TREAT

Transforming Healthcare Through Semantic Interoperability and Self-Efficacy

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D1.1 – State-of-the-art and use case descriptions

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Author(s): ISEP, CHTMAD, PLUX, My Viva, Rehabtronics, Almende, DEMCON, Eindhoven University of Technology, Elitac Wearables, Maastricht University, MEDrecord BV, Roessingh Research and Development, GLINTT, DEXTROMEDICA, LUDACREATE, INGUBU, Anadolu Sigorta, ARD GROUP, E-Kalite, LiveWell

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Description: This Deliverable provides the baseline state-of-the-art and the refining of the use cases of the project. It provides a general description of the intervention area, and survey the current status of data collection and processing, decision making and platforms.

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Glossary

Abbreviation / acronym	Description
TREAT	Transforming Healthcare Through Semantic Interoperability & Patient Self-Efficacy
NCD	Non-Communicable Disease
API	Application Programming Interface
SaaS	Software as a Service
NLP	Natural Language Processing
AI	Artificial Intelligence
GDPR	General Data Protection Regulation
HL7	Health Level Seven set of standards
FHIR	Fast Healthcare Interoperability Resources standard
ML	Machine Learning
SotA	State-of-the-art
CNN	Convolutional Neural Network
MRI	Magnetic Resonance Imaging
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
LLM	Large Language Models
NER	Named Entity Recognition
EHR	Electronic Health Records
XAI	Explainable AI
SHAP	SHapley Additive exPlanations
ECG/ EKG	Electrocardiogram
SpO2	Oxygen saturation
AI-CDSS	AI-based Clinical Decision Support System
PHC	Primary Healthcare
IDF	International Diabetes Federation

1. Executive Summary

This deliverable provides the initial description of the TREAT demonstrators and the associated state-of-the-art. It is the result of the first phase in task 1.1 of work package 1.

WP1 provides the baseline for the other work packages in the TREAT project, by providing the requirements and related workflows of the project use cases, to be used as reference in the development of the technical solution of the project: these requirements will guide the work of WP2 on data collection, algorithms, and privacy and security issues, WP3 in AI technologies and methodologies, and WP4 on the development of the project platform, software, and semantic interoperability concepts.

Task 1.1 refines the set of use cases of the project. The use cases will be demonstrated through specific scenarios, through the integration of the different technologies, both existing and those developed as part of the project, and validated against the project's technical requirements, as well as by healthcare professionals.

2. Introduction

The role of this document is to provide the initial set of use cases defined for the TREAT project. The work started from the initial specification of the use cases considered in the proposal, which provides the scenarios considered for the project, leading to the specification of five use cases:

- **UC1: Patient-centric digital ecosystem**

  This use case concentrates on the development of a patient-centric digital ecosystem to improve self-efficacy for patients to manage cardiac metabolic diseases, specifically type 2 diabetes at home and the hospital. Further, the development of a wearable device that supports interoperability and can provide real-time decision-making data to both clinicians and patients at an institutional level. This use case supports TREATs goal to increase patient self-efficacy in managing non-communicable diseases (such as type 2 diabetes) by developing a patient centred platform that addresses interoperability between health institutions, decreases the reliance on healthcare providers, and increases patient adherence

- **UC2: Integrated System for Osteoarthritis Patients**

  The goal of the use case is to realize an integrated system for osteoarthritis patients which can be used by physical therapists and lifestyle coaches to administer and remotely monitor interventions/training programs, supported by automated personalized coaching. This use case supports TREAT's overall goals of improving individualized clinical care, specifically focusing on long-term adherence of individuals with diabetes mellitus and osteoarthritis to norms of healthy physical activity. This process will be optimized through remote physical monitoring, semantic interoperability and the use of AI for personalized recommendations. Each partner of the consortium will provide their expertise to work on this common goal.

- **UC3: Recommender SaaS Platform**

  This use case considers the integration of data from various sources (diet, pharmacological treatment, out-of-hospital monitoring, care pathways) into a platform which is able to provide personalized recommendations and improve the effectiveness of treatment for patients with chronic non-communicable diseases. (NCDs). This will include collaboration between health professionals, pharmacists and advanced artificial intelligence (AI) technologies. The platform will be provided through an API, which will allow us to offer it as a Software as a Service (SaaS) solution, allowing its use by other entities and facilitating its integration into various health platforms.

- **UC4: Diabetes monitoring**

  This use case will focus on a diabetes-specific solution aimed at enhancing self-efficacy and improving clinical workflows. The solution will provide a multi-layered framework, including collecting data from patients using two types of wearable devices, measuring the glucose level in the blood and record the electrical signals in the heart, which will be processed using AI on the platform for semantic operability.

- **UC5: Distributed Diagnoses and Home Healthcare**

  This use case pertains to distributed diagnoses and home healthcare, aiming to develop economically efficient methods for user-centered and home-based systems. These systems focus on monitoring health-related quality of life, particularly for patients with chronic diseases. In this context, the integration of personal devices (such as smartphones and wearables) with hospital information systems allows for remote patient monitoring. The system collects data from sensors, patients, families, and primary care professionals, integrating it with information from the hospital's individual personal care system. This integration enables the development of various services, including information dissemination, coaching, analysis, and alarming

For each use case, a chapter is provided with the associated state-of-the-art, and the use case description.

3. UC1: Patient-centric Digital Ecosystem

3.1 State-of-the-art

Cardiometabolic diseases may consist of varying disease types such as diabetes, obesity, heart disease, arthritis, depression and anxiety. Cardiometabolic diseases can affect individuals of any age but typically have a higher incidence in older age groups. The Canadian healthcare system is currently facing capacity pressures and with an aging population, both the Canadian healthcare system and cardiac metabolic patients could benefit. There are approximately 12.9M Canadians affected by cardiometabolic disease.

Diabetes is a leading cause of mortality worldwide, contributing to approximately 1.5 million deaths annually. The condition significantly increases the risk of cardiovascular diseases, which are responsible for about 50% of deaths among individuals with diabetes. Globally, diabetes is associated with severe complications, including kidney failure, blindness, and lower limb amputations, dramatically impacting quality of life and longevity. Approximately 19–34% (depending on the region) of people with diabetes will develop a foot ulcer at some point in their lives. These foot ulcers can lead to amputations and patients who acquire foot ulcers typically have a 5-year mortality rate of 50–70%.

Clinical pathways are often complex due to the uncoordinated nature of the healthcare system. Patients are initially tested for various clinical indicators (blood sugar levels, etc.) and monitored via clinicians (dieticians, nurses) or medical devices (glucose monitor, etc). Patients often rely on the expertise of medical professionals during this phase before a diagnosis and treatment may follow and visits typically shift between at home monitoring and clinic visits. The patient's journey from initial testing to diagnosis may span long periods. In addition to being exposed to a fragmented healthcare system, low patient self-efficacy often delays diagnosis and fosters increased mental stress. This can be particularly problematic as diabetes progresses and medical complications such as diabetic foot ulcers make the care pathway more complex.

The current standard of care is not standardized across healthcare institutions, contributing to low patient self-efficacy. As cardiometabolic diseases are often chronic in nature, patient adherence to traditional interventions (nutrition, exercise, medications) varies as do patient success rates.

Traditional technologies include glucose and monitoring devices, lifestyle education (eating habits, fitness, etc) and various health management programs (apps, fitness programs). Health management programs are typically offered via paper handouts or applications not technologically enabled or used in the medical field. There is currently no interoperability between healthcare institutions and patient management programs making it difficult to offer better clinical decisions for the patient.

3.2 Use case description

The common use case involves the application of My Viva Plan, YARO, the MOX Activity Tracker, and an AI/ML wound prevention algorithm.

- **My Viva Plan (MVP)**: Helps individuals take control of their chronic health conditions such as diabetes. MVP automates individuals personalized plan to enhance their mind, nutrition, and fitness, helping to support goal planning and reduce reliance on healthcare providers.

- **You-AR-Ok (YARO)**: an augmented reality-based avatar that helps support individuals with adherence to their personalized plans.

- **MOX Activity Tracker**: a wearable device suited for diabetics, in-patients with low ambulatory, and patients with low Braden scores to improve patient monitoring. The tracker may function in two different activity modes:

- The "**MISS Activity**" mode which is tailored for in home use. Auxiliary and extended care patients as well as patients requiring additional skilled nursing.

- The "**Hospital Fit**" mode which is tailored for hospitalized patients. Implementation of this mode is preferred as MOX must be worn with a patch.

- **AI/ML Wound Risk Prediction**: Diabetic patients are at high risk of developing foot, leg and sacral ulcers. By developing a prediction model for these wounds intervention and recommendations can be made for those who are identified to be at a high risk for these ulcers.

My Viva Plan is a patient-centric platform that promotes self-efficacy through tailored clinical pathways, and which can create care plans to better manage cardiometabolic diseases at home. Increased patient self-efficacy would lead to increased patient adherence and reduced emphasis on healthcare providers. Further, the development of an augmented reality (AR), YARO, to act as an accountability buddy would further promote patient self-efficacy to help increase and sustain patient engagement. Current IT infrastructure between healthcare institutions and clinics has major interoperability gaps.

The MOX activity tracker measures and transfers wirelessly high-resolution activity parameters that allows for easy 24/7 patient monitoring, patient-doctor data sharing, and real-time data streaming. Activity parameters include physical activity modes and posture detection to seamlessly track mobility.

The initial data set that will be used to train the AI/ML algorithms for ulcer prediction will be from EHR (Electronic Health Records). Rehabtronics plans to obtain data sets from Providence Health as well as Alberta Health. These data sets consist of high-quality data with proper labels and identifiers. Once the algorithms are generated from these datasets the applicable key risk factors identified will be integrated into the Use Case. The EHR records used for the initial training will provide more extensive data than what would be available in the Use Case but there will be data that is common such as age, BMI, type of diabetes and core morbidities.

A patient-centric model requires data interoperability between various healthcare institutions and partners. Security and privacy mandates require PIPEDA (Canada), PHIPA (Ontario), PIA/HIA (Alberta), PIPA (British Colombia), SOC2, and GCP / GDPR compliance. Several players must interact to coordinate interoperability of patient care. Data interoperability between secure portal login, mobile app, wearable devices and healthcare data systems and institutions must be coordinated.

4. UC2: Integrated System for Osteoarthritis Patients

4.1 State-of-the-art

Available wearables for home monitoring to measure activity and heart rate / ECG are roughly categorized in sports trackers such as chest belts, consumer products such as smart watches and clinical devices such as 12-lead ECG measurements. However, none of these wearables combine accurate and comprehensive data logging and processing with sufficient effectiveness, cost-effectiveness and ease-of-use. Advanced but power efficient algorithms beyond the state-of-the-art need to be developed to be able to extract and store raw data and to consequently analyze this data. This enables the development of a recommendation system for the best individualized treatment-patient combination throughout time using the most efficient engagement technique for each individual, whilst ensuring privacy and security.

Current running initiatives only cover some of these main challenges – either on improving the interaction between patient and professional (INNO4HEALTH, SAFHE) or are focusing on a particular topic or functionality (IWISH -hospitals, DAISY -Depression-, X-AID, Secur-e-Health -privacy, security-, PANACEA, RE-SAMPLE, LifeSytlePE -subject-at-risk-), but leaving aside self-efficacy and/or semantic interoperability.

Development of advanced algorithms that can actually take over coaching tasks from the physiotherapist and give the patient more awareness and insight in their own progress constitutes a huge challenge. An important part of the TREAT platform functionality is the personal recommendation of the best treatment-patient combination and the most efficient engagement technique for each individual, at each moment in the treatment program, while ensuring privacy and security.

Almende, TUe, Maastricht University and Roessingh Research and Development will work together to achieve this. Roessingh Research and Development and Maastricht University will be collecting stakeholder needs, wishes and opinions (patients, therapists/activity coaches in Beweeghuis) to feed into the functional specifications/technical requirements. Almende will focus on a digital solution to promote mental health and to facilitate patient activation in treatment exercises, by means of automated data-driven chat messages. These messages will be provided by AI algorithms which will experiment with several behavior change strategies to determine a personalized approach, making use of the data provided by the platform and that of the other partners. TU/e and Maastricht University will develop data analysis algorithms using Federated Learning for safely and privately assessing patient status and progress, which will be the basis for patient feedback, providing insight on progress to practitioners and suggestions for treatment adaptation. Various recommender system methods will be explored to develop adequate decision support models for optimizing patient-practitioner interaction.

4.2 Use case description

The goal of the use case is to realize an integrated system for osteoarthritis patients which can be used by physical therapists and lifestyle coaches to administer and remotely monitor interventions/training programs, supported by automated personalized coaching.

The system will be based on physical sensors and algorithms developed by DEMCON, Elitac Wearables and Maastricht University as well as advanced coaching technology developed by Almende and Eindhoven University of Technology. The system will be validated with end-users from the physical therapist network Beweeghuis by Roessingh Research and Development and Maastricht University. Finally, the system will be interoperable with relevant health data exchange standards through the efforts of KnowL Solutions.

In 2021, there were an estimated 1.2 million individuals in the Netherlands that are known to have diabetes. One of the comorbidities of diabetes is stiffening of connective tissue which, in turn, may lead to increased joint loading and osteoarthritis. The presented percentage of individuals with diabetes that also have osteoarthritis varies in literature between 30 and 50%. This is explained that also other factors play a role in the risk of developing osteoarthritis (age, sex, BMI etc.) which may have been different between studies. The specific clinical consideration is to ensure sustained healthy movement behaviour in a group with a relatively low social economic status as well as limited health literacy.

The specific use case focuses on individuals with diabetes mellitus in combination with osteoarthritis that are receiving guidance from Maastricht Sports in the southern part of the Netherlands. The patient journey is graphically represented in Figure 1.

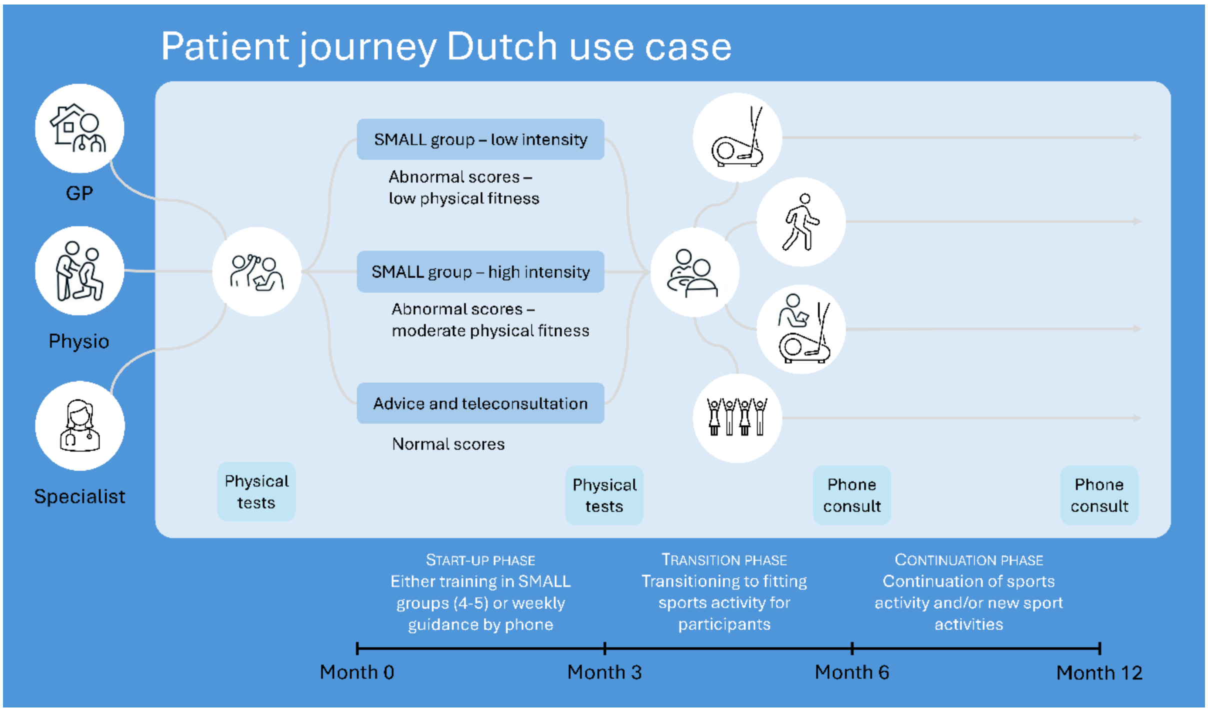

Figure 1: Patient journey use case

The use case is embedded within Maastricht sport. Maastricht sport is an organization that offers sport and movement activities for the municipality of Maastricht for a broad range of individuals. Amongst others they offer 'Beweeg Bewust' ['Move consciously'], which is a special program that has the aim to improve health through sport and physical activity. This physical activity intervention has been developed in a collaboration between Maastricht sport and medical professionals. While Maastricht Sport offers their services to all inhabitants of the municipality, the Dutch use case will focus on individuals with diabetes mellitus and osteoarthritis. They generally will follow the 'Beweeg Bewust' program.

Participants can be referred to the program through their general practitioner, physiotherapist or a medical specialist. After receiving the referral, an intake is planned that consists of questionnaires and tests to determine the participants' fitness level and movement motivation. The applied physical tests are:

- BMI;
- Flexibility (sit and reach test);
- 4-stage balance test;
- Hand grip strength;
- Six minute walk test.

Based on the scores on these tests, participants can follow three different trajectories during the first 12 weeks. Before they join one of the three tracks, participants together with a movement coach set specific movement goals for these first 12 weeks.

If they score below the norm, they follow the Small Group program. Within these groups, four to five participants train weekly under a movement coach's supervision. Individuals participate in a SMALL group – low intensity or in a SMALL group – high intensity. The choice for the low or high intensity variant is based on the scores on the physical tests that were administered during the intake. Both groups are supervised by Maastricht Sport.

If participants score on or above the norm, they are referred to a sports activity that aligns with their wishes and values. This can be a sports activity supervised by Maastricht Sport, but this is not a requirement. During the first 12 weeks, Maastricht Sport has weekly phone calls at a fixed time with the participant to check how they are doing and to monitor progress on the set movement goals.

After the 12 week period, all participants return to Maastricht Sport. During this meeting, the physical tests that were applied during the intake are re-applied to get insight into the progress. After this, the movement coach and the participant discuss sports activities that align with the wishes and values of the participants.

There are several options available that can be discussed:

- Physical exercise in groups of 15-30 participants that are guided by Maastricht Sport;
- Other sport activities (such as hiking groups, badminton etc.) that are provided and guided by Maastricht Sport;
- Medical fitness training offered by physical therapist in the neighborhood;
- Sport activities initiated by local sport associations or local gyms;
- Sport activities initiated by the participants themselves (such as hiking or biking).

After participants made the transition to a fitting sport activity, there is no longer weekly contact between the movement coach and the participant. There are phone calls scheduled at month six and month twelve to discuss how the participant is doing, the current and potentially new movement goals and/or wishes for (new) sports activities. Twelve months after the participant entered the trajectory, the trajectory is completed and there is no longer contact between the movement coach and the participant. When necessary, a former participant can be referred to start another trajectory.

The success rate of these interventions heavily relies on long-term adherence rates which vary between patients. In addition, the amount of information available for therapists to steer and motivate on varies between patients. Consequently, the success rate, in particular the long-term success rate, varies from patient to patient.

In the current use case, there is no standard application of technology. Some participants use a smartwatch or use a health app on their smartphone. If participants are willing to share that data, they can be incorporated in the supervised training period of twelve weeks. In the current patient journey, no other technologies are typically available for patients. In addition, there is currently no interoperability between the typically involved technologies and the patient management programs. This will change once the integrated sensor system is implemented during the evaluation. In that situation, all data that will be received from the wearable devices needs to be stored, processed to actionable insights and integrated in the clinical workflows. Current technologies focus on hospitals, with limited attention given to homes.
Semantic interoperability remains challenging, with a lack of standards or vocabulary for non-structured data and proprietary storage structures hindering comprehensive interoperability. Within TREAT, KnowL Solutions will take the lead in the development of a semantic interoperable e-health platform with patient-centric extensions, with a focus on integration of data streams into clinical workflows and avoidance of security and privacy risks. The innovative contribution will be the common technical interface to enable communication and interaction by usage of open APIs, which can allow streamlined access to a defined set of data or functionality. The key challenges lie in developing common modules that are able to work with the semantic trees of different localities and user groups. For this, we will explore the use of Reinforced Learning based upon human language modelling. KnowL Solutions will work together with Demcon and

Elitac Wearables to ensure compatibility with the wearable devices and with Maastricht University for data management and system validation, including final integration of the app with the platform.

5. UC3: Recommender SaaS Platform

5.1 State-of-the-art

5.1.1 Natural Language Processing – NLP

In the field of Natural Language Processing (NLP), state-of-the-art (SotA) Machine Learning (ML) techniques have revolutionized how language data is processed and understood. These advancements enable applications ranging from text analysis to machine translation and sentiment analysis, crucial for enhancing healthcare interventions like those in the TREAT project.

In the context of the TREAT project, both Natural Language Processing (NLP) and Machine Learning (ML) models for recommendation play fundamental roles in improving the management of chronic non-communicable diseases (NCDs) and optimizing medical care. Here are some key applications:

1. Analysis of Clinical Data and Medical Documentation

NLP is used to process and analyze large volumes of clinical data, including electronic medical records and notes from healthcare professionals. This makes it easy to extract relevant information, such as diagnoses, previous treatments and test results, which are essential for the personalization of healthcare.

2. Text Interpretation and Improved Communication

NLP technologies allow improved communication between patients and healthcare providers. This is achieved through chatbots and automatic response systems that can understand and respond to patient queries efficiently, providing relevant information on the management of their health conditions.

3. Process and Workflow Optimization

NLP helps automate administrative tasks and improve clinical workflows. For example, automatic classification of medical documents or extraction of structured information from clinical reports can reduce the administrative workload of healthcare professionals and improve accuracy in data management.

Use of Machine Learning in Recommendation Models in TREAT:

1. Personalized Treatment Recommendations

ML models, such as recommender systems based on advanced algorithms (e.g., based on collaborative filtering or matrix factorization methods), can analyze historical treatment and outcome data to suggest personalized treatment options. This helps healthcare professionals make informed decisions and improve clinical outcomes for patients.

2. Optimization of Tracking and Adherence Protocols

ML-based recommender systems can also optimize patient monitoring protocols and improve adherence to prescribed treatments. By integrating continuous monitoring data and patient feedback, these systems can tailor recommendations to the specific needs of everyone, thus promoting effective and ongoing management of chronic conditions.

3. Continuous Improvement with Transfer Learning and Pre-trained Models

The use of transfer learning techniques allows us to take advantage of pre-trained models, such as BERT and other large language models, to adapt them to specific domains within healthcare. This not only accelerates the development of new models, but also improves their accuracy and ability to handle complex and varied medical data.

In summary, both NLP and ML in recommendation models play crucial roles in TREAT by improving semantic interoperability, optimizing personalized patient care, and facilitating data-driven decision making in the field of chronic non-communicable diseases. These technologies not only promote more efficient healthcare, but also contribute significantly to the continuous improvement of clinical outcomes and quality of life for patients.

5.1.2 NLP State-of-the-art

Convolutional Neural Networks (CNNs)

CNNs (Convolutional Neural Networks) are a type of deep neural network architecture specifically designed to process grid-structured data, such as images and videos. They are composed of convolutional layers that apply filters to extract key features from the input data, followed by pooling layers that reduce the dimensionality of the extracted features.

In the context of TREAT, CNNs can mainly be used to:

1. Analysis of Images and Visual Data:

- Interpretation of Medical Image Results: CNNs can analyze medical images such as x-rays, computed tomography (CT) scans, magnetic resonance imaging (MRI) to aid in the early detection and diagnosis of medical conditions.
- Wearable Data Monitoring: Some medical devices such as health monitors can capture visual data that can be analyzed by CNNs to detect anomalous patterns or health trends.

2. Data Segmentation and Characterization:

- Image Segmentation: CNNs can segment medical images to identify specific regions of interest, such as tumors or areas of inflammation.
- Visual Data Characterization: CNNs can extract relevant visual features from complex medical data, facilitating personalized diagnosis and treatment.

3. Optimization of Clinical Processes:

- Task Automation: CNNs can automate the interpretation of medical images and the classification of visual data, reducing the workload of healthcare professionals and improving operational efficiency.
- Decision Support: By providing accurate and rapid analysis of medical images, CNNs can support physicians in making informed, evidence-based clinical decisions.

In summary, CNNs are powerful tools in TREAT for the interpretation and analysis of visual data in the medical field, facilitating more accurate diagnoses, personalized treatment, and optimization of clinical processes to improve care and outcomes for patients with chronic non-communicable diseases.

LSTM´s

LSTM (Long short-term memory) is a type of recurrent neural network (RNN) used in deep learning to process and predict sequences of data. LSTM was designed to address the problem of gradient disappearance in traditional recurrent neural networks, which occurs when error is backpropagated across multiple layers and important information is lost in the process. LSTM uses a gated cell structure that allows the network to control the amount of information that is stored and forgotten at each time step, making it especially suitable for processing long-term data streams. LSTMs have been successfully used in a wide variety of deep learning applications, such as natural language processing, speech recognition, text generation, and time series prediction.

First described in a 1997 paper, Long Short-term Memory networks (called LSTMs) are a type of RNN with the ability to learn long-term dependencies. They were proposed as a way of overcoming the problem of vanishing or exploding gradients: i.e. that back-propagated error signals decay exponentially in the various network layers or they explode exponentially in the same[1].

In the context of TREAT, LSTMs (Long Short-Term Memory) can be used for several key purposes:

1. Time Series Analysis: LSTMs are effective for modeling and predicting data that exhibits complex temporal dependencies, such as continuous patient monitoring data through sensors. For example, they can be used to predict the evolution of health parameters over time, such as glucose in diabetic patients.

2. Personalized recommendation: LSTMs can learn behavioral patterns from sequential data, such as records of past drug treatments and patient responses to different therapies. This allows the development of personalized recommendation systems that suggest treatments based on the patient's history and expected response.

3. Prediction and diagnosis: In the diagnosis of chronic non-communicable diseases (NCDs), LSTMs can be trained with longitudinal patient data to predict the risk of complications or to identify patterns that indicate the need for adjustments in the treatment.

4. Optimizing the care pathway: Using data from multiple sources, including patient interactions with various points of care (clinics, pharmacies, etc.), LSTMs can help optimize the patient's care pathway by prediction of future needs and efficient coordination of services.

LLM´s

Large Language Models (LLMs) are advanced artificial intelligence models designed to understand and generate human text more effectively. These models use deep learning techniques to capture complex patterns in natural language data, enabling tasks such as text generation, machine translation, automatic responses, and much more.

In the context of TREAT, LLMs can be applied in several ways:
Analysis and generation of medical text: LLMs can analyze large volumes of medical data, such as electronic health records and clinical notes, to extract relevant information about patients' health status, treatment results, etc.

Conversational interaction with patients: LLMs can power chatbot systems and virtual assistants to interact with patients in a conversational manner, providing automatic responses to common questions, medication reminders, symptom tracking, etc.

Personalization of recommendations: Using transfer learning techniques, LLMs can be adapted to offer personalized recommendations on treatments, dietary modifications, chronic disease management, based on analysis of medical data and patient history.

Optimization of clinical processes: LLMs can be used to improve the efficiency of clinical processes, automating tasks such as writing medical reports, classifying clinical documents and data management in hospital environments.

GPT

[1] Hochreiter, S., & Schmidhuber, Jürgen. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.

Recent advances in natural language processing (NLP) have led to the development of large language models such as GPT, which has shown promising results in various applications, including healthcare (Chen et al., 2021). GPT is a next-generation language model that can generate human-like text by predicting the most likely next word in a sentence based on the input text. This technology has the potential to serve as an interface for home patient care, especially in the fields of precision medicine and dietary recommendations.

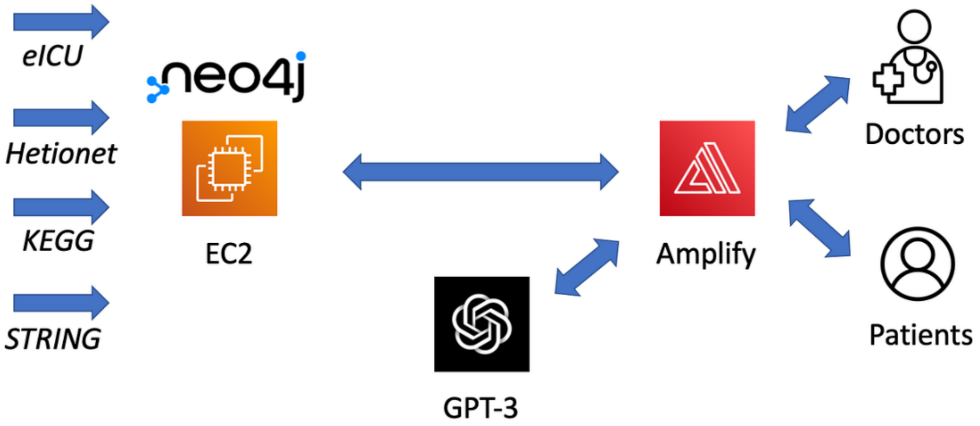

Figure 3: English to Cypher with GPT-3 in Doctor.ai

5.1.3 Evolutionary Learning

NER – Name Entity Recognition

Named Entity Recognition (NER) is a Natural Language Processing (NLP) technique that automatically identifies and classifies specific entities within a text into predefined categories such as person names, organizations, locations, dates, and more. In healthcare, NER can be customized to identify and tag entities like disease names, drug names, symptoms, and medical institutions.

The first attempts at NER were rule based, using domain-specific gazetteers and syntactic-lexical patterns (Nltk.org). Unsupervised approaches to NER included techniques such as inverse document frequency or noun phrase chunking. Supervised learning approaches have also been applied to BER problems where features are designed to represent key features in the documentation, then an ML model is trained to recognize these features.

These attempts have included “semi-supervised learning techniques, which extracts useful features from transferring information from resource -rich language toward resource-poor language [2] as well as Distantly Supervised NER [3], in order to automatically populate annotated training data without human cost. Another advance for NER was Distributed Word Representation [4] (Word2Vec [5], etc.).

[2] A. Zafarian, A. Rokni, S. Khadivi and S. Ghiasifard, "Semi-supervised learning for named entity recognition using weakly labeled training data," 2015 The International Symposium on Artificial Intelligence and Signal Processing (AISP), Mashhad, Iran, 2015, pp. 129-135, doi: 10.1109/AISP.2015.7123504.

[3] Yang, Y., Chen, W., Li, Z., He, Z., & Zhang, M. (2018). Distantly Supervised NER with Partial Annotation Learning and Reinforcement Learning. International Conference on Computational Linguistics.

[4] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Distributed representations of words and phrases and their compositionality. In Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2 (NIPS'13). Curran Associates Inc., Red Hook, NY, USA, 3111–3119.

[5] https://en.wikipedia.org/wiki/Word2vec

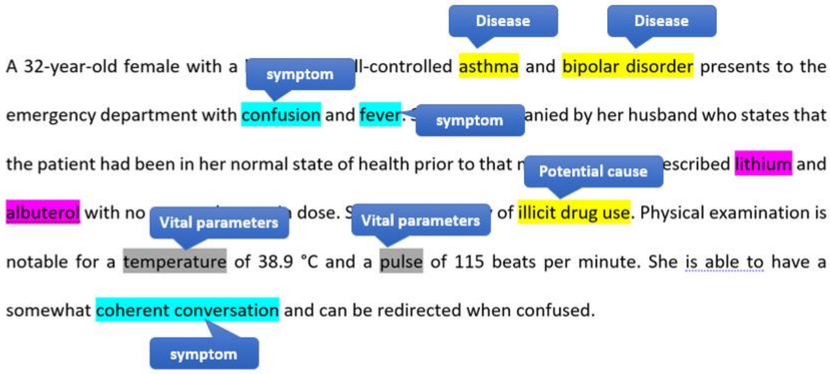

Figure 4: Example of NER in the context of health

Healthcare generates vast amounts of structured and unstructured data from various sources like electronic health records (EHRs), research articles, and patient interactions.

NER can enhance this data by extracting key terms and tagging them appropriately, making the content more discoverable and useful for various applications. This micro-structuring of content helps build robust healthcare applications.

In the TREAT project, NER can significantly enhance patient care by improving data accessibility by identifying and tagging crucial medical terms from patient records, research papers, and clinical notes, making it easier to access and analyze relevant information. It enhances decision support systems by recognizing and correlating entities such as symptoms, disease names, and drug names to support predictive models that suggest potential diagnoses and treatment plans.

NER supports personalized medicine by extracting and analyzing patient-specific data (like symptoms and medication history), helping to tailor personalized treatment plans and dietary recommendations. Additionally, it facilitates research and development by tagging and organizing information from research articles, helping researchers identify emerging trends and gaps in medical research.

Knowledge Graphs

The use of knowledge graphs has emerged as a prominent technology that has shown significant advances in recent years. Knowledge graphs are based on intelligent algorithms that facilitate machine learning, which in turn generates knowledge structures by building relationships between structured and unstructured data. As a result, virtual layers are created that help organize data sets in a similar way to how our brain processes information [6].

The integration of sophisticated algorithms into knowledge graphs has significantly improved their ability to accumulate and organize data, opening numerous possibilities for their use in various applications in the business sector. A major advance in the application of knowledge graphs is the development of a framework that provides a schema for agile data acquisition and production of understanding. This framework has led to the creation of more refined and tailored recommendation models that address the unique needs of each user [7].

[6] Alam, M. M., Xu, X., & Yin, H. (2020). Intelligent knowledge graph: A review. Information Processing & Management, 57

[7] Himmatz, J., Lee, D., Lee, D., & Kang, S. (2018). Agile knowledge graph production for a recommendation system. Journal of Internet Technology, 19

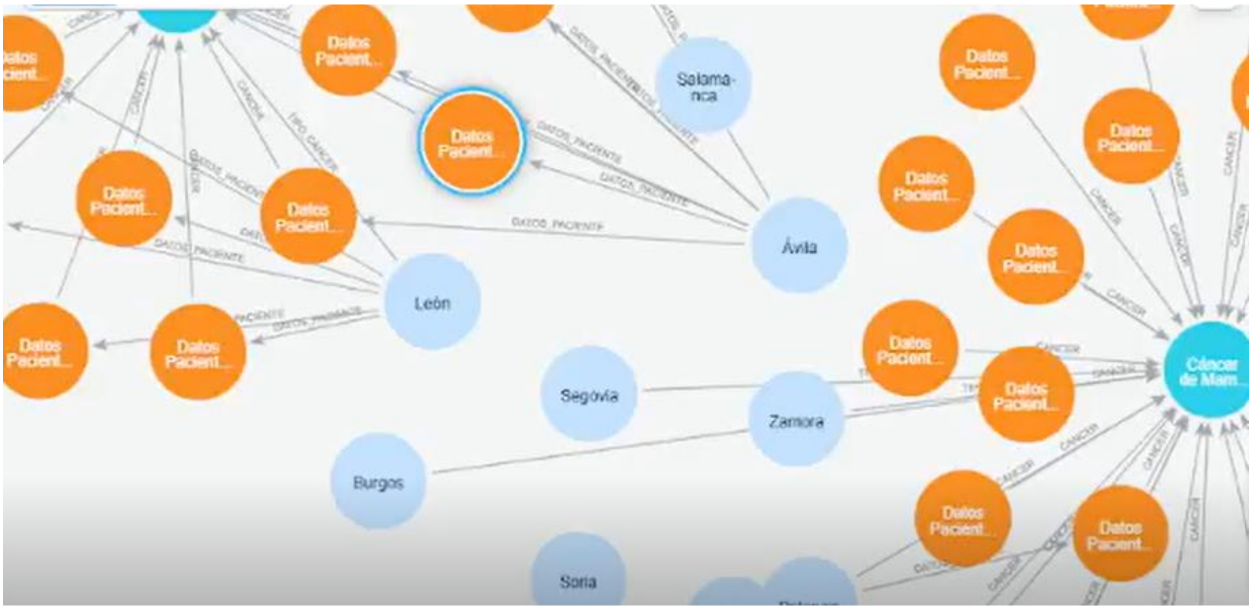

Figure 5: Food Knowledge Graph representation in the Neo4j environment.

Sentiment Analysis

Sentiment Analysis, also known as sentiment analysis, is a natural language processing (NLP) technique used to identify and extract opinions and emotions expressed in text. This technique evaluates the words, phrases, and context of a message to determine whether the tone is positive, negative, or neutral. Sentiment analysis can be applied to various text sources, such as social networks, product reviews, emails, among others.

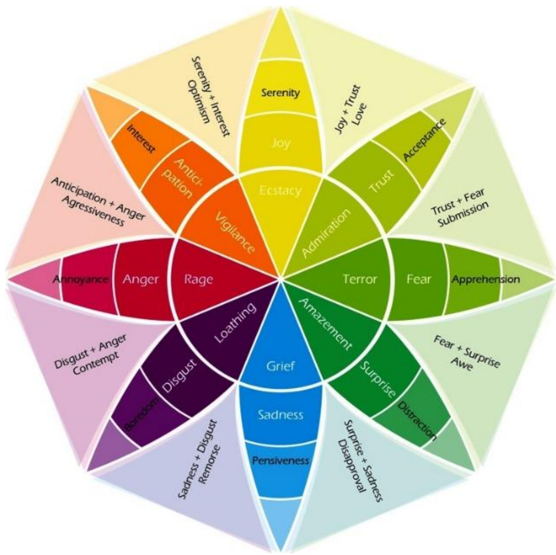

Figure 6: Wheel of emotions [https://www.betterup.com/blog/emotion-wheel]

In the context of the TREAT project, sentiment analysis is used to improve patient care by assessing satisfaction, early detection of problems, and monitoring mental health through the emotions expressed in their emotions. interactions. This technique allows you to optimize health services, adjust recommendations and improve the relationship between patients and health professionals, promoting personalized and empathetic care. Benefits include early detection of problems, continuous improvement of services, increased treatment adherence and patient empowerment, all of which contribute to more effective and satisfying healthcare.

Virtual Assistants

Virtual assistants are software programs designed to perform specific tasks through interactions with human users, typically through natural language processing (NLP) and other artificial intelligence (AI) techniques. These assistants are designed to simulate conversation with a real person and can perform a variety of useful functions, such as answering questions, performing actions on connected systems, providing contextualized information, reminders, and performing transactions, among other applications. Its main goal is to improve efficiency and user experience by offering fast and accurate responses through intuitive user interfaces such as mobile applications, smart devices and websites.

"The use of virtual healthcare assistants has gained popularity as a solution to challenges in patient care. Recent studies demonstrate its effectiveness in improving care in various areas. Ahmed Kamal et al. They found that these assistants have greater accuracy in diagnosis and treatment compared to health professionals. Viswanathan et al. demonstrated that virtual assistants better promote medication adherence in patients with chronic diseases. In remote areas, Batsis et al. confirmed that these assistants improve access to health services. However, there are concerns about the loss of human contact and the potential for diagnostic errors, as indicated by studies by Fadhil et al. and Tugrul et al. Despite these challenges, virtual healthcare assistants have the potential to improve care and access to medical treatments, with continued development and evaluation needed to address their limitations." [8]

Explainable AI

The opacity of artificial intelligence systems often results in a lack of clarity around the reasons behind their conclusions, which can be problematic in various situations, especially those where decisions can have significant impacts on the real world, such as in the fields of medicine, defense, justice and sports [9].

[8] Rawas, Soha & Samala, Agariadne. (2024). Generative AI as Virtual Healthcare Assistant for Enhancing Patient Care Quality. International Journal of Online and Biomedical Engineering (iJOE). 20. 10.3991/ijoe. v20i05.45937.

[9] Adadi, A. and Berrada, M. (2018) Peeking inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). IEEE Access, 6, 52138-52160

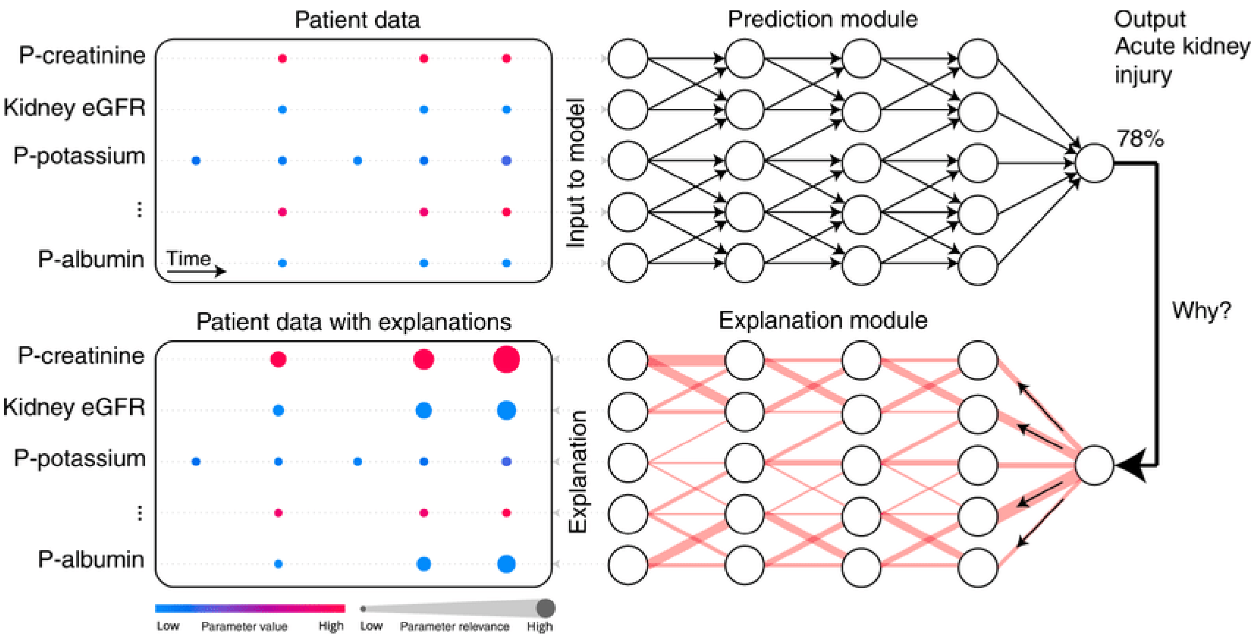

Figure 7: Explainable artificial intelligence model to predict acute critical illness from electronic health records.

To address these issues, during TREAT we will improve the transparency, reliability and accountability of artificial intelligence algorithms by improving their explainability. Explainable AI (XAI) refers to the ability to understand the reasoning underlying the decisions and predictions made by an algorithm, as well as the ability to justify the result. This approach can help identify any potential errors or biases that may exist in the results produced by the algorithm[10].

To realize the full potential of AI, it is essential to understand the logic behind an algorithm, which would allow impartial assistance and support to those in need. By enabling understanding of the decision-making process, XAI has the potential to eliminate errors and biases and provide unbiased support to people in need, especially in contexts where decisions can have far-reaching consequences.

Figure 8: Example of explainability with SHAP

SHAP (SHapley Additive exPlanations) is a methodological approach used in the interpretation of machine learning models, belonging to the field of Explainable Artificial Intelligence (XAI). SHAP is based on Shapley's theory of value, a game theory concept that assigns fair values to each player in a cooperative game. In the context of machine learning models, the "players" are the features of the model, and the "game" is the prediction made by the model.

[10] Doshi-Velez, F., & Kim, B. (2017). Towards A Rigorous Science of Interpretable Machine Learning. *arXiv: Machine Learning*.

SHAP has several important applications in the context of XAI:

- Model Interpretation: Provides clear and consistent interpretations of model predictions, showing how each feature contributes to a particular prediction.
- Transparency: Improves the transparency of complex machine learning models, such as Random Forests, gradient boosting models, and deep neural networks.
- Bias Detection: Helps identify and understand biases in models, ensuring that automated decisions are fair and equitable.
- Feature Validation: Facilitates validation of feature importance, allowing developers to understand which features are most influential in predictions.
- Regulations and Compliance: Supports compliance with regulations that require interpretability in artificial intelligence systems, such as the GDPR in Europe.

5.2 Use case description

The use case in TREAT focuses on the creation of a platform that integrates data from various sources (diet, pharmacological treatment, out-of-hospital monitoring, care pathways) to provide personalized recommendations and improve the effectiveness of treatment for patients with chronic non-communicable diseases. (NCDs). The intervention encompasses collaboration between health professionals, pharmacists and advanced artificial intelligence (AI) technologies to offer continuous and coordinated care. In addition, the associated recommender will be exposed through an API to offer it as Software as a Service (SaaS), allowing its use by other entities and facilitating its integration into various health platforms.

Figure 1: Software as a Service

The Software as a Service (SaaS) model is highly beneficial and especially suitable for the use case in the TREAT project for several reasons:

1. Accessibility and Availability: By offering the associated recommender as SaaS through an API, it is guaranteed to be available to any entity that wishes to integrate it into their own health platforms. This facilitates access to the tool without the need to install and maintain complex software on each user's premises.

2. Reduced Costs: The SaaS model eliminates the need for significant investments in infrastructure and maintenance. Organizations can subscribe to the service and pay only for what they use, which is particularly advantageous for healthcare institutions and pharmacies with limited resources.

3. Updates and Maintenance: With SaaS, updates and maintenance are managed centrally by the service provider. This means that users will always have access to the latest version of the software with the latest improvements and security fixes without interruptions or complications.

4. Scalability: SaaS allows for easy and fast scalability. As demand or user numbers increase, the service can seamlessly scale to accommodate this growth, ensuring performance is not compromised.

5. Interoperability: Exposing the recommender through an API facilitates its integration with other health systems and platforms, promoting interoperability. This is crucial in the context of the TREAT project, where collaboration and data sharing between various entities is essential to improve patient care.

6. Flexibility and Customization: SaaS offers great flexibility, allowing organizations to adapt and customize the tool according to their specific needs. This is particularly useful for adjusting dietary and treatment recommendations to the particularities of each patient.

7. Security and Compliance: SaaS providers generally implement high security standards and comply with regulations such as GDPR. This ensures that patient data is protected and handled securely, a critical aspect in managing health information.

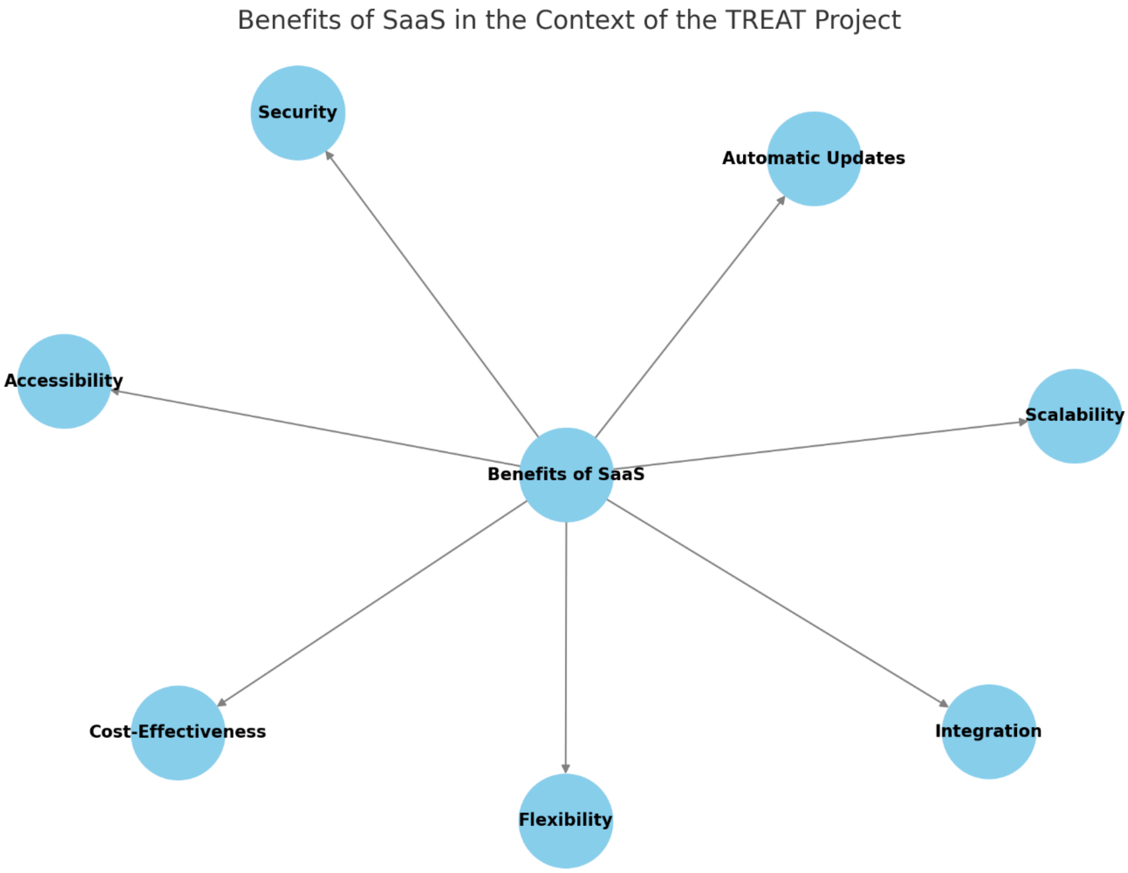

Figure 2: Benefits of SaaS

In the use case of the TREAT project, the choice of SaaS is fully justified by its ability to improve accessibility, reduce costs, ensure continuous updates, allow scalability, facilitate interoperability, offer flexibility, and guarantee security and regulatory compliance. These advantages contribute significantly to the effectiveness and efficiency of the health system, allowing better management of chronic diseases and improving the quality of life of patients.

This use case supports TREAT's overall goals of improving individualized clinical care, increasing patient adherence to treatments, and optimizing care processes through semantic interoperability and the use of AI. Each company in the consortium will contribute with its specialty to create a comprehensive solution. Regarding the relevant techniques, continuous monitoring sensors, electronic health records and mobile applications will be used for data collection; data cleaning and normalization algorithms and knowledge graphs for data processing; AI models such as neural networks and deep learning for decision making; and interoperability platforms such as HL7 and FHIR for data management.

The common use case involves the collaboration of three companies in the TREAT consortium: GLINTT, which provides services to identify patterns in the interaction between diet, drug treatment and patient, contributing components for patient support and statistics; LUDA, which develops services that combine AI and semantic interoperability to improve the effectiveness of out-of-hospital treatment, capturing pharmacy requirements and developing personalized algorithms and interfaces for pharmacists; and DEXTRO, which optimizes and controls healthcare processes through automation and digitalization, implementing AI-based recommendation techniques and an AI assistant for workflows.

In Spain, chronic non-communicable diseases such as heart disease, diabetes and obesity are highly prevalent, affecting a large part of the adult population and contributing significantly to the burden on the health system. The clinical pathway includes diagnosis through electronic health records and medical consultations, continuous patient monitoring through sensors and mobile applications, and adjusted treatment based on personalized recommendations.

The patient's journey involves regular interactions with clinicians, pharmacists and technologies, with continuous monitoring at home and regular visits to clinics and pharmacies. Current interventions include standard pharmacological treatments and nutrition and physical activity programs, with success rates varying depending on patient adherence and coordination of care.

Technologies involved throughout the patient journey include monitoring sensors, mobile applications and electronic health records, in addition to telemedicine devices and health management platforms. The IT infrastructure that supports the patient's journey includes interoperable systems, distributed databases, and cloud analytics platforms.

Privacy and security considerations include GDPR compliance, encryption measures, and access control. Interoperability considerations are based on the use of HL7 and FHIR standards, and available data types include clinical, pharmaceutical, and monitoring data.

6. UC4: Diabetes Monitoring

6.1 State-of-the-art

The TREAT project represents an important initiative in health technology integration and Livewell is playing a key role with its smart ECG shirt. This shirt is equipped with advanced sensors that allow users to continuously monitor their heart health. Currently in the development stage, the shirt successfully collects ECG signals and enables observation of these signals on mobile devices. This allows users to monitor their heart rhythms in real-time and detect potential issues early. The shirt is designed to collect only EKG data, but in the project, this data will be seamlessly integrated with other health measurements. Continuous blood sugar measurement, body temperature, blood pressure, and SpO2 data will be collected using different devices. This data will be combined with EKG data to create a more comprehensive health monitoring system. This integration will provide users with a wider and more accurate data set regarding their overall health.

All data collected in the project will be transmitted in real-time to mobile devices and then sent to consortium companies for analysis. This enables real-time monitoring of users' health status and quick intervention when necessary. The project also emphasizes the importance of detecting certain arrhythmias from EKG data. Livewell emphasizes that these arrhythmias will be accurately and quickly detected and integrated with other data through their developed algorithms.

Apart from hardware integration, AI-based Clinical Decision Support Systems (AI-CDSSs) have advanced significantly, especially in primary healthcare (PHC). These systems enhance healthcare by providing evidence-based recommendations, thereby improving decision-making and patient outcomes. Studies like that conducted by Gomez-Cabello et al. (2024) demonstrate the capabilities of AI-CDSS in diagnostic support, treatment recommendations and complication predictions in several countries[11].

However, the effectiveness of AI-CDSSs often depends on doctor acceptance and the specific clinical context. While some systems increase diagnosis rates and adherence to treatment guidelines, still some others face challenges related to user acceptance and contextual adaptation. Some doctors expressed their concerns about the suitability and usefulness of AI recommendations, which may affect overall adoption and effectiveness[12].

A systematic review done by Ben Khalfallah et al. (2023) categorizes Decision Support Systems (DSS) in healthcare into warning systems, monitoring systems, recommender systems and prediction systems. They highlight the critical role of machine learning (ML) techniques in supporting clinical decision-making, especially in early disease detection, treatment evaluation and patient monitoring[13]. While the integration of AI into CDSS improves diagnostic accuracy and reduces medical errors, challenges remain in terms of user-friendliness and seamless integration into clinical workflows.

ARD GROUP will be working on personalized and timely recommendations for the management of non-communicable diseases (NCDs) by developing a patient-centric platform that integrates various data sources for the use case and leverages the latest artificial intelligence and advanced user interfaces. The AI-based-CDSS to be developed aims to increase both patient self-efficacy and patient engagement with their treatment plans, as well as patient follow-up. Focusing on a specific use case for diabetes, the

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[11] "Artificial-Intelligence-Based Clinical Decision Support Systems in Primary Care: A Scoping Review of Current Clinical Implementations." *EJIHPE*, 2024

[12] "Artificial-Intelligence-Based Clinical Decision Support Systems in Primary Care: A Scoping Review of Current Clinical Implementations." *EJIHPE*, 2024

[13] "Decision support systems in healthcare: systematic review, meta-analysis and prediction." *AIMS Press*, 2024

consortium will collect and process data from wearable devices to enable semantic interoperability and generate insights, ultimately improving patient outcomes, reducing healthcare provider burden and enhancing clinical workflows. Through these developments, the TREAT project aims to create innovations in AI-driven healthcare solutions.

Enhancing the data capabilities of the project, E-Kalite's business intelligence platform, TURBOARD, significantly contributes by offering advanced visualization and analysis capabilities. TURBOARD is designed to handle a wide variety of data types from different sources seamlessly, which sets it apart from traditional platforms. This flexibility is critical for the TREAT project, where data comes in numerous formats and from diverse sources, such as sensors and health devices. TURBOARD's ability to integrate and analyze this data effortlessly ensures comprehensive and accurate insights.

One of the standout features of TURBOARD is its unique AI-driven Query Assistant. This innovative tool empowers users to conduct complex analyses and generate insightful reports without requiring technical expertise. The AI-driven Query Assistant simplifies the data querying process, allowing users to ask questions in natural language and receive accurate and detailed responses. This feature democratizes data access, making it possible for users across all levels of the organization to leverage data for decision-making.

Additionally, TURBOARD's customizable dashboards are designed to cater to different user personas. In the context of the TREAT project, whether you are a patient, healthcare provider, or administrator, TURBOARD ensures that you receive tailored insights that enhance your decision-making process. For patients, this means having access to their health data in an understandable and actionable format, enabling them to manage their health proactively. Healthcare providers benefit from detailed analytics that help in monitoring patient progress and outcomes, while administrators gain a comprehensive view of operations, facilitating better resource allocation and strategic planning.

Furthermore, TURBOARD enables anomaly detection of users' health status, which is crucial for timely intervention. The platform's ability to process and visualize real-time data means that any deviations in a user's health status can be detected immediately, allowing for quick and effective responses. This capability is particularly valuable in managing chronic diseases, where continuous monitoring and prompt intervention can significantly improve health outcomes.

In conclusion, TURBOARD stands out in the business intelligence landscape due to its advanced features, ease of use, and the ability to provide tailored insights. By empowering users with AI-driven tools and customizable dashboards, TURBOARD not only enhances decision-making but also ensures that data analytics becomes an integral part of the TREAT project's operations.

Expanding the AI capabilities of the project, Anadolu Sigorta will be developing sophisticated AI models that leverage deep learning and advanced analytics for computer-aided clinical decision systems. These models will assist in diagnosing conditions, predicting disease progression, and recommending personalized treatment plans. Unlike existing systems that often rely on a single data source, planned infrastructure will integrate data from wearable technologies and electronic health records (EHRs). This comprehensive approach provides a richer dataset (i.e. multi-modal data) for more accurate and holistic patient assessments. Multi-modal data can improve the predictive capabilities of AI models. For instance, combining wearable device data with EHRs can help predict acute events such as hypoglycemia or hyperglycemia by identifying early warning signs from continuous blood sugar monitoring data. Wearable devices provide real-time data, enabling continuous monitoring and timely interventions. AI models can analyze this data in conjunction with historical health records to detect anomalies and provide alerts to healthcare providers and patients.

Furthermore, Anadolu Sigorta will integrate their AI models into interactive technologies, which patients can use in their home environment. This innovative approach will help patients manage their health conditions more effectively. Specifically, our AI-driven recommendation systems will provide personalized suggestions to patients, enhancing their compliance with medical advice and fostering self-management of chronic conditions. This approach aims to reduce the incidence of complications and improve overall patient outcomes.

The TREAT project exemplifies a pioneering integration of cutting-edge technologies across its consortium, setting a new benchmark in healthcare innovation. Livewell's smart ECG shirt, equipped with advanced sensors, stands at the forefront of real-time cardiovascular monitoring, integrating seamlessly with other health metrics for a comprehensive health assessment. E-Kalite's TURBOARD enhances data visualization and analysis, facilitating insightful, AI-driven reports across diverse data sets that improve decision-making and operational efficiency. Anadolu Sigorta's development of AI models leveraging deep learning and advanced analytics marks a significant advancement in computer-aided clinical decision systems, offering personalized treatment plans and improving the predictive capabilities of health monitoring. ARD GROUP's development of AI-CDSS is particularly notable for its potential to revolutionize clinical decision-making by integrating seamlessly into healthcare workflows. These collective efforts not only enhance individual patient care but also streamline healthcare processes, demonstrating the transformative potential of integrated, AI-driven healthcare solutions within the TREAT project.

6.2 Use case description

6.2.1 Rationale and use case description

The healthcare market is one of the fastest-growing markets in Türkiye. The population has reached 86 million people. In 2022, total healthcare expenditures increased by 71.5%, reaching 606 billion 835 million TL. In the same year, the total number of hospitals in Türkiye reached 1555, with the Ministry of Health operating 915 hospitals, the private sector 572, and universities 68. Additionally, the healthcare workforce included a total of 1,350,528 personnel, comprising various healthcare professionals and support staff.

According to the International Diabetes Federation (IDF), in 2021, Turkey had a diabetes prevalence of 15.9% among adults, amounting to 9 million cases. Also, researchers estimate that about one-third of people with diabetes remain undiagnosed. These statistics underscore the significant burden of diabetes in Turkey and highlight the urgent need for effective management and prevention strategies.

In 2021, the Social Security Institution allocated 8.6 billion TRY to support diabetic patients, representing a significant portion of national healthcare spending. The development of a self-efficacy platform for both patients and healthcare professionals will introduce innovative approaches to combating diabetes and insulin resistance in Türkiye.

Diabetes is a disease that is increasingly common despite the advancements in its treatment. Individuals at risk are often detected in the pre-diabetic phase of impaired glucose tolerance, and early measures can be taken to prevent diabetes and its complications. Obesity and a sedentary lifestyle are strong determinants of diabetes, so our target population includes existing diabetic patients and obese patients at risk of diabetes.

The diabetes-specific use case aims at enhancing self-efficacy and improving clinical workflows. This initiative will feature a multi-layered framework with contributions from various consortium members. In this use case, data will be collected from patients using two types of wearable devices. One of these devices will measure the glucose level in the blood and transfer its data in real-time to the TREAT platform. The other device will record the electrical signals in the heart with a special electrode that is inside the shirt. All the data collected from these devices will be processed using AI on the platform for semantic operability.

Types of Data will be Continuous Glucose Monitoring (CGM) and Electrocardiogram (ECG) Monitoring.

6.2.2 Partners Contributions to the Use case

LiveWell is tasked with managing the Data Collection Layer, which encompasses both Wearable Technologies and Applications. This layer will consolidate various biometric readings—like ketone levels, heart rate, oxygen saturation, EKG, body temperature, blood pressure, and glucose measurements—onto a unified platform. Additionally, LiveWell will develop a mobile app to enable the monitoring and transmission of this data from the devices. A key part of their responsibility includes creating an EKG t-shirt to monitor heart rhythms and analyze arrhythmias with specialized software. Ultimately, LiveWell's role is to gather diverse health metrics, create the EKG t-shirt, and centralize the data for access by other project participants.

ARD is set to build the Smart Engine components, integrating AI/ML capabilities and support systems for explainable data and AI. ARD will ensure the privacy, security, and transparency of the use case. Furthermore, ARD will create web applications for both professionals and patients and work alongside its subcontractor hospital to enhance the Logic Layer, which includes Patient Support, Medical Data from EHR, HIS, GP Systems, and Medical Dataspaces.

Anadolu Sigorta will enhance the Smart Engine by focusing on the development and training of NLP algorithms. They will work with both newly collected data from the mobile app and existing medical records to refine their NLP capabilities.

E-Kalite is developing a statistics module within the Logic Layer, incorporating advanced analytics and strategic planning capabilities. This module will enhance data analysis and decision-making processes. To support the Business Layer, E-Kalite will provide mobile applications for both Android and iOS, designed to meet the needs of patients and healthcare professionals. These apps will facilitate easy access to health data and insights. Additionally, by collaborating with a subcontractor hospital, E-Kalite leverages expert domain knowledge to enhance the platform’s overall effectiveness.

To safeguard data storage, processing, and transmission, cutting-edge encryption methods will be employed, ensuring that only authorized individuals can access anonymized data. This will uphold compliance with both the General Data Protection Regulation (GDPR) and Türkiye's Personal Data Protection Regulation (KVKK).

6.2.3 Main Challenges & Proposed Solutions

The main challenges related to the development and implementation of Livewell's smart ECG shirt as part of the TREAT project include:

Data Privacy: Ensuring the privacy and security of the data collected from users is a major concern. Livewell must comply with legal regulations such as GDPR and HIPAA, which mandate strict guidelines for handling personal health data. To address this, Livewell can implement encryption protocols for data transmission, secure storage solutions, and obtain explicit consent from users regarding data collection and usage.

Ethical Considerations: Ethical issues related to the use of personal health data must be carefully addressed. Livewell should prioritize transparency in their data collection practices, inform users about how their data will be used, and allow users to control their data through opt-in/opt-out mechanisms. It's also essential to ensure that the algorithms used for data analysis are unbiased and do not discriminate against any group.

Data Transfer: Real-time transmission of health data from the shirt to mobile devices and then to consortium companies requires a robust and secure data transfer infrastructure. Livewell can use encrypted communication protocols such as HTTPS or MQTT for data transmission and implement authentication mechanisms to ensure that only authorized devices can access the data.

Lack of Data: Ensuring a continuous and reliable data stream is crucial for the effectiveness of the health monitoring system. Livewell can address this by implementing data validation techniques to detect and correct errors in the collected data. Additionally, they can use machine learning algorithms to predict missing data points based on existing data. By addressing these challenges, Livewell can ensure the successful development and implementation of their smart ECG shirt, providing users with a reliable and secure health monitoring solution. The main approaches Anadolu Sigorta plans to use in the TREAT project to improve data security and ensure ethical AI practices are as follows:

Ethical AI and Interpretable Models: By prioritizing ethical AI practices and robust data privacy measures, models will be designed to be interpretable. This will ensure that healthcare professionals can understand and trust AI-based recommendations.

Data Security Protocols: Patient information will be protected with data security protocols. State-of-the-art encryption methodologies will secure the storage, processing and transmission of data. Regulatory Compliance: Access to anonymized data will be restricted to authorized parties, ensuring compliance with GDPR (General Data Protection Regulation) and KVKK (Turkish Personal Data Protection Regulation).

Accurate Diagnosis through Data Analysis: One of the significant challenges for TURBOARD in the TREAT project is the accurate diagnosis of conditions such as diabetes from the data. Diagnosing diabetes involves interpreting complex health metrics like hemoglobin A1c (HbA1c) levels. HbA1c is a crucial indicator of long-term glycemic control, reflecting average blood glucose levels over the past three months. It is critical that TURBOARD accurately identifies whether a patient has diabetes and, if so, whether it is type 1 or type 2 diabetes. Misdiagnosing a non-diabetic patient as diabetic or failing to diagnose an actual diabetic patient can have serious consequences. To address this challenge, TURBOARD will implement a process for regular model retraining. As new data becomes available, the models should be updated to reflect the latest trends and patterns in the data. This practice helps maintain high diagnostic accuracy and adapts to any changes in patient demographics or health trends.

Data Quality: Maintaining high data quality is essential for accurate analysis and decision-making. E-Kalite will conduct thorough data quality analyses to verify the accuracy and reliability of the data, identify missing data points, and perform data format checks to ensure consistency. By addressing these issues, E-Kalite will ensure that the data used in the TREAT platform is of the highest standard.

User-Friendly Dashboards: Creating user-friendly dashboards that are clear and easy to understand is crucial. E-Kalite will focus on intuitive design principles to ensure that the dashboards are accessible to users with varying levels of technical expertise. This includes using clear visualizations, logical layouts, and interactive elements that allow users to explore the data effectively.

7. UC5: Distributed Diagnoses and Home Healthcare

7.1 State-of-the-art

Background and opportunity – one of the issues the use case addresses is the delivery of care within rural communist, a more and more prevailing issues in the EU (more than 25% of the EU-28 population lived in a rural area in 2015 [14]). Integrated care is more difficult to achieve in rural communities [15] due to gaps in the underlying delivery system, limited access to quality primary care, specialists, and, in some cases, hospital care. Additionally, the cost of infrastructure and capacity is spread over fewer people. Thus, in rural areas care is more expensive and has limited economies of scale than in urban areas. In this ecosystem, the introduction of integrated care is a unique opportunity not only to improve health and social care delivery, but also to boost its societal and economic impact in EU.

In the EU, care provision (health & social) is complex and care models are changing in order to tackle the needs of ageing populations and management of chronic diseases including comorbidities. Since the 1990s integrated care has been offered as an approach to achieve such transitions. There are several definitions for the term 'integrated care' [16] 1 In this project, integrated care is defined as those initiatives that proactively seek to structure and coordinate care for chronical diseases based in their own home environments, centred around their needs [17,18], encompassing prevention, diagnosis, treatment, rehabilitation, mobility and security that enable independent living, active assisted living, virtual assisted living.

The approach for integrated care in hospitals, primary care, and home can be define in an Individual Care Plan (ICP) [19]. The ICP is a design principle and a means to achieve person-centered, equitable access to services that are efficient and provide safe care through networks of organizations that provide a coordinated continuum of services to a defined population [20]. Integrated care pathways are particularly useful in identifying care variations or gaps when the services provided do not match some aspects of the established standardized pathway. That said, it matters how integrated care is designed and implemented to fit local contexts.

In this context, the use case to be considered in Portugal relates to distributed diagnoses and home healthcare, supporting the development of economically efficient methods for user-centered and home-based systems [21] to monitor particularly those that have more impact in health-related quality of life. Low-cost sensors are the technology that supports this view. In recent years the evolution of the miniaturization of electronic components has led to the creation of devices of small size and low cost. This evolution associated with progress in the communication industry has made it possible to integrate monitoring devices into real context [22].

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14 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:CH-14_living-in-rural-areas_RYB17.png

15 Griffin, E., & Coburn, A. F. (2014). Integrated care management in rural communities. (Working Paper #54). Portland, ME: University of Southern Maine, Muskie School of Public Service, Maine Rural Health Research Center.

16 Goodwin, N, Stein, V and Amelung, V. What Is Integrated Care? In: Amelung V, Stein V, Goodwin N, Balicer R, Nolte E and Suter E, (eds.) Handbook Integrated Care. Cham: Springer International Publishing; 2017. p.3–23. DOI: https://doi. org/10.1007/978-3-319-56103-5_1

17 Wagner, EH, Bennett, SM, Austin, BT, Greene, SM, Schaefer, JK and Vonkorff, M. Finding common ground: Patient-centeredness and evidence-based chronic illness care. Journal of Alternative and Complementary Medicine, 2005; 11 Suppl 1: S7–15. DOI: https://doi.org/10.1089/acm.2005.11.s-7

18 Raleigh, V, Bardsley, M, Smith, P, Wistow, G, Wittenberg, R, Erens, B and Mays, N. Integrated care and support pioneers: Indicators for measuring the quality of integrated care. 2014, Policy Innovation Research Unit (PIRU).

19 WHO, Integrated care models: an overview, Working document, October 2016

20 Integrated health networks are characterised by their integration width (number of different services provided across the care continuum), integration depth (extent to which a given service is provided at multiple operating units within the network), geographic concentration of services, level of internal production of services and their inter- organisational relationship

21 Kim Y. Sustainable Healthcare Delivery Paradigm for the 21st Century - IEEE Journals & Magazine. Proceedings of the IEEE. 2007;95(10):1895-7

22 Weiser M. The computer for the 21st century. 1999.

During the last decade, a multitude of solutions was presented to monitor human activities and physiological signals[23,24,25]. Initially, these patient screenings were mainly in hospital environments, preventing continuous monitoring of the patient and possibly failing to capture relevant information for the medical diagnosis process. More recently, thanks to the emergence of smartphones and wearable devices, a multitude of different systems were presented to daily monitor the patient. In detail, wearable devices integrated: (i) accelerometers to estimate physical activities, promoting healthy habits and preventing sedentarism; (ii) global positioning systems to monitor sports activities; (iii) digital thermometer to measure the body temperature; (iv) pulsatile photoplethysmography (PPG) sensors to measure heart rate (HR) and (v) contact sensors to measure electromyogram (EMG). These different sensors were mainly incorporated into wrist-worn devices, smartwatches, and t-shirts, being of simple configuration and promoting, therefore, its continuous use in the daily routine. Other devices are currently being explored to capture other relevant biosignals, e.g. electroencephalogram (EEG) [26].

7.2 Use case description

The CHTMAD Hospital Centre has 3 hospital units in 3 different municipalities (Vila Real City, the headquarters), Chaves and Lamego cities, serving an area of 13 thousand square km, with a population of approximately 400 thousand people, with an aging index (number of older people per 100 young people) of 316,7 [27]. The distance between hospital headquarters and the other units is about 70 kilometres. In 2021, around 3045 professionals worked in the 3 hospital units, of which 508 are physicians and 1158 are nurses. Important aspects of the targeted population are its dispersion, the age average (elderly population with deficit of adherence to digital technologies), the reduced mobility, low levels of literacy and low economic resources.

To enable care delivery program that are customized to the needs of the individual patient and manage the cooperation of medical professionals in both hospitals and primary care, as well as engaging patients and communities, an approach of Individual Care Plan is followed. This is supported by a specific digital solution (PIC).

The use case will address distributed diagnoses and home healthcare in the global scope of diabetes mellitus and cardiovascular risk, considering intervention in two different situations:

1) Preventive care of pediatric obesity
2) Cardiac rehabilitation and heart failure

In the first, the goal is to identify and intervene in obesity disorders, promoting the ability of children to self-manage their situation, making informed decisions. The prevalence of pediatric obesity has grown incessantly, being associated with cardiovascular risk, diabetes mellitus and also psychosocial disorders, and it is necessary to intervene early in order to reduce the negative impact on adult life.

The goal is to provide a continuous, interactive and collaborative process that involves the child, the family and health professionals, with organized intervention, attentive to correct dietary advice and increased physical activity. Technology can play an important role, supporting guidance and feedback activities, monitoring physical activity, and promoting healthy lifestyle habits using, e.g., gamification.
In the second case, the goal is to support cardiovascular rehabilitation to increase the quality of life, autonomy and remote monitoring of the patient. Patients will be heart patients for life and therefore must include exercise in their lives on a permanent basis.

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27 PORDATA 2019, https://www.pordata.pt/en/portugal

Rehabilitation programs focus on physical exercise, include individualized aerobic and strength training, under medical supervision and continuous monitoring. Important aspects are aerobic endurance (continuous or interval), strength/endurance and respiratory. Promoting and monitoring physical activity is fundamental, including monitoring vital signs and ECG.

In this context, the use case considers the integration of personal devices (both smartphones and wearables) and hospital information systems, to remote follow patients, potentially with chronic disease. The system will integrate the data collected from the sensors, from the patients and families, as well as from primary care professionals, with the information available in the hospital individual personal care system. This will enable a set of services to be developed, from information and coaching, to analysis and alarming.

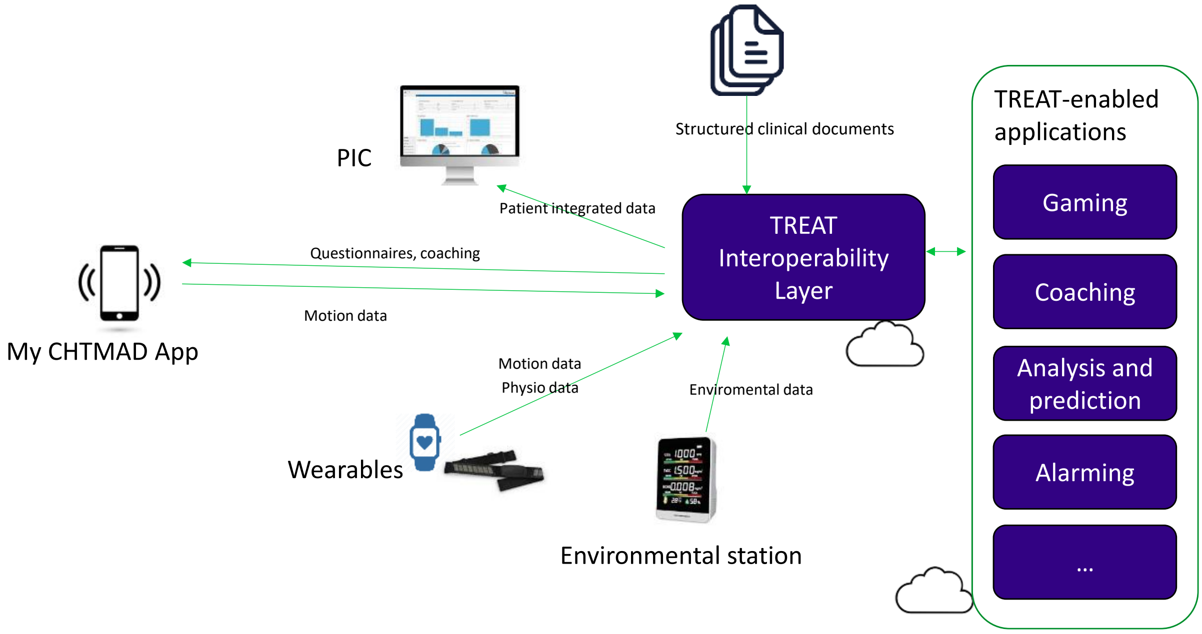

Figure 8: General Overview of the Use Case

8. Conclusions

This deliverable provided the description of the TREAT demonstrators and the associated state-of-the-art. It is the result of the first phase in task 1.1 of work package 1.

The use cases will be refined in the second phase of the task, where a set of specific requirements criteria will be identified through a co-creation process. The requirements will cover different aspects; the functional requirements representing the user perspective, and the technical requirements which specify the technological solution required to achieve the functional requirements.