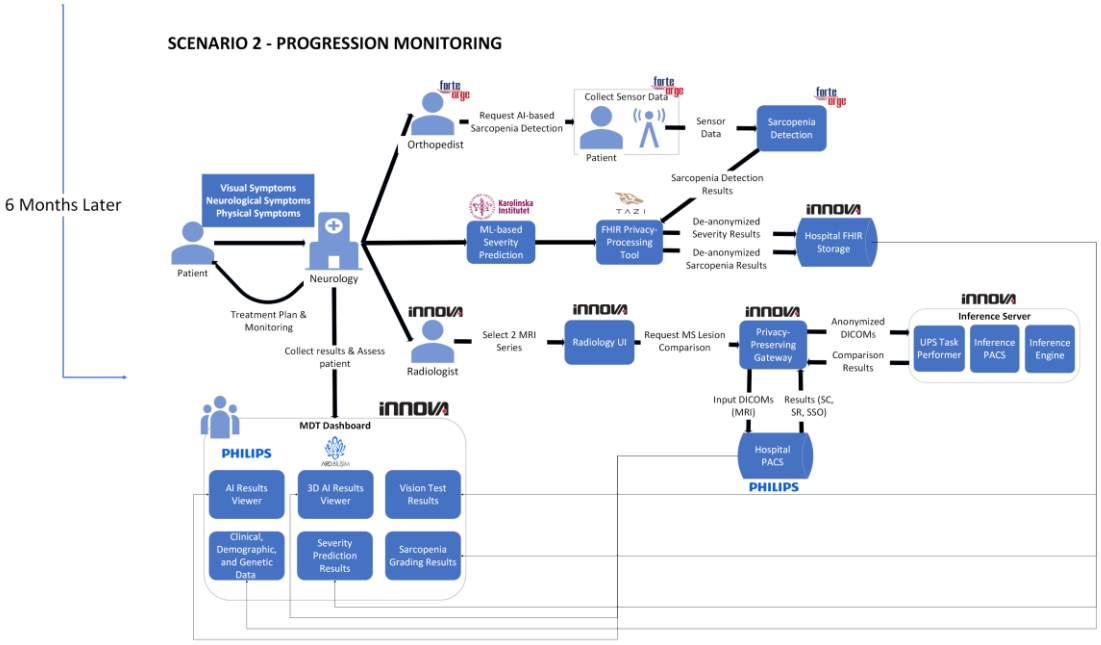
Demonstrations include two clinical scenarios (Diagnosis and Progression Monitoring) and four departments (Neurology, Radiology, Ophthalmology, Orthopaedics). We focus on all possible combinations of sub-workflows and generate a comprehensive MDT dashboard to support decision-making.

The sub-workflows include:

- Ophthalmology: Early Detection of Optic Neuritis
- Orthopedics: Sarcopenia Detection and Grade Assessment
- Neurology: MS Severity Prediction, Smart Health Questionnaires, Rule-based MS Detection and Final Clinical Assessment
- Radiology: MS Lesion Segmentation and Longitudinal Comparison for Progression Monitoring

When the main workflow starts, the Clinical Workflow Orchestrator automatically routes the patient into relevant sub-workflows based on symptoms. After evaluations across departments are completed, all results and analytics are consolidated in the MDT dashboard to make the overall assessment process easier and more robust.





The demonstrator components are described below under the relevant medical departments:

Radiology

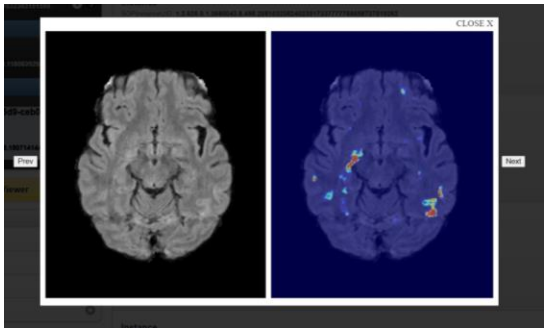
MS Lesion Segmentation System

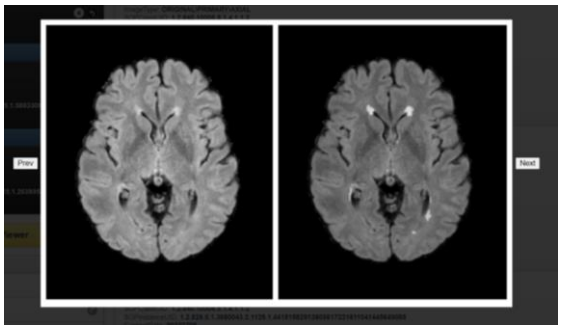
The MS Lesion Segmentation System is an AI-powered inference engine designed for automated detection and delineation of Multiple Sclerosis (MS) lesions from brain MRI data. At its core, the system employs a Convolutional Neural Network (CNN)-based deep learning model that processes T1-weighted and FLAIR MRI series to accurately identify and segment demyelinating lesions. The engine is architected to support

multiple disease models within the same framework, enabling scalable deployment for additional neurological conditions beyond MS.

The system generates structured and standardized outputs in several interoperable DICOM formats to ensure seamless clinical integration. Segmentation masks and explanatory Grad-CAM heatmaps are exported as DICOM Secondary Capture objects aligned with the original MR images. Quantitative lesion characteristics—such as volume, count, and spatial distribution—are encoded in DICOM Structured Reports (SR). Additionally, dynamic lesion segment point clouds are provided using DICOM Surface Segmentation Objects (SSO), enabling advanced 3D visualization and longitudinal comparison.

Fully compliant with DICOM Unified Procedure Step (UPS) and IHE AI Workflow for Imaging (AIW-I) standards, the system integrates into hospital PACS environments and AI marketplaces in a vendor-neutral manner. This standards-based architecture ensures secure orchestration, traceable workflow execution, and interoperability across clinical infrastructures while maintaining extensibility for future AI models and disease domains.





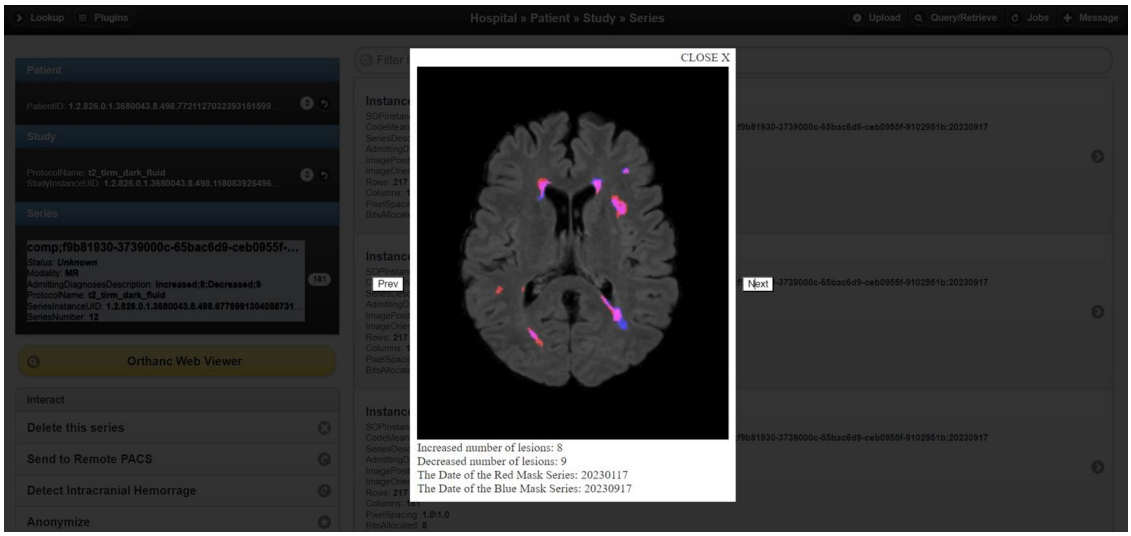
Time-based MS Lesion Comparison System

The Time-based MS Lesion Comparison System is an advanced analytical extension of the MS Lesion Segmentation System, designed to enable longitudinal assessment of lesion progression in brain MRI. The system accepts two MRI studies of the same patient—typically from different time points—and performs automated comparison of segmented lesions to evaluate temporal changes. By leveraging the segmentation outputs of the underlying CNN-based inference engine, the system aligns, analyzes, and quantifies lesion-level differences in a standardized and reproducible manner.

The platform generates both intuitive visual outputs and structured analytical reports. Visually, lesion masks from each time point are overlaid using distinct color coding to clearly differentiate stable, increased, decreased, newly appearing, and resolved (missing) lesions. This facilitates rapid clinical interpretation and supports multidisciplinary review settings. Quantitatively, the system produces detailed reports identifying lesion dynamics, including changes in volume, size, count, and spatial coordinates. These metrics provide objective evidence for monitoring disease progression, treatment response, and relapse activity.

All outputs are generated in interoperable DICOM-compliant formats, ensuring seamless integration with PACS and clinical workflow systems. Designed to operate

within standardized AI workflows, the system enhances longitudinal imaging analysis while maintaining traceability, reproducibility, and regulatory-aligned documentation across imaging time points.



Privacy-Preserving Gateway

The Privacy-Preserving Gateway functions as the central orchestrator and workflow conductor for AI-based medical imaging processes. Architected as a modular microservices-based platform, it enables secure, standardized, and traceable execution of AI inference tasks within hospital environments. The Gateway includes core components such as a de-identification and re-identification service, a temporary PACS repository for intermediate storage, and a DICOM Unified Procedure Step (UPS) Manager to support standardized AI workflow management in alignment with IHE AIW-I profiles.

The workflow begins when a clinical client requests an AI inference task through the DICOM UPS Manager. The Manager retrieves the required MRI series from the hospital PACS and transfers them into the temporary PACS environment, where all protected health information is systematically de-identified. Once anonymization is complete, the Gateway notifies the designated task performer—such as the MS Lesion Segmentation inference engine—that a new workitem is available. The AI engine claims the workitem via the UPS mechanism and securely retrieves the anonymized images for processing.

After inference, the AI engine generates structured outputs (e.g., segmentation masks, reports, surface objects) and notifies the UPS Manager that the task is complete. The Gateway then re-identifies the AI outputs using the secure mapping maintained during de-identification, ensuring patient-context restoration without exposing sensitive data externally. Finally, the validated and re-identified results are transmitted back to the hospital PACS, and the original task requester is notified that the inference process has been finalized.

Through this architecture, the Privacy-Preserving Gateway ensures secure data handling, regulatory-aligned anonymization, workflow traceability, and full compliance

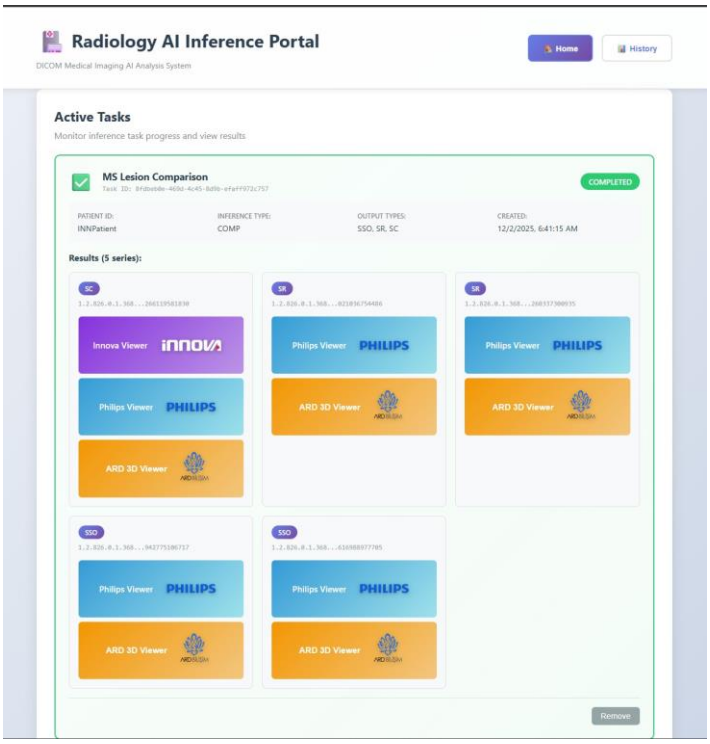
with DICOM UPS and IHE AIW-I standards, enabling scalable and vendor-neutral deployment of AI solutions in clinical imaging environments.

Radiology UI Application

The Radiology UI Application is a clinician-facing interface designed to facilitate seamless interaction between radiologists and AI-based imaging services. The application provides a centralized dashboard where clinicians can browse and select patients and their corresponding imaging series directly from the hospital environment. Through an intuitive workflow, users can configure AI inference requests by specifying the relevant clinical problem, selecting the appropriate AI model, defining the MRI sequence (e.g., T1, FLAIR), and choosing the desired output formats such as DICOM Secondary Capture (SC), Structured Report (SR), or Surface Segmentation Object (SSO).

Once configured, the request is transmitted to the AI inference engine via the Privacy-Preserving Gateway, ensuring secure orchestration and standardized workflow execution. The application monitors task status through the DICOM UPS mechanism and provides feedback to the clinician regarding processing progress and completion.

Upon completion of the AI task, results are made available for visualization through direct integration with advanced imaging viewers, including Philips AI Results Viewer and ARD 3D AI Results Viewer. This enables radiologists to interactively review lesion masks, quantitative reports, 3D segmentations, and comparative analyses within familiar clinical viewing environments. By acting as a bridge between clinical users and backend AI infrastructure, the Radiology UI Application enhances usability, accelerates decision-making, and ensures smooth adoption of AI tools in routine radiology workflows.



Clinical Platform Components for AI Results Visualization

The Clinical Platform Components for AI Results Visualization provides a set of reusable, product-agnostic components that enable multiple clinical software products from Philips to visualize the outputs of artificial intelligence algorithms alongside the original medical image data from which these results were generated. Rather than delivering a single standalone application, we have developed an extensible visualization framework that can be integrated across different Philips solutions, ensuring consistent display, interaction, and interpretation of AI-derived results.

These components support synchronized visualization of both the source medical image series and the AI-generated findings—such as segmented lesions or quantitative metrics extracted from those segmentations. By displaying the original image data together with the algorithm results, the platform allows clinicians to review AI findings in a clinically meaningful context, ensuring that outputs are correctly spatially registered to the underlying anatomy.

A key capability of the platform is its ability to consume and display results that are communicated in standard DICOM Surface Segmentation Objects (SSO) and DICOM Structured Reports (SR). Communicating the results using these standardized formats ensures vendor-agnostic interoperability and allows seamless integration into diverse imaging workflows.

The viewer supports both 2D slice-based and 3D volumetric visualization modes. When quantitative findings are communicated via DICOM SR, the platform presents a structured list of detected lesions or findings—such as volume, size, count, or spatial descriptors. These structured entries remain linked to the corresponding anatomical segmentations delivered via DICOM SSO. Selecting an item in the structured report dynamically highlights the associated segmented region in the 3D viewer, enabling an immediate visual correlation between the structured data and the spatial anatomy.

This bidirectional, synchronized interaction between structured reporting and spatial segmentation enhances interpretability, supports lesion-level validation, and facilitates efficient clinical decision-making. By providing a standardized, interoperable, and reusable visualization framework, the AI Results Viewer platform strengthens Philips' ability to deploy AI results consistently across multiple products within the Symphony project and beyond.

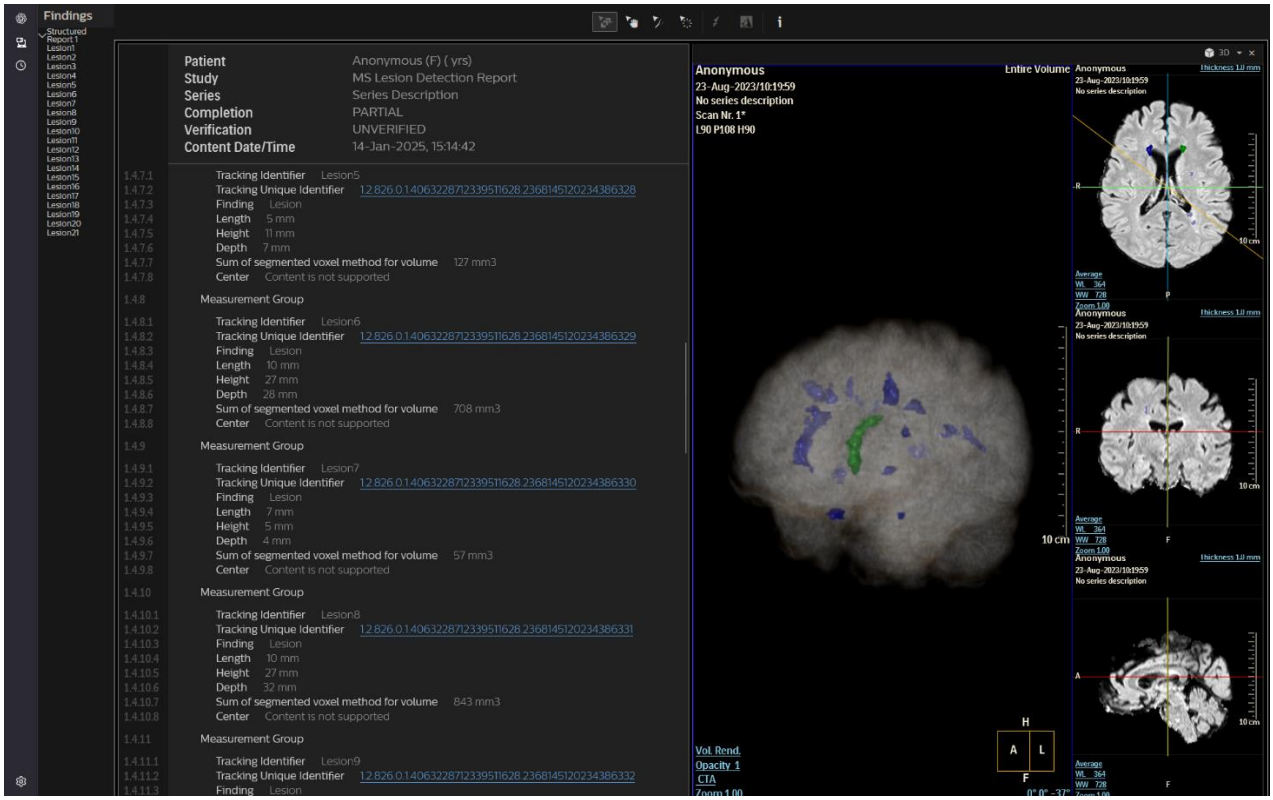


Figure 3 Screenshot of Clinical AI Results Visualization Components from Philips

ARD's 3D AI Results Viewer & Data Backbone

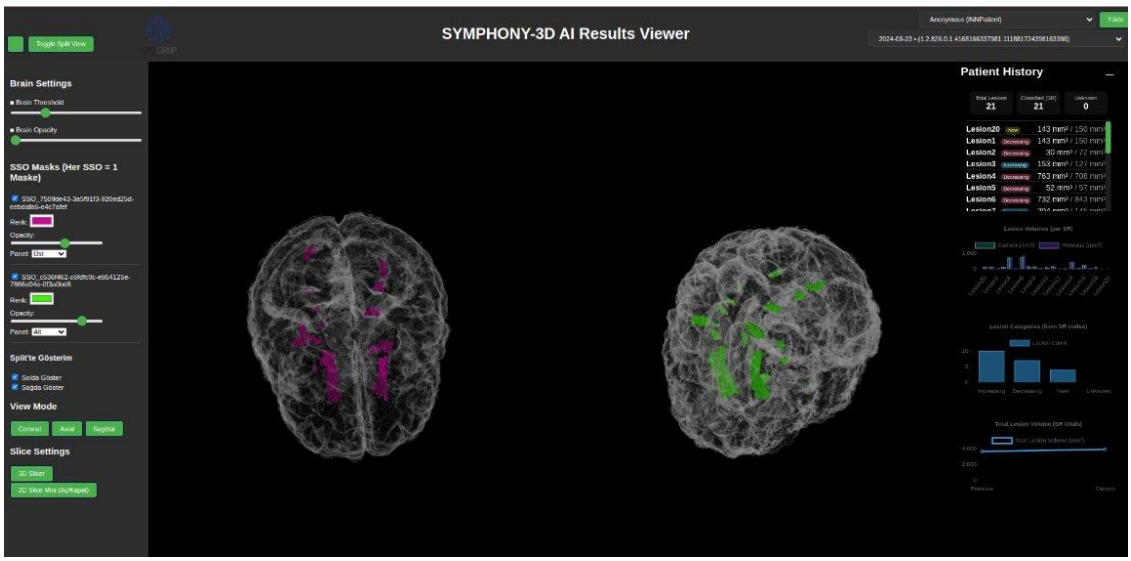


Figure 4

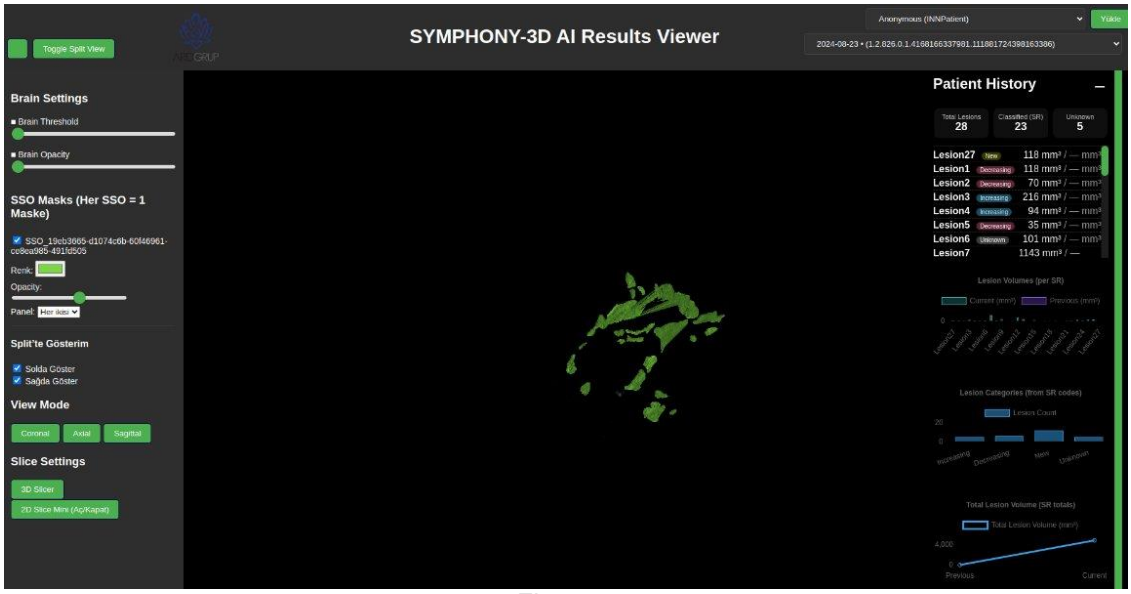


Figure 5

- The application has been developed by ARD Group to show 3D brain and lesion images provided by Innova.
- Opacity of both the brain and lesion tissues can be adjusted like demonstrated in Figure 4.
- More than one lesion mask can be displayed at the same time or separately.
- The desired masks can be seen on the screen with the on/off feature.
- The existing split view structure has been extended to manage mask distribution on a per-panel basis. In addition, in the “Patient History” panel integrated with DICOM SR data, clinical indicators and comparison charts are generated automatically.
- With these adjustments, data preparation steps have been reduced, and multi-mask management and the visualization of clinical summaries have been unified within a single interface.

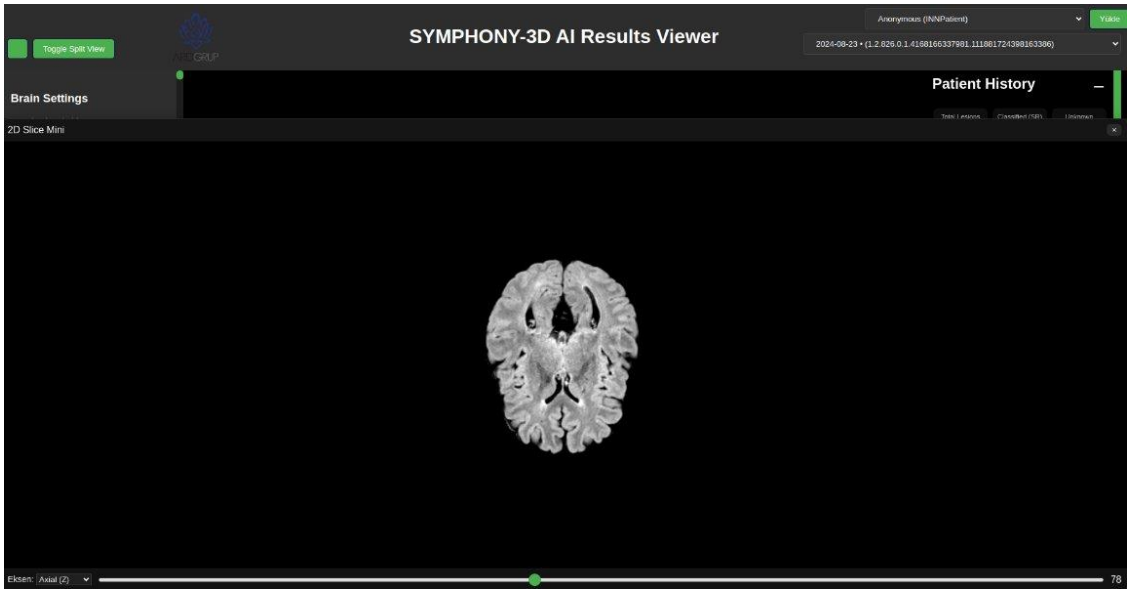
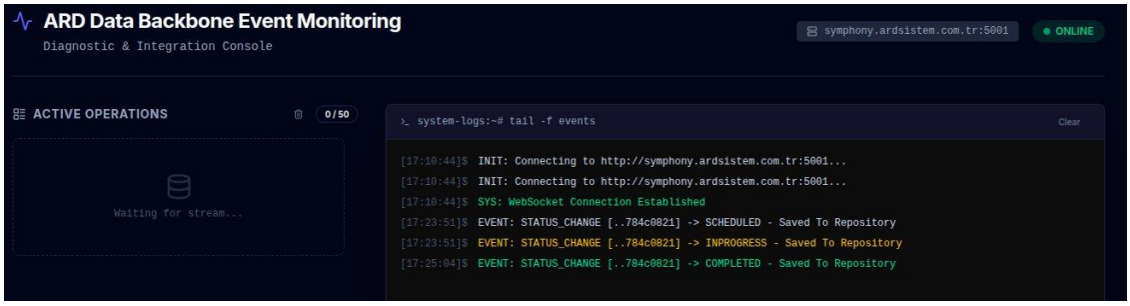


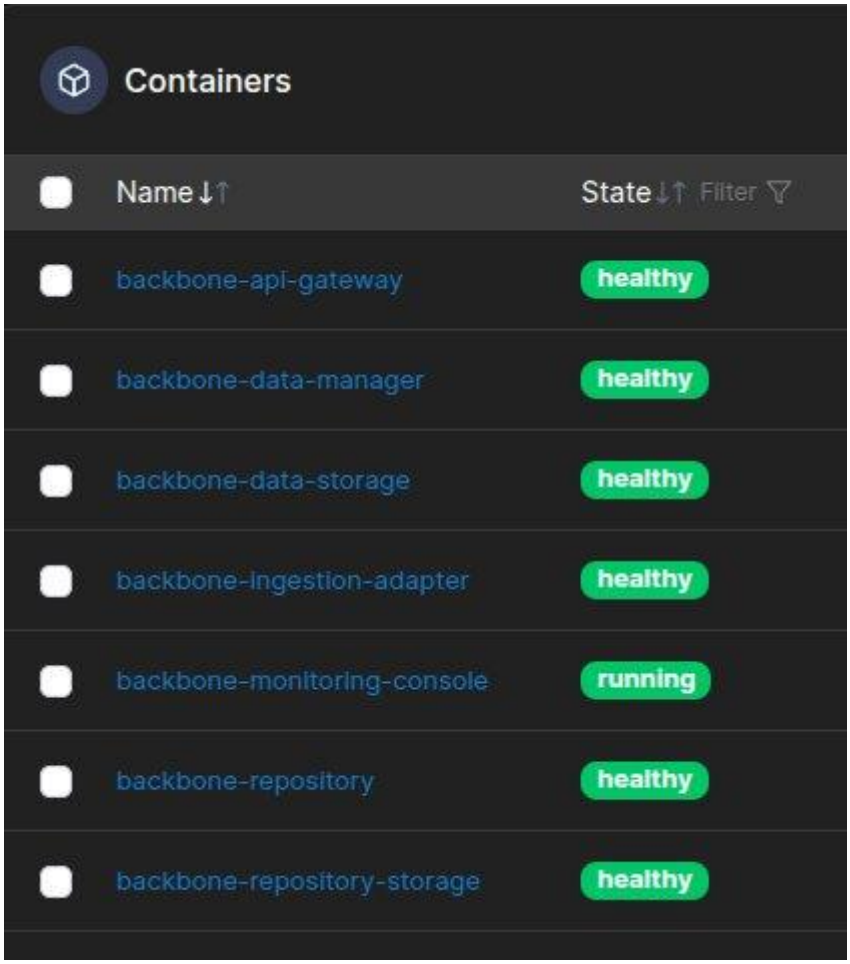
Figure 6

- In addition to the 3D feature, sections of the relevant brain can be examined layer by layer with the 2D Slice Viewer feature as shown in Figure 6.

- AI Result Viewer now complies with the IHE Invoke Image Display (IID) profile, enabling standards-based interoperability.
- The data processing pipeline has been redesigned to run natively on DICOM, removing the need for NIfTI and automatically converting DICOM SSO content into 3D mesh surfaces, enabling multi-mask management with per-mask color, opacity, and target panel controls.



- Our Databackbone continuously listens to the websocket of Innova's UPS server to track lifecycle events of work items including creation, progress updates, completion, and cancellation.
- These events, along with the associated work item data, are systematically retrieved and stored in the data repository for further processing.



- The Data backbone system is built on a microservices architecture, with its containerized components illustrated in the referenced screenshot.

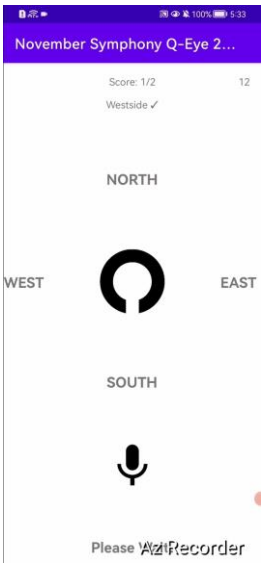
- As shown, the service names are self-descriptive, and the overall architecture is designed to support a complete data lifecycle from capturing to processing and presenting the data.

Ophthalmology

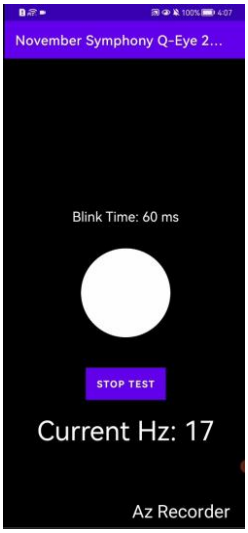
Early Detection of Optic Neuritis with Mobile App.

The Early Detection of Optic Neuritis Mobile Application is an Android-based digital health solution designed to enable remote monitoring of visual function and support early identification of optic neuritis in patients with neurological risk factors. The application allows patients to perform clinically inspired vision assessments from home while maintaining standardized measurement logic and secure integration with hospital systems.

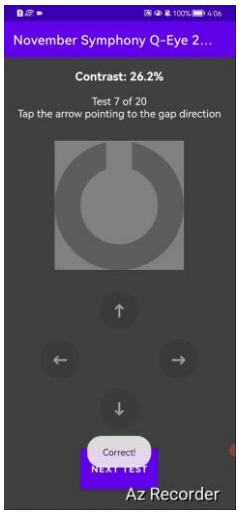
The application provides three core vision tests. The first is a Visual Acuity Test, based on logMAR principles. During the test, the patient is positioned at an approximate distance of 150 cm from the device, which is continuously monitored by an embedded iris-detection model to ensure correct testing conditions. A Landolt-C optotype appears on the screen, and the patient verbally indicates the direction of the opening (north, south, east, or west). At each round, the optotype progressively scales down in size to determine the patient's visual acuity threshold and compute a logMAR-equivalent value.



The second assessment is the Critical Flicker Fusion (CFF) Test, which evaluates the frequency threshold at which a flickering stimulus is perceived as steady. A white circular stimulus is presented on the screen with gradually increasing vibration frequency. When the patient indicates that the flicker is no longer perceivable, the system dynamically decreases the frequency to determine the perceptual fusion interval. This provides an objective indicator of visual pathway integrity and potential demyelinating impact.



The third assessment is the Contrast Sensitivity Test, which follows a similar interaction model to the visual acuity test. However, instead of reducing optotype size, the system progressively modifies the contrast between the optotype and its background. By identifying the lowest contrast level at which the patient can correctly detect the optotype orientation, the system quantifies contrast sensitivity performance.



The mobile application includes a patient dashboard that allows users to track assigned tests, monitor completed assessments, and review their testing history. Through seamless integration with the clinical environment via a secure Data Ingestion and Privacy-Processing Tool, results are transmitted in real time to the Multidisciplinary Team (MDT) dashboard. This architecture enables clinicians to monitor patient-reported outcomes remotely, detect early functional changes, and integrate mobile-derived biomarkers into longitudinal neurological care workflows.

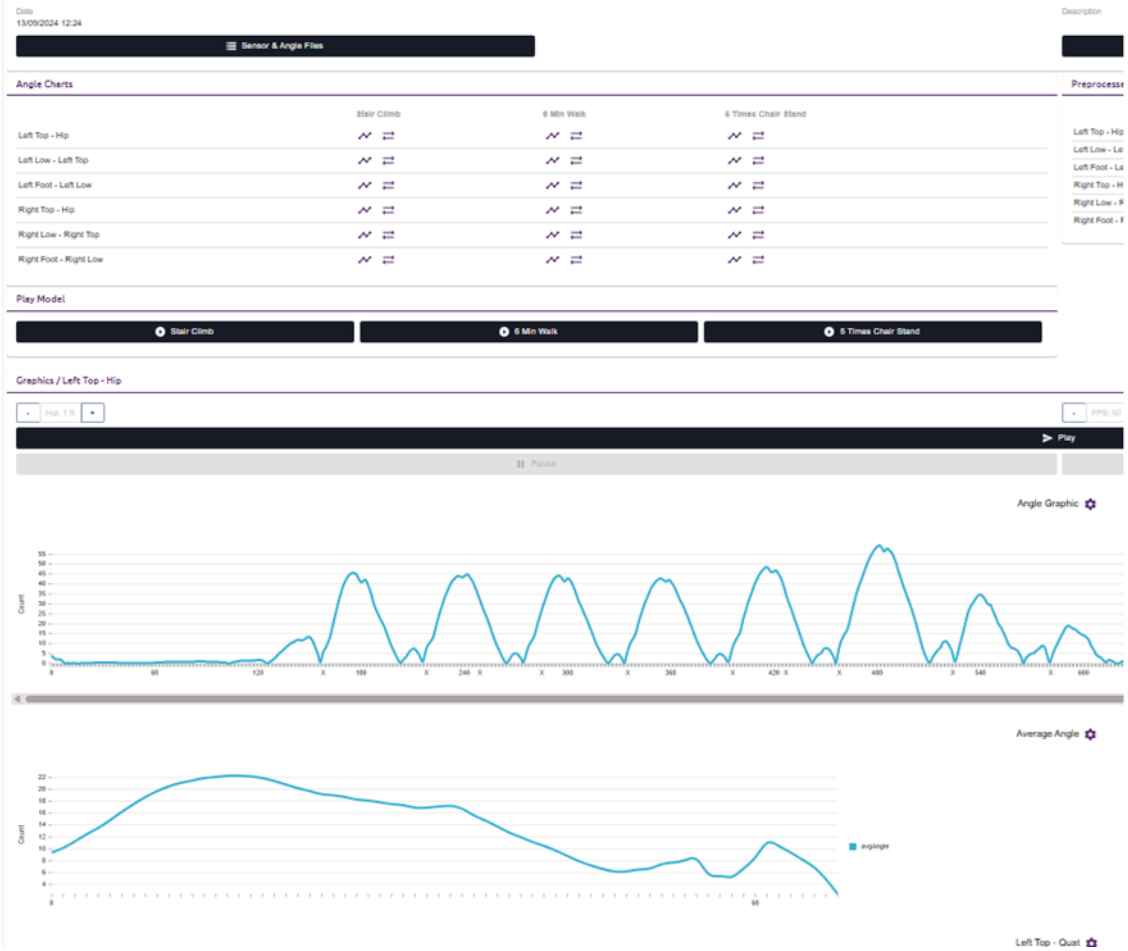
In addition to imaging and workflow interoperability, the mobile application ecosystem is designed with FHIR (Fast Healthcare Interoperability Resources) compliance to ensure structured and standardized exchange of clinical data. Vision test results are transformed into FHIR-compatible resources (e.g., *Observation*) before being transmitted to hospital information systems. This enables seamless integration with

Electronic Health Records (EHR), clinical decision support systems, and multidisciplinary dashboards without vendor dependency.

Orthopedics

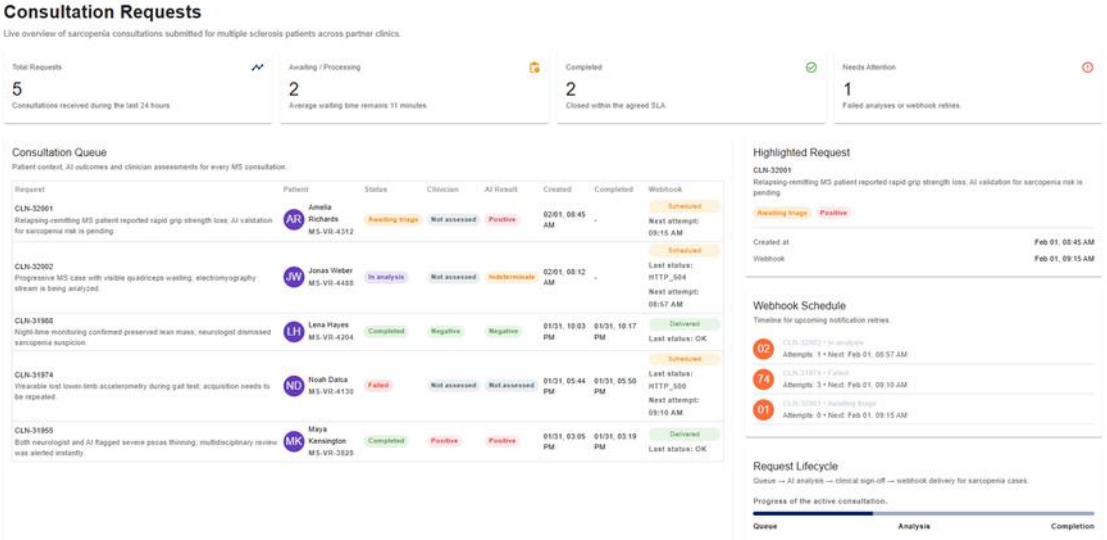
Sarcopenia Detection and Grade Assessment
IntellectiaCS implemented the sarcopenia sub-workflow covering consultation, AI-based evaluation, follow-up monitoring, and data integration.
In the consultation scenario, a sarcopenia request is initiated via the MDT Dashboard and automatically forwarded to the SarkoMonitor system. During standardized exercise sessions, motion data are collected using Xsens IMU sensors and processed within SarkoMonitor. The recorded signals undergo preprocessing, feature extraction, and model-based analysis to determine sarcopenia status and grading. The evaluation results are returned to the MDT Dashboard for clinical review.

For follow-up monitoring, a virtual patient identity is used to enable privacy-preserving integration with the AICRUM health platform. Exercise and sleep metrics collected via smartwatch devices are periodically transmitted to SarkoMonitor, where longitudinal analyses are performed. Updated assessments are made available to clinicians and patients within the monitoring interface.



On the AI side, IMU sensor data collected from MS patients are preprocessed and labeled to support supervised machine learning and deep learning experiments. In addition, synthetic data generation studies using GAN-based approaches have been conducted to explore dataset augmentation. Initial evaluations indicated limited impact

on model performance, and further experimentation continues as additional real-world data are incorporated.

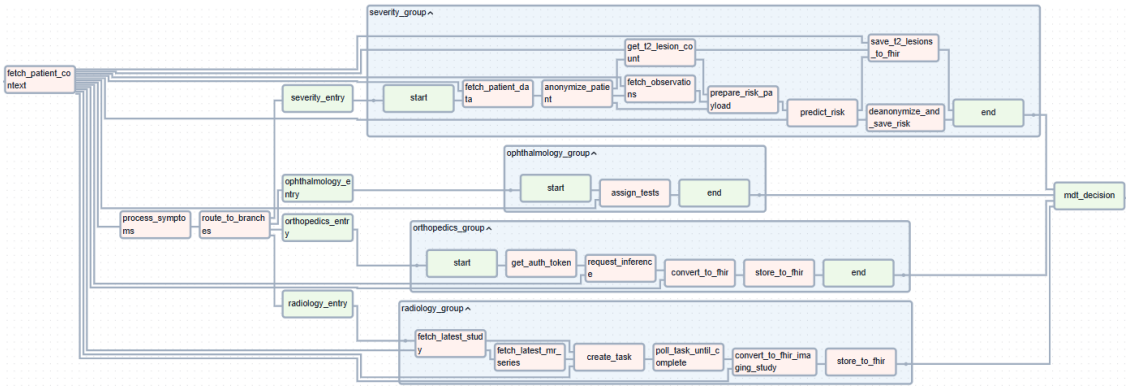


When sensor data need to be shared externally, the requested datasets are processed through a containerized anonymization service deployed alongside SarkoMonitor. After anonymization, data can be exported in FHIR-compliant format to support standardized and privacy-preserving integration.

Neurology

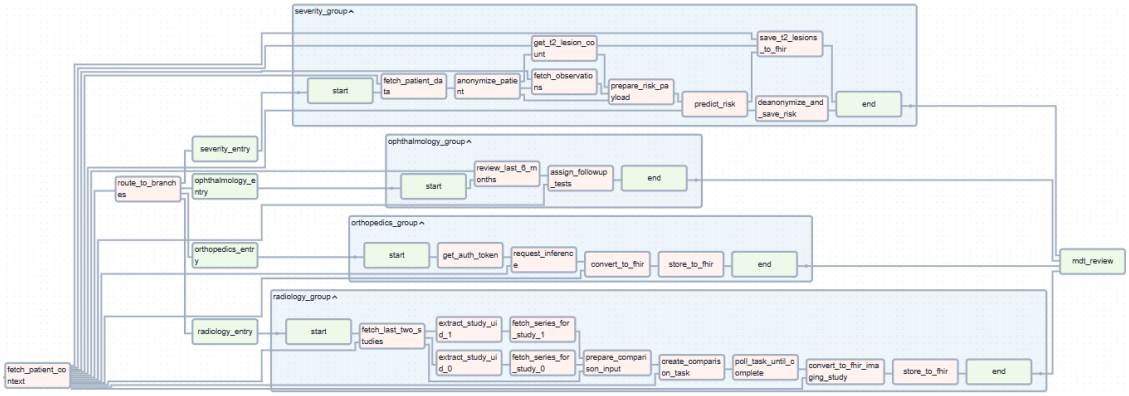
Clinical Workflow Orchestrator

The Clinical Workflow Orchestrator is a centralized coordination engine developed using Apache Airflow to manage and automate multidisciplinary clinical pipelines. It is designed to ensure structured, traceable, and fully automated execution of integrated diagnostic and monitoring workflows within the hospital ecosystem. The system currently supports two primary clinical scenarios implemented as Directed Acyclic Graphs (DAGs): MS Diagnosis and MS Progression Monitoring. Each scenario consists of four specialized sub-workflows that collectively provide a comprehensive, patient-centric evaluation framework.



The sub-workflows span radiology, neurology, orthopedics, and ophthalmology domains, enabling a holistic multidisciplinary approach to Multiple Sclerosis management. Each sub-workflow integrates distinct project components—such as AI-based lesion segmentation, time-based comparison systems, mobile vision testing,

structured reporting modules, and analytics services—ensuring seamless interoperability across imaging, functional assessment, and clinical evaluation layers.

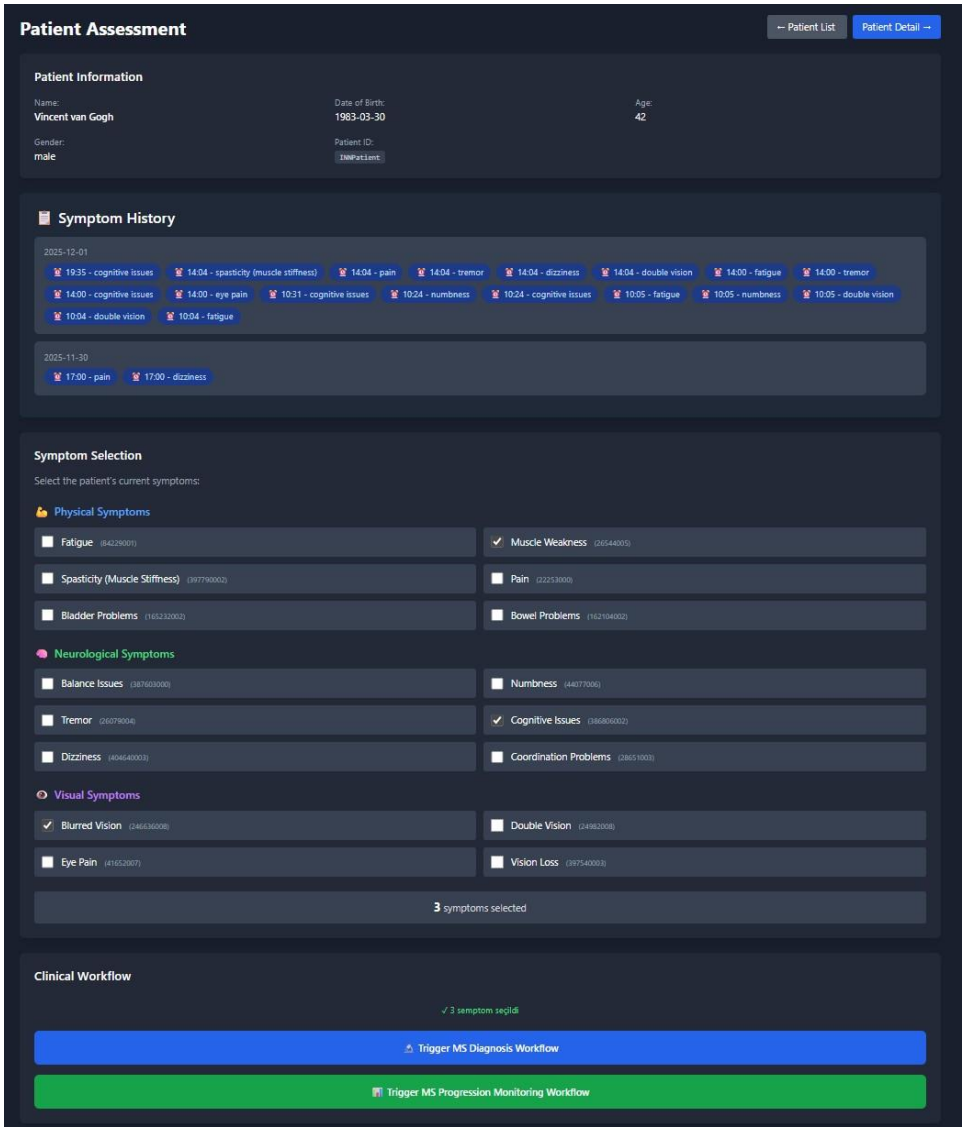


The orchestrator dynamically triggers and routes sub-workflows based on patient symptoms, clinical inputs, or predefined decision rules. It ensures that dependent pipelines execute in the correct sequence without manual intervention, handling task dependencies, data exchange, and execution monitoring in a standardized manner. Upon completion, all generated analytics, structured imaging outputs, and derived clinical indicators are consolidated into the hospital's PACS and FHIR-compliant databases. This enables unified visualization and longitudinal follow-up within the MDT dashboard, supporting coordinated decision-making across clinical disciplines.

MDT Dashboard

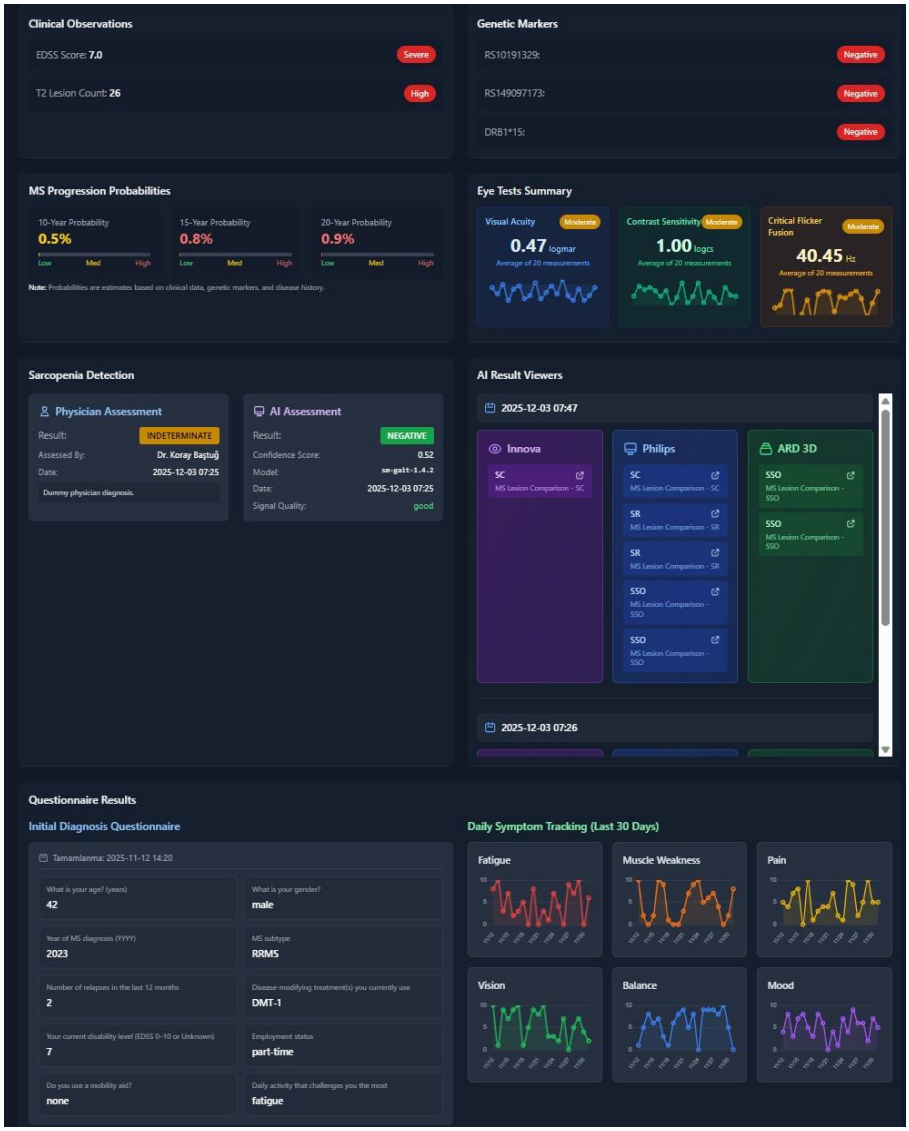
The MDT (Multidisciplinary Team) Dashboard is a web-based clinical decision support platform designed to centralize patient information, analytics, and AI-generated insights into a unified environment. It serves as the primary interface for multidisciplinary collaboration, enabling coordinated evaluation and medical decision-making across radiology, neurology, ophthalmology, orthopedics, and related specialties.

The application consists of three core modules. The first is the Patient List Page, which provides structured access to registered patients, enabling filtering, search, and status tracking. The second is the Patient Assessment Page, where clinicians can record presenting symptoms during a visit and trigger the appropriate clinical workflows. Through direct integration with the Clinical Workflow Orchestrator, symptom-based selections automatically initiate relevant diagnostic or progression-monitoring pipelines without manual coordination.



The third module is the Detailed Analytics Page, which aggregates comprehensive patient-level insights. This includes demographic and genetic data, long-term disease severity risk predictions (e.g., 10-, 15-, and 20-year forecasts), sarcopenia detection outcomes, vision test results from the mobile application, structured questionnaire responses, and direct viewer links to AI-generated imaging outputs such as lesion segmentations and comparison analyses. All structured reports and imaging-derived metrics are presented in an organized and clinically interpretable format.

The MDT Dashboard is fully integrated with the hospital's PACS infrastructure and FHIR-compliant clinical databases, ensuring standardized and interoperable data exchange. It operates in real time, reacting dynamically to updates within connected systems so that newly generated analytics, imaging outputs, or assessment results are immediately reflected in the interface. By consolidating multimodal data streams into a single collaborative platform, the MDT Dashboard supports evidence-based discussions and facilitates timely, coordinated medical decisions.



Data Ingestion & Privacy-Processing Tool
This tool is a core component of the larger medical decision support platform. It functions as a microservice responsible for the ingestion, processing, and symmetric two-way anonymization of sensitive patient data. The service handles data formatted according to the **HL7 FHIR** (Fast Healthcare Interoperability Resources) standard and **DICOM metadata**.

The primary goal is to create a secure, configurable gateway for healthcare data:

- **Rule-Based Encryption**: Encrypts specific, configured fields within any FHIR resource or metadata tags within a DICOM file.
- **NER-Based PII Removal**: Uses presidio-analyzer to detect and encrypt PII (names, locations, etc.) within unstructured text fields (specifically div tags in FHIR Narrative resources).

This allows for data to be securely processed by other components and fully de-anonymized later using the same service.

Key Features

- **Symmetric Anonymization**: Provides endpoints to both anonymize and de-anonymize individual FHIR resources and full FHIR Bundles.
- **Hybrid PII Detection**: Combines rule-based encryption for known sensitive fields with powerful NER-based analysis for finding PII in unstructured text.
- **Configurable**: The secret key and the list of structured fields to encrypt are managed via environment variables.
- **Self-Contained**: Uses a local spaCy model for NER, requiring no external LLM or cloud services.
- **RESTful API**: Built with FastAPI for high performance and automatic, interactive API documentation.
- **Containerized**: Includes a Dockerfile for easy and consistent deployment.

Usage:
Image URL:

- registry2.tazi.ai/symphony/data-ingestion-and-anonymization/ingest-and-anonymize
- Image pull token: contact support@tazi.ai for the token

Configuration

Environment Variables:

Name	**Sample (default values)**
SECRET_KEY	ubtJ…0MR2gU=
ANONYMIZE_FIELDS	"family,given,line,city,district,state,postalCode,country,display"
ANONYMIZE_FIELDS_TO_IGNORE	"birthDate,issued,effectiveDateTime,effectiveInstant"
ANONYMIZE_DICOM_TAGS	"PatientName,PatientID,PatientBirthDate,PatientSex,PatientAge, PatientAddress,OtherPatientIDs,OtherPatientNames,PatientBirthName, PatientMotherBirthName,MedicalRecordLocator,ReferringPhysicianName, InstitutionName,InstitutionAddress,OperatorsName,PhysiciansOfRecord"

The cryptographic SECRET_KEY is generated with the following function:

python -c "from cryptography.fernet import Fernet; print(Fernet.generate_key().decode())"

ANONYMIZE_FIELDS_TO_IGNORE lists the entities that should not be anonymized because in medical applications these may be relevant for the downstream processes.

Deployment

You can run the container standalone, via a compose file, or in a kubernetes cluster.

Standalone example:

docker run -d --name anon \
-e SECRET_KEY=ayT76eRS5u[REDACTED]]UwoQn0MR2gU= \

-p 8000:8000 \
registry2.tazi.ai/symphony/data-ingestion-and-anonymization/anonymize

Docker Compose example:

```
services:
  anonymization:
    image: registry2.tazi.ai/symphony/data-ingestion-and-anonymization/anonymize
    container_name: anon
    restart: unless-stopped
    environment:
      - SECRET_KEY=ayT76eRS5u[REDACTED]]UwoQn0MR2gU=
      # the lists below are optional unless you want to change the defaults
      -
ANONYMIZE_FIELDS="family,given,line,city,district,state,postalCode,country,display"
      -
ANONYMIZE_FIELDS_TO_IGNORE="birthDate,issued,effectiveDateTime,effectiveInstant"
      -
ANONYMIZE_DICOM_TAGS="PatientName,PatientID,PatientBirthDate,PatientSex,PatientAge"
    ports:
      - 8000:8000
```

API

Two encryption versions are available:

- **v1** (default paths): Fernet symmetric encryption. Well-established, longer ciphertext (~100+ chars per field).
- **v2** (/v2/ prefix): AES-256-GCM + ASCII85 encoding. ~50% shorter ciphertext, same SECRET_KEY, same processing logic.

v1 and v2 ciphertext are **not cross-compatible** — always use the matching version to decrypt.

FHIR Endpoints

Operation	**v1 Path**	**v2 Path**
Anonymize Bundle	POST /fhir/anonymize-bundle	POST /v2/fhir/anonymize-bundle
De-Anonymize Bundle	POST /fhir/deanonymize-bundle	POST /v2/fhir/deanonymize-bundle
Anonymize Resource	POST /fhir/anonymize-resource	POST /v2/fhir/anonymize-resource
De-Anonymize Resource	POST /fhir/deanonymize-resource	POST /v2/fhir/deanonymize-resource

DICOM Metadata Endpoints

Operation	v1 Path	v2 Path
Anonymize Metadata	POST /dicom/anonymize-metadata	POST /v2/dicom/anonymize-metadata
De-Anonymize Metadata	POST /dicom/deanonymize-metadata	POST /v2/dicom/deanonymize-metadata

All endpoints accept the same request format and return the same response structure — only the encryption algorithm differs.

- OpenAPI-3.0-compliant endpoint documentation

MS Severity Prediction

The MS pilot demonstrates how a disease-specific severity prediction model can be integrated into a clinical data ecosystem using interoperable services and healthcare data standards. The objective of the demonstration is to show how patient-specific clinical information can be analysed through a predictive algorithm to estimate the risk of disability progression in patients with MS. The developed MS severity prediction model is based on a nonlinear logistic regression algorithm trained on retrospective MS cohort data. The model predicts the likelihood of disability worsening at the time of MS diagnosis. It uses a set of routinely available clinical and demographic variables, including year of birth, sex, age at disease onset, the first Expanded Disability Status Scale (EDSS) score, age at first EDSS measurement, genetic markers and MRI-derived indicators such as T2 lesion number and lesion load. The model is implemented as a REST-based prediction service. The service allows external systems to submit patient-specific information and receive severity predictions in a standardized format. The predictive service processes the input data and returns the calculated probability of disease progression together with the contribution of the individual variables used in the model. The integration of the predictive service follows interoperable healthcare data standards. The demonstration illustrates the following workflow: Patient clinical data are retrieved from the MS clinical data repository using standardized data structures. Relevant patient attributes are transferred to the severity prediction service via a REST API request. The prediction service processes the data using the model. The model calculates the probability of disability progression and identifies the contribution of the individual predictors. The prediction results are returned through the API and reported as part of the MS clinical workflow.

Smart Health Monitoring & Questionnaires (CareMe)

CareMe at Home is a Tele-medicine platform that strengthens the bond between patients and medical teams, through the optimisation of resources such as time, costs or distance. CareMe operates as a communication channel between patients and doctors.

- Patients have the possibility to access all information related to their health: medications, reminders, individualised recommendations, medical reports, analyses, or results, and interact directly with their medical professionals.

- Doctors can monitor the health of their patients and get into communication with them when necessary.

Main features:

- Communication: CareMe provides a direct and secure communication channel between the medical team and patients. It offers the possibility of instant messaging and encrypted and secure video calls.
- Information: CareMe enables not only a repository of patient data, but also the personalisation of diets, health advice or health-related news for each patient to enhance patient co-responsibility for their health.
- Monitoring: Monitoring through external medical devices, wearables, and personalised data collection forms, analysing all data obtained and applying strategies in terms of alarms and actions. Regardless of the source, it enables proactive medicine through remote monitoring.
- Questionnaires: doctors can create questionnaires with different questions for patients to answer, e.g. ad hoc, mandatory questionnaires.
- Adherence: Adherence through gamification motivates patients not only to improve their consistency in their treatments, but also to achieve healthy habits, establishing a system of challenges and rewards. It enables an improvement in habits and empowers the patient through training and information in a fun way.
- Interoperability: CareMe is interoperable with any health information system and can integrate third-party solutions; It is an end-to-end tele-medicine solution.

CareMe was integrated with Accolade from Sopheon (see below) and with Innova (questionnaire feature).

Rule-based MS Detection

Sopheon will demonstrate how its Accolade system is configured to a. edit complex algorithms in human language b. apply these to a specific patient, c. receive patient specific vital sign data, d. use the algorithms to analyze the data and calculate the correct notifications, e. report the explainable notifications in multiple forms. Sopheon will also demonstrate that an algorithm can be connected to e.g. Pubmed for latest evidence alerts, using an NLP enabled search engine.

The demonstration will show how the integration is realized with the AICRUMIT app called CAREME, using various APIs.

The Sopheon system contains a MS specific algorithm that can predict problems for the patient based on vital signs and other data. These data are in the CAREME database. The Sopheon system invokes these data over an API into its own database, calculates these using its algorithms and generates the appropriate notifications. These are reported in various ways. One is into the CAREME app over a special integration.

5.4 References

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6 Conclusions

In this deliverable the major demonstration and pilot results of the SYMPHONY project were highlighted, providing a final overview of the project this respect.

The demonstrators and other project end points created significant exploitation potential towardse solutions and services in the near future.