ITEA 3

INNO4HEALTH

ITEA-2019-19008
Inno4Health

Stimulate Continuous Monitoring in Personal and Physical health

State of the art description for the healthcare and sport use cases in the INNO4HEALTH project

Start date of Project: 01 November 2020

Duration: 36 months

Dissemination level		
PU	Public	✔
PP	Restricted to other programme participants (including the Commission Service	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (excluding the Commission Services)	

0 DOCUMENT INFO

Author

Author	Company	E-mail
Alberto Bonomi	Philips	alberto.bonomi@philips.com
Marly Sluijsmans	TUe	m.sluijsmans@tue.nl
Luís Conceição	ISEP	msc@isep.ipp.pt
Lonneke Fruytier	MMC	Lonneke.Fruytier@mmc.nl
Serdar Sultanoğlu	ForteArGe	serdar.sultanoglu@fortearge.tr
Kristupas Survila	Lipse	kristupas@e-lipse.com
Begüm Sağcan	Teknasyon	begumsagcan@teknasyon.com
Sharon Lewinson	RideShark	Sharon@RideShark.com
Loes Janssen	MMC	Loes.Janssen@mmc.nl

Documents history

Document version #	Date	Change
V0	01-11-2022	Starting version, template
V1	14-11-2022	Final version

Document data

Keywords	Use cases, preparation for sport, rehabilitation, cardiovascular disease management, injury management, cognitive preparation, sleep quality
Editor Address data	Name: Alberto Bonomi Partner: Philips Address: HTC36, Eindhoven (The Netherlands) Phone: +31643478577 Fax: NA

Table of Contents

1 Executive summary

This document describes the state of the art for each use cases in the following healthcare and sports areas:

- Preparation for surgery
- Preparation for sport/athletic competition
- Recovery from surgery
- Recovery from training and injury
- Healthcare data summarization and decision support for clinicians
- Athletic performance and salient event analytics for sport coaches.

A strong overlap is observed in the user journey and technology solution for patients, athletes and professionals when dealing with the issues of providing unattended support to individuals before or after a trying event such as surgery or a sports competition. A total of 8 use cases are being disclosed in this document 5 in the healthcare and 3 in the sports domain. The project will use this information to innovate on wearable sensors, data collection infrastructure and artificial intelligence to address unmet needs identified in the state of the art for the technology available in the various use cases.

2 Introduction

This document defines the state of the art of the INNO4HEALTH healthcare and sports use cases. The focus is on identifying the the current challenges and highlight the ambition of the project to move towards a solution in the various healthcare and sports use cases. The document will present user needs from professional and patients or athletes perspective.

The following use cases are further described in the document:

ID	Name	Partner	Domain
1	Screening for sudden cardiac arrest and monitoring functional capacity in athletes and subjects at risk	NL-MMC	Healthcare
2	Recovery monitoring in claudication, venous ulcers and diabetic foot patients	PT-Uni.Porto	Healthcare
3	Recovery monitoring after orthopaedic surgery	TR-ForteArGe	Healthcare
4	Cognitive preparation of athletes	LI-LIPSE	Sport
5	Holistic preparation for football and hockey competition and safe return to play after injury	NL-TUe CA-XCO	Sport
6	Sleep analysis and support application for healthy life	TR-Teknasyon	Sport
7	Monitoring patients participating in a pre-habilitation programs prior to cancer surgery	NL-MMC	Healthcare
8	Disease Prevention by Big Data Aggregation	CA-Rideshark	Healthcare

3 Use cases

3.1 Screening for sudden cardiac arrest and monitoring functional capacity in patients and recreational athletes

Higher levels of physical activity (PA) and fitness are associated with a lower all-cause mortality, lower burden of cardiovascular disease (CVD), and a lower prevalence of several malignancies. Despite the substantial health benefits from regular PA, intense exercise may paradoxically act as a trigger for life-threatening complications in the presence of underlying CVD. The overwhelming majority of sports-related SCD occur among athletes aged > 35 years. The risk of adverse cardiovascular events during exercise increases with age because of the greater prevalence of atherosclerotic disease in those older than 35. The incidence is 10-fold higher in individuals >35 years old than below 35 years (3.0 per 100 000 person-years versus 0.3).

Sudden cardiac death (SCD) in young athletes is caused by a variety of congenital, structural and electrical disorders of the heart, whereas in master athletes (≥ 35 years old) atherosclerotic coronary artery disease (CAD) is the primary condition (80%) leading to major adverse cardiovascular events (MACE). It is known that vigorous exercise is associated with an increased risk of acute myocardial infarction (AMI) due to plaque rupture or could cause demand ischemia which both could serve as a trigger for the occurrence of (fatal) ventricular arrhythmia’s and SCD. The proportion of AMIs associated with exertion ranges from 4.4% to 13.6%. Worldwide, increasing numbers of master athletes are participating in organized endurance and competitive sporting events. Therefore, the incidence of sports-related SCD in master athletes is expected to increase.

Exercise-induced MACE include a variety of diagnoses, including sudden cardiac arrest (SCA) and sudden cardiac death (SCD). Other MACE are acute coronary syndromes (ACS) such as myocardial infarction, transient ischaemic attacks (TIA), cerebrovascular accidents (CVA) and (supra-)ventricular tachyarrhythmia’s. Most of these events occur during exercise or within 24 hours post-exercise.

People can have undetected atherosclerotic CAD, the so called subclinical/silent CAD. In fact, more than 50% of the athletes who suffered from an acute MI and/or SCA did not have pre-existing symptoms or a known history of CAD. In this specific population pre-participation screening (PPS) can be useful to detect those athletes with an increased risk for developing cardiovascular events. This helps the clinical practitioner to give preventive recommendations and an individual sports advise.

Exercise stress tests are needed to safely guide patients during pre-habilitation, rehabilitation and sport practice. However, in-hospital tests may not accurately reflect risk profiles during exercise in daily life and cannot be used to track progress over time due to their sporadic nature. Screening for sudden cardiac arrest in master athletes (>35 years) should target the presence of atherosclerotic coronary artery diseases (CAD). Aerobic capacity is also a strong predictor of readmission and mortality related to cardiovascular disease. Current protocols are not sufficiently sensitive because of the low positive predictive value of in-hospital exercise testing in asymptomatic adults. Development of new non-invasive methods and long-term monitoring with wearable devices are necessary to improve pre-participation screening. Wearable sensors data such as ECG, PPG and body movement will be used to identify novel digital biomarker indicative of sudden cardiac arrest and aerobic capacity in patients. This information will help clinical practitioners defining risks associated to clinical interventions and exercise programs for patients. This use case will therefore describe the specific needs for i) screening patients and athletes for sudden cardiac arrest risk as well as ii) enabling continuous monitoring of aerobic capacity outside of the hospital walls to help clinicians guiding remotely intervention programs and sport practice for individuals at risk.

3.1.1 State of the art

3.1.1.1 Screening for sudden cardiac arrest

Current guidelines recommend PPS protocol which include medical and family history, physical examination and resting ECG. In addition to this, there is a heavily debate regarding the routine use of (cardiopulmonary) exercise testing (CPET). This is mainly because exercise testing in asymptomatic adults showed a low positive predictive value and a high number of false-positive tests. However, recent studies shows that athletes with abnormal results during ET have an higher risk for MACE than athletes with a normal test result. An attenuated microvascular function can be a cause for this observation, which means there are certain athletes that are at risk. Therefore, (CP)ET can be helpful to detect subclinical coronary artery disease in asymptomatic athletes. Other diagnostic modalities that can be used are coronary computed tomography angiography (CCTA) and/or coronary artery calcium scoring (CACS). This helps to estimate the risk of CAD in middle-age athletes.

As screening in master athletes should target the presence of atherosclerotic CAD, current protocols are not sufficient. Development of new non-invasive methods are necessary to improve pre-participation screening.

3.1.1.2 Monitoring functional capacity

The assessment of functional capacity reflects the ability to perform activities of daily living that require sustained aerobic metabolism. The integrated efforts and health of the pulmonary, cardiovascular, and skeletal muscle systems dictate an individual's functional capacity. Numerous investigations have demonstrated that the assessment of functional capacity provides important diagnostic and prognostic information in a wide variety of clinical and research settings.

The functional evaluation of a subject may be performed by measurement of the functional aerobic capacity by means of exercise-stress tests. The maximal oxygen consumption (VO2max) is the best parameter to establish this. A frequent consideration in the assessment of functional capacity, especially in nonclinical settings, is whether to perform maximal or submaximal testing. Although maximal testing provides the only accurate determination of aerobic capacity, submaximal testing may be desirable in several situations.

Submaximal exercise evaluation is for example the 6- or 12-minute walk test, which has become widely applied to assess the responses to various treatment interventions, particularly pharmacological therapies or exercise training, in patients with pulmonary disease or heart failure. The distance covered during the time period also can be a powerful prognostic indicator. Additional advantages of such testing protocols are their simplicity, safety, negligible cost, and applicability to everyday activities. In patients with pulmonary disease, the distance covered in these timed-walk tests is highly reproducible and correlates moderately well with peak VO2 (r = 0.52 to 0.71).

The longstanding use of exercise testing in the diagnostic and prognostic evaluation of patients with suspected or known coronary artery disease (CAD) has provided a large body of data on the utility of functional capacity assessment in such populations. Using the Duke University database of patients undergoing diagnostic exercise testing, patients who exercised into stage 4 and beyond on a standard Bruce protocol (4.2 mph, 16% grade) with a negative or indeterminate ST-segment response had 15% prevalence of CAD.

Numerous additional studies have verified the strong prognostic effect of exercise duration and functional capacity in patients with suspected or documented CAD. Among patients with CAD, those with prior myocardial infarction underlying reduced functional capacity appear to have reduced survival compared with similarly reduced capacity in the absence of infarction. Exercise testing in CAD patients referred for cardiac rehabilitation is essential for a baseline assessment of functional capacity, development of an appropriate exercise prescription, and evaluation of the results of training.

Determining the functional capacity and general health status of elderly patients is essential to assess health risks related to invasive hospital treatment like surgery. Health risk associated to treatment for those patients is routinely assessed by office consultation. Geriatric assessment can take up to 60 min and it is up to the clinician's discretion to link the outcome to an appropriate treatment. Elderly patients are at high-risk of complications (13%), prematurely terminated surgery (8%) and in-hospital mortality (3.2%). In addition, hospital readmissions have been recognized as a common and costly occurrence among high-risk patients.

3.1.2 Challenges

3.1.2.1 Screening for sudden cardiac arrest

Currently, athletes undergo pre-participation screening in the hospital or a sports medicine centre. For some competitions an eligibility screening with PPS is mandatory. Other athletes undergo voluntary screening to evaluate their exercise capacity and set their (heart rate) training zones and thresholds. Typically, the exercise test is performed in a standardized laboratory setting and consists of a 10-15 minutes cycling (or running) performance. For most athletes this is not the type of sport, the intensity or the setting the athlete is used to. In addition to a traditional ET, breath-by-breath analysis of O2 consumption and CO2 production could be monitored via CPET. CPET is a non-radiation, non-invasive test. Other diagnostic modalities are used additionally when PPS is abnormal.

CPET is an important clinical test to evaluate the cardiopulmonary function and to detect potential subclinical CAD. If we can use accurate wearables, it is beneficial to test athletes in their own sports. More continuous monitoring in home-setting provides a lot more information. It shows data during the athletes' daily sporting activities and therefore helps to improve professional decision making. Decision support systems based on algorithms supports health care professionals in identifying high risk patients. Interesting aspects are cost effectivity and patients satisfaction.

The current available ECG monitoring systems are not well suited for extended PPS in a home-based setting. This in mainly due to that the signal quality degrades over time due to wet-electrode technology. Also, the design of wearables devices typically does not accommodate the usability requirements of both athletes and patients. New wearable systems with good ECG-signal quality, noise reduction and multiple-lead monitoring are needed to have predictive value in detecting subclinical CAD. At the same time the sensors need to be comfortable to be suitable for continuous monitoring.

Currently there are no specific algorithms to detect subclinical ischemia, other than the use of an exercise ECG. We suppose that there are multiple (medical) parameters which can help us to develop algorithms.

3.1.2.2 Monitoring functional capacity

Monitoring functional capacity for the risk assessment of SCA, the evaluation of peri-operative risk, and the assessment of progress during rehabilitation or pre-habilitation programs requires frequent cardio-pulmonary testing and by means of tests which are carried out in daily life environment. Office-based assessment of functional capacity in the elderly is a time consuming process which requires clinicians to invest time during the examination process. At the same time the collected information is not particularly informative as not captured in the context of daily life. Data may be often poorly objective, for example when relying on self-report questionnaires, prone to errors when relying on subjectively perceived physical limitation to continue an exercise like a 6-min walk test or a cycling test. In addition, the performance of the cardio-pulmonary system during exercising on a stationary bike may not represent fully the capacity of the individual to sustain physical and aerobic stress in daily life during normal circumstances. The challenges that we have identified are the time consuming nature of clinic-based functional capacity testing, the poorly-objective and sporadic nature of the examinations and the challenge of obtaining aerobic test results which are reproducible in daily life circumstances.

3.2 Recovery monitoring in claudication, venous ulcers and diabetic foot patients

As populations worldwide age faster and at an unprecedented rate, health care stakeholders are urging to introduce interventions that address the profound effects of ageing on all aspects of life, with reference to improvement and adaptation of current health care processes. In this sense, key strategies must involve the definition of personalized care measures aimed at delaying or preventing the overall decline in health and in daily activities from a physiological perspective. The "Recovery monitoring in claudication, venous ulcers and diabetic foot patients" use case will focus on the non-invasive remote monitoring aiming the pre-habilitation of patients suffering from vascular disease by providing a set of intelligent services that intend to evaluate the patient's adhesion and response to therapeutic interventions.

Intermittent Claudication (IC) is a highly prevalent and debilitating condition affecting 6% of patients above 60 years old of age [1], being associated with increased risk of cardiovascular morbidity and mortality [2]. The standard treatment for IC patients relies in supervised exercise programs aimed at improving walking distances and quality of life, as well as management of risk factors and drug therapy [3]. Nevertheless, poor patient compliance with supervised exercise programs, which can be as low as 34% [4], is a major constraint to IC treatment, where the benefit in walking distance is highly dependent on the frequency and maintenance of the exercises after the completion of the program. In this sense, incorporating supervised exercises into the daily routine in an easy manner is of utmost importance. The use of non-invasive wearable activity trackers can be an important ally for the management of IC [5] through solutions aiming at minimizing the use of healthcare resources, increasing patients' engagement and promoting physical activity. In this use case, the main goal is to develop a wearable activity monitor system to improve walking distances and thereby quality of life in patients suffering from IC, in order to increase the effectiveness of home exercise interventions and promote behavior change by including self-monitoring approaches and performance feedback. Therapeutic success at this stage prevents disease progression to more ominous outcomes.

Amongst the consequences of aging to be addressed, chronic venous disease is a frequent and often underdiagnosed condition, which can progress to chronic skin trophic changes and venous ulcers, which in turn may require extensive treatment and need for hospitalization [6]. The evolution of chronic venous disease can negatively impact quality of life, often due to pain, and may incur substantial burdens on healthcare costs. Varicose ulcer or venous leg ulcers (CEAP C6 level) is the last stage of the chronic venous disease. Initially, skin discoloration resulting in brown or red appears on the medial aspect of the leg, usually above the ankle. Venous ulcers occur when the valve function is seriously affected, resulting in venous reflux and/or hypertension. If timely and proper care is not given, the affected skin gets swollen and tight, leading to dull but heavy pain. Apart from age and obesity, one of the main risk factors for varicose veins is long-time working in standing position or reduced mobility, being more frequent among females [7] and affecting over than 23% of the adult population [8]. Over the last years, development of innovative wearable health monitoring solutions targeting numerous applications has attracted considerable attention in the industry and academia. Among those solutions, wearable sensors with providing non-invasive and continuous health monitoring that is also comfortable for patients have been the frontier of this trend [9]. In the context of chronic venous disease, sensors can be used for monitoring, evaluating compliance to therapeutic measures and its outcomes on individual patients. In this use case, we focus on a wearable monitoring solution to address interface pressure monitoring in chronic venous disorder, where the compression therapy for chronic venous disorder is guided by periodic and continuous monitoring of interface pressure. Therefore, this use case aims to implement a novel wireless wearable pressure sensing system to perform continuous monitoring of interface pressure (and other variables) in patients assigned to the C6 stage (open ulcer, often located in the ankle area) of the standard CEAP classification (Clinical-Etiological-Anatomical-Pathophysiological) for chronic venous disease. The impact of this solution is to guide routine compression therapy and health care interventions in order to achieve an optimal healing time for patients with venous leg ulcers.

Diabetic foot ulcers (DFU) are among the most frequent and costly lower extremity complications of diabetes. Around 25% of diabetic patients will develop DFU, which comprises up to one-third of the direct costs associated with diabetes care, apart from being the leading cause of hospitalizations related to diabetes [10], further accounting for one-fifth of the amputations of the lower limb in diabetic patients [11,12]. The chance of recurrence of patients that have developed DFU is estimated at 40% in the first year, increasing to almost 100% over a 10 years-period [10]. Therefore, DFU constitutes an important public health issue and concern, being associated with poor quality of life. Family history of DFU, diabetic peripheral neuropathy, foot deformities and high plantar pressures are amongst the main clinical risk factors for DFU [10,13,14]. Prevention-based interventions are the most cost-effective methods for managing DFU in order to ensure the disease’s remission and avoid further complications. The current standard methods for DFU prevention include a series of interventions, namely screening high-risk insensate foot, regular footcare, adoption of standard therapeutic shoes and insoles to accommodate foot deformities and control high plantar pressures, as well as diabetic foot education [10]. The medical literature points to sufficient and good-quality evidence to support the adoption of custom-made footwear designed for plantar pressure relief in order to prevent DFU recurrence. Additionally, good patient’s adherence to daily wearing of this therapeutic footwear is required to achieve treatment effectiveness [15]. Furthermore, the use of technologies aimed at alerting the patient regarding periods of high-risk plantar pressure during daily activities may provide an effective and practical tool to guide the patient into actively correct plantar pressure during these periods, resulting in a potentially beneficial DFU prevention strategy. In this use case, we aim to develop an in-shoe insole sensing system for barefoot pressure analysis destined to detect and prevent DFU.

In these use cases, a set of intelligent services that allow the remote monitoring and smart coaching of patients will be developed, focusing on the measurement of parameters related to the diseases such as: walking distance to symptom-forced stop (for patients with claudication), body position and respective time periods spent in the position and pressure under compressive apparatus throughout the day (for patients with venous ulcer), and plantar pressure distribution while standing (for patients with diabetic foot).

3.2.1 State of the art

Vascular diseases, such as claudication, venous ulcer and diabetic foot, affect a large percentage of the worldwide population, conditioning the patients' day-to-day lives. These diseases affect the mobility of the patients and may lead to a mobility loss. Due to their severity, these diseases require frequent follow-ups and regular hospitalizations [1, 2]. A traditional approach is followed, consisting of medical appointments where treatment plans are defined based on the patient's health condition. The treatment plans comprise the pharmacological intervention and activities that the patient needs to perform in order to control and improve their condition. However, this follow-up is only done sporadically, being difficult to monitor the patient's condition outside of healthcare settings.

Studies show that the continuous monitoring of patients leads to an improvement of their health condition [1, 3, 4] and, as such, it has been sought the development of solutions that address the current difficulties in the healthcare of vascular diseases. The evolution of information technologies and their application in the health sector has opened a possibility for a shift towards personalized healthcare, based on the patient's clinical information [5], instead of the health professional's experience (traditional healthcare). An example of personalized healthcare is the use of smart coaching techniques to motivate the patient to adopt healthy behaviours and thus improve their health condition. Innovative solutions have already been proposed for the regular monitoring of the health condition of patients that generate high volumes of data, such as monitoring sensors, however the collected data is not processed [6], due to the lack of solutions focused on data analysis. One of the main approaches that has been followed in order to address the current difficulties in the healthcare of vascular diseases and provide personalized healthcare is the use of recommendation systems. These systems are able to perform a predictive analysis based on the patient's clinical data. The literature presents recommendation systems for personalized healthcare aimed at both health professionals and patients. For health professionals, recommendation systems are used to support the clinical decision-making process, predicting the patient's condition and which treatment is the most appropriate. For patients, recommendation systems are used to monitor several parameters, such as physical activity, and recommend behaviours that the patient needs to adopt to improve their health condition.

The analyses carried out by this type of systems use several artificial intelligence methods, such as machine learning. Various machine learning techniques such as classification, clustering, and association algorithms, have been used in the literature to extract knowledge from patient data. Classification algorithms are mostly used for pattern detection, disease prediction, and detection of the patient's activity. Clustering algorithms are used to identify the disease and they are also used to predict it. Association algorithms are used in the clinical domain for the identification of relationships between diseases.

Although the application of information technologies has resulted in innovative solutions for the personalization of healthcare, these are still rarely used for the support of patients with vascular diseases [7]. Recent studies have sought to develop solutions for delivering personalized healthcare to patients with vascular diseases [8-10]. These solutions focus mainly on the monitorization of clinical information and on the presentation of personalized recommendations about physical exercises that the patient can perform, lacking functionalities regarding the disease management and the presentation of recommendations about which treatment to follow. In addition, the proposed solutions lack interfaces aimed to support the health professional in the clinical decision-making.

3.2.2 Challenges

This use case presents several challenges regarding the monitoring sensors, data exchange between the modules, intelligent algorithms, coaching applications, as well as challenges regarding the adhesion to the proposed solution.

In terms of monitoring sensors, the challenges encompass the size of the sensors (must be small for comfort reasons) and the energy consumption (must be low). Regarding the exchange of data, the challenges are focused on the optimization of parameters such as exchange rate, data volume, and energy consumption.

Concerning the intelligent algorithms and coaching applications, the main challenge is to ensure the accuracy of the patient-related insights as well as the need of a high-level personalization in order to accurately predict the responses of the patient regarding interventions such as treatment or surgery. Another challenge is the need of the presentation of the coaching information at the right time in order to achieve the coaching plan's optimal results.

In terms of the challenges related to the end users of the proposed solution, in this use case being the patients and health professionals, the main challenge is the adhesion to the system, being imperative the development of a solution that motivates the users to interact with the system, and thus achieve good results regarding the improvement of the patients' health condition.

3.3 Rehabilitation of Knee Osteoarthritis

Osteoarthritis (OA) is a progressive disease that develops due to wear and tear on the joints. It is manifested by pain and restriction in movements. It mostly affects the elderly population. OA is one of the diseases that cause the most disability.

Although there is no treatment for the disease with non-invasive methods, it is possible to control the symptoms. For this, the correct application of physical therapy guidelines, continuous monitoring and feedback, and effective management of the process are required. Today, such a continuous monitoring facility is only available in health centres and cannot be performed widely due to limited resources.

It this use case; it is aimed to make progress in the field of continuous monitoring and assistive feedback on OA disease by analysing personal activity data collected with wearable sensors and smart devices. In this context, it will also be shown that self-supervised machine learning approaches can be effectively applied end-to-end on real data of OA disease.

3.3.1 State of the art

Remote Monitoring of KOA

Even though KOA is a degenerative disease with no known cure without invasive methods, its symptoms and progression can be managed using intensive monitoring and assistance. Currently intensive monitoring is not prevalent out of medical centres. On the other hand wearable device data open new avenues for achieving intensive monitoring, remotely. Moreover, analysis and evaluation of KOA is a data hungry task. Data needed to characterize KOA is high dimensional, heterogeneous, and high volume. There are many studies in the literature in the field of posture, balance and movement analysis with wearable devices. Research in this area remains popular because wearable devices are economically accessible, usable in daily life, and provide objective data. Two studies examining the literature and their summary findings are given below. [16] conducted a study examining 56 studies that met the quality criteria from a total of 1677 studies. According to this research, studies in the literature have demonstrated that wearable devices' eligibility for rehabilitation monitoring. In addition, it has been shown that machine learning-based methods can produce scores in accordance with the methods used for objective scoring in posture and balance assessment. It was stated that new studies to be done should give results in comparison with gold standards.

[23] also conducted a study evaluating the effectiveness of the use of wearable sensors and machine learning in evaluating the results of joint transplant surgeries. In the study, 18 of 55 studies that met the selection criteria were examined in detail. Accordingly, although there is no change in the rate of re-admission, it has been reported that there are studies showing that the duration of hospitalization is shortened.
Literature studies show that prediction and classification of KOA status can be improved by using biomechanical, clinical and self-reported data. But traditional data analysis methods are not enough for analysis of such a large and high dimensional data [18]. Many studies have shown that ML is an effective tool to analyse OA objectively and tele-health is able to perform remote monitoring and rehabilitation for some meaningful assessments and predictions like PROMs [16]. Therefore, more personalized

rehabilitation that is given remotely will be necessary soon. When designing such studies, comparison with gold standard is a requirement.

In order to increase prevalence of remote monitoring, new studies should improve clinical outcomes, and present affordable economical models for their deployment. Also, calculations for gait parameters such as step length, step width, and walk deviation using wearable sensors need to be improved upon [17].

Self-Supervised Learning

One of the main problems of deep learning is the need for large and labelled data. Most high-achieving AI models today learn through supervised learning. Supervised learning requires massive amounts of data labelled by experts. Acquiring these data is time consuming, expensive and difficult. However this situation is different humans. Babies learn by observation and incrementally, requiring much less information and much more efficiently. Learning based on observation, as babies, is a research topic in the field of artificial intelligence.

One of the most promising of the artificial intelligence approaches that provide learning based on observation is self-supervised learning. (SSL: Self-supervised learning) SSL aims to learn basic structural features in data, with the labels already present in it. For example, it tries to predict the future (which is masked) by looking at the past or it tries to predict the invisible part (which is masked) by looking at the visible. So the technique is guessing the masked part by looking the visible part. Since masked part already exist in data, the technique is called self-supervised. Using this technique, representational features from the data itself can be extracted. This is called pre-training in SSL. Once basic representational features are extracted from the data, these can be transferred to be employed in real task, which is called downstream task in SSL. SSL benefits can be summarized as below:

- Learns high-level structural features and causality relationships from the data itself. These features are useful for general purpose and special analysis tasks.
- Reduces the need for massive amounts of labelled data.
- Reduces the need for expensive and limited resources such as time and expertise of humans.

SSL have shown very promising results and outperformed state-of-the-art in natural language processing and computer vision domain. Although not as much compared to these domains, there are a few studies conducted in recent years on human activity analysis.

[21] This study was conducted to evaluate the usability of SSL for gesture recognition from wearable device data. Here, it is tried to estimate the transformation applied to the data as a pre-training task.

[22] In their study the authors presented SelfHAR, an education pipeline consisting of self-supervised pre-learning and self-education. Here, a small amount of labelled data and unlabelled data were enriched, and these data were used for preliminary training. This study demonstrated the potential of combined pre-education practices.

[19] This study used federated learning and SSL techniques together to solve privacy problems in the analysis of wearable device data.

[20] This study addressed the extraction of physiological representational features by self-supervised learning using wearable device data. Unlike the others, a pre-training task is defined that estimates the heart rate sensor data instead of the transformation.

These studies have shown the potential to address the need of improvement in calculations for gait parameters such as step length, step width, and walk deviation using wearable sensors.

3.3.2 Challenges

- Scientific perspective:
  - Requirement of large, high quality data for deep learning creates high cost in time and money.
  - The research question here is, can self-supervised learning help reduce this costs while providing high performance for time-series sensor data analysis by employing open datasets in pre-training tasks.
- Usability perspective:
  - Affordability and comfort of wearables are important restrictions.
  - Monitoring of patients intensively is only possible in health centres. Transportation to health centres is expensive, time consuming, health resources are restricted.
  - These difficulties will be tried to be overcome with remote monitoring solutions.
- Functional perspective
  - Assistive feedback and objective evaluation functionalities for Knee OA based on consumer-grade wearable sensor data analysis in commodity mobile devices under the umbrella of a secure and interoperable health platform may help clinicians and patient to better manage the disease.
  - Easily reporting of measures like pain and other inputs in a form designed by clinician from mobile devices will help clinicians to provide timely feedback to patient and update the deep model continuously.

3.4 Cognitive preparation of athletes

Cognitive-mental abilities like reaction times, anticipation, risk taking, etc. influence the performance of an athlete to a high extent. This is mostly evident when comparing high-performance athletes to novices – certain mental abilities like decision making or anticipation are much more developed in elite athletes [24, 25]. Another aspect that influences performance is psychophysiological parameters. Biofeedback and Neurofeedback are integrated into self-regulation programs of athletes.

From practical experience it is known that athletes can have deficiencies in certain cognitive factors that influence their performance. Currently there are some distinguished digital solutions for testing of these cognitive-mental abilities (like WTS) [26]. However, digitalized training is only available in non-professional format (like MPU-easy). The problem is that there is not a solution that would test and train cognitive-mental factors in a purposeful definite manner, which is required for athletes. A centralized, user-friendly and purpose-built tool would be a cost-efficient alternative to what is currently available on the market.

Our use case focuses on the creation of a cognitive training package that encompasses testing and training of these mental factors in conjunction with monitoring of psychophysiological factors. In this use case, a set of intelligent services that allow the continuous monitoring and smart coaching of athletes will be developed, focusing on the measurement of parameters related to the psychophysiological state and cognitive tests.

3.4.1 State of the art

Sport performance depends on many factors, including mental. And training of these mental functions for the preparation of athletes is gaining traction worldwide. While digitalization of psychological tests is well underway with market leaders like “Vienna Test System” [26], they are poorly, if at all, adopted for preparation of elite athletes. This is due to the fact that these companies put their product focus on the testing itself, without highlighting and training mental factors that are bottlenecking performance. There are some digital solutions for training like MPU-easy [27], yet these are not tailored to athletes, for example the main goal of MPU-easy tool is to prepare persons for driving fitness examination. Furthermore, the existing state of the art testing/BFB monitoring systems are very expensive and complicated to the average target user.

3.4.2 Challenges

Three main challenges pose themselves in the success of the use case. Starting with sensors- an accurate wireless ECG sensor that is available in the market will be required. The following requirements pose a challenge: accuracy (high accuracy with low data loss via wireless transfer), form format (must be comfortable to wear, not distracting), connectivity and ease of use (the data collection and transfer process must be easy, synchronized with the application). When it comes to the AI algorithms, challenges here are to provide high accuracy in the real-time adaptation of the testing and training algorithms, classification of athlete data, also to devise accurate personalized training plans with prudence. Last challenge is acquiring reliable safe solutions for the managing and protecting of the sensitive data of athletes.

3.5 Holistic preparation for football (PSV Eindhoven) and hockey (Testify Performance) competition and safe return to play after injury

In recent years, monitoring solutions for athletes have gained a lot of traction particularly to determine the efficiency level of players. The term “holistic coaching”, which indicates the inclusion of daily activities in the actual training program of athletes, has recently gained attention and is shifting from top athletes to lower level leagues, junior athletes and teams. Holistic coaching includes the determination of the adequate amount of exercise, sleep and nutrition in order to provide personal guidance for individual athletes.

Decision support systems designed to help professionals and users to manage their condition before and after competitions are poorly developed. The reason being that training effects are not continuously measured. The influence of daily living conditions inducing physical and psychological stress on the individual are assessed only using “paper and pen” questionnaires during face-to-face interviews with either the performance coach or psychologist in the sport context. Elite athletes routinely carry out questionnaires on sleep quality, stress and activity in the recovery days and prior to the competition. There is no technology solution on the market to help sports coaches to review athletes’ condition in preparation for training or competition.

The introduction of novel wearable and home monitoring devices for supporting holistic coaching has large potential particularly in lower leagues and junior athletes because the financial resources are rather limited, and professional coaching is not available to everyone. Therefore, affordable digital tools can provide coaches with scalability and efficient solutions for serving large groups of athletes.

This use case aims at improving the “paper-and-pen” methodologies used to assess users’ physiological and mental status in order to optimize training trajectories to maximize sport performance and enable prompt recovery after surgery.

The overall goal is to enable athletes to safely and confidently return to sport through the completion of a series of comprehensive assessments and activities supported by AI data and interactive monitoring and engagement tools. The system will support the athlete during training as well as during the recovery from an injury.

Further, the application will offer the option of providing feedback to the athlete, coach and clinician in order to improve the daily activities proposed as part of training or rehabilitation to achieve high-level of personalization in the solution. Lastly, biometric authentication will be incorporated in this software application.

This use case will be demonstrated by the following scenarios:

- Injury risk assessment of athletes, pre-habilitation and rehabilitation.
- Personalized fitness / performance improvement.

3.6 Sleep Analysis and Support Application for Healthy Life

One of the most crucial aspects of living a happy and healthy life is getting enough sleep. Sleep is more than just a period of time that is removed from daily life; it is a critical requirement for a healthy and long life, as it lets the body renew itself. People who don't get enough sleep feel tired, exhausted, and sleepy throughout the day. Productivity, the capacity to focus, as well as the ability to communicate effectively also suffer. Regular, uninterrupted, and enough sleep at the appropriate time is critical for human health and survival.

Excessive stress we face in our modern life, poor and unhealthy nutrition, anxiety problems, and a variety of psychological and physiological illnesses all contribute to poor sleep quality. While the number of complaints about sleep problems grows by the day around the world, there is a significant increase in feedback about the quality of life decreasing as a result of sleep issues.

So, apps that provide answers to problems with people's sleep patterns and quality, as well as assist them, are needed. We think that the app that will be built will bring value to the lives of many individuals, particularly with the help of a medical professional, so that they can get to a point where they can go about their everyday lives without any ill effects while keeping their sleep patterns and quality monitored.

Sleep Analysis and Tracking Application is a mobile app that helps people improve their sleep quality, track their sleep patterns, and perform other sleep-related tasks. In an increasingly globalizing society, diseases affecting human health are becoming more common by the day and factors such as stress, a fast-paced lifestyle, and an improper diet have a negative impact on sleep. We've started to work on the Sleep Analysis and Tracking app development with the assumption that it would be helpful to use an app to analyze and minimize the impact of these factors on human sleep.

3.6.1 State of the art

3.6.1.1 What does normal (quality) sleep look like?

This is one of the most commonly asked questions concerning sleep, but despite all scientific studies, there still is no definite answer to this question. Despite all of the research, the best response to this question can be found in the literature: "Everyone has different sleep-related needs." A good night's sleep is defined as one that makes a person feel psychologically and physically fit during the day and allows them to get out of bed effortlessly.

The personal accounts of people who have been diagnosed with sleep disorders have been taken into consideration to identify the leading causes of sleep-related issues.

3.6.1.2 Medical Opinions

First and foremost, referring to previous scientific studies on the effects of sleep on human health should demonstrate the connection between sleep and health. Specialists focusing on diverse domains such as psychology and neurology agree that sleep health, patterns, and quality are among the most important aspects of human life. To list a few topics on this, we can make use of a table that's been prepared to reflect the Chronological Timeline of the Evolution of Sleep Research;

- Sleep disorders can manifest themselves in the following forms:
  - Sleep Respiratory Disorders (Obstructive Sleep Apnea Syndrome)
  - Insomnia
  - Adjustment Insomnia
  - Chronic Insomnia
  - Persistent Psychophysiological (learned) Insomnia (PPI)
  - Comorbid Insomnia
  - Psychiatric Disorders
  - Sleep-Related Breathing Disorders
  - Restless Legs Syndrome (RLS)
  - Gastroesophageal Reflux (Heartburn)

It is evident that helpful techniques that support better sleep for all patients with sleep problems are needed. In particular, an application that can assess their sleep and track their progress can be a helpful tool for people who want to sleep better.
People who claim they do not have any sleep disorders but are continually weary and do not feel lively during the day believe they should improve their sleep efficiency in order to have more energy during the day.

People who said that they have problems with their sleep pattern and amount of sleep made the following comments:

One of the most important aspects that affects sleep quality is having enough sleep on a regular basis, which allows us to wake up refreshed. People who have complained about this issue emphasized the need for an app they can use to check their sleep patterns and amounts and get them back on a true sleep schedule. People who get regular and adequate sleep have improved sleep quality, according to studies. While this amount varies between 6 and 8 hours in adult humans, it varies from one person to another.

The following is a list of leading issues related to sleep disturbance and sleep quality:

- Lack of sleep quality
- Adverse effects of sleep disorders
- Inability to sleep on a regular basis and being unable to maintain a sleep pattern
- Inability to determine or track the amount of sleep
- Inability to wake up on time, or waking up late
- Snoozing the alarm constantly
- Inability to keep track of sleep data

By combining insight from the sufferers of sleep disorders and external perspectives, the identified needs are listed below:

- Ability to assess and interpret sleep on a personal level
- Ability to keep track of sleep data and statistics
- Ability to set sleep and wake-up times on a weekly or daily basis
- Ability to keep track of how much sleep one gets each week or day
- Ability to fall asleep quickly and sleep without interruptions
- Ability to set sleep goals

Having an alarm clock that will wake you up at the moment you specify

3.6.1.3 The Connection Between Sleep and Phone

According to recent research by the Pew Internet and American Life Project, 44 percent of cell phone owners (and 83 percent of teenagers) sleep with their phones on or near their mattresses, and many use them as alarm clocks.

The apps were rated 3.8/5 on both stores, with an average price of $1.12 on the iOS store and $0.58 on the Google Play store. More than half of sleep apps track sleep phases, including duration, wake time, and light/deep sleep time.

The following are some applications that are considered as competitors in the sleep analysis space and have the biggest market share.

3.6.2 Challenges

A sleep tracking app might assist you in gaining insight into your sleeping habits. These applications can help you figure out how much sleep you're getting if you're uncomfortable at night, albeit they're not completely accurate.

A sleep tracking app can help you discover sleep difficulties and, in certain situations, provide tips.

Many sleep monitoring applications have smart alarms that wake you up based on your progress through various stages of sleep. This can help you avoid feeling groggy or confused when you wake up.

3.7 Monitoring patients participating in a prehabilitation program prior to cancer surgery

Prehabilitation is the program to optimize the patient's physical and mental condition prior to major surgery. The program consists of five pillars that putatively work synergistically: 1/ supervised training to improve strength and condition. 2/ nutritional support with supplementation of protein and vitamins. 3/ cessation of smoking and lifestyle changes. 4/ mental support. 5/ Patient hemoglobin management. The period between diagnosis and surgery is limited to 3-4 weeks and training must therefore be of high intensity.

There is increasing evidence that prehabilitation leads to faster recovery and reduction of complications after surgery, leading to a shorter hospital stay, improved quality of life and a reduction of hospital costs. Maxima MC is leading a large international RCT to demonstrate these effects in patients that need surgery for cancer of the colon and rectum, the PREHAB-trial.

A number of in-hospital tests are performed to monitor the patients' functional capacity These tests are performed to monitor progress both for individual patients and for the cohort of patients. Measurements at the start are also done for patient safety and determination of eligibility to the program. However, in-hospital tests may not accurately reflect risk profiles during exercise in daily life, cannot be used for registration of activity patterns nor track progress over time.

Development of new non-invasive methods and long-term monitoring with wearable devices are necessary to obtain continuous registration of the patients' functional capacity and actual performance. Development of new interfaces to communicate the data of these wearables with both the patient and health care professionals are necessary for patient safety and optimization of individual prehabilitation programs. Furthermore, with the use of Artificial Intelligence (AI), interpretation of the data will help to understand physiological processes and give input for prediction models that relate physical performance to surgical outcomes.

The use case will therefore describe the specific needs for 1/ continuous monitoring, 2/ the selection of appropriate wearables, 3/ interpretation of the data. 4/ improvement of prehabilitation programs for individual patients.

There is great potential for a use case for development of an interface for communication with patients or their peers and with health care professionals but this is beyond the scope of our prehabilitation research group.

Work to be done:

- Inventory of potential measurements derived from wearables
- Determination of a data bundle of interest in combination with non continuous (existing) data
- Collection of data in patients with colorectal cancer that do (and do not) participate in the prehabilitation program
- Interpretation of the data
- Optimizing prehabilitation programs

3.7.1 State of the art

3.7.1.1 Monitoring functional capacity

Prehabilitation programs aim to improve the patients' functional capacity in the short period prior to surgery.
Various tests are performed before the start of the training program. The results of the tests are used to set the training targets for individual programs but also to detect patients that should not participate in a highly intense training program without comprehensive cardiopulmonary testing (CPET) by a sports physicians or cardiologist.

Various tests are available to measure functional capacity such as the Steep Ramp Test (SRT), 6-minute walking test (6MWT), Stair Climb Test (SCT), sit to stand test, and CPET as a gold standard. Strength is expressed as 1 Repetitive Movement (1RM), a calculation of the maximal power for various muscle groups.

Repetition of these measurements at the end of the preoperative training period is used to monitor the effect of the training program in individual patients and also to monitor the effect of the cohort to demonstrate the effectiveness of the program.

The third set of tests taken six weeks after surgery will quantify the level of recovery or inversely quantify the impact of surgery.

With these measurements, we have demonstrated that patients improve in condition and strength prior to surgery and that prehabilitation helps reduce complications, lead to a faster recovery and a shorter hospital stay,

The current measurements however have their limitations. Besides the fact that they are non-continuous, they might not be the best to monitor functional capacity. Real-life measurements have a high potential to be more discriminative such as pulse frequency decrease after exercise.

Measurements at the three set time points (prior to the training program, at the end of the program and 6 weeks after surgery) will not give detailed information of the stepwise progression. Real-time monitoring will give more detailed information for each individual patient. This information might help in adjusting individual programs.

3.7.1.2 Registration of activity patterns

We lack detailed information on the activity patterns of individual patients. They will surely be active during training but how about the intervals between training. It might be that patients are less active because of fatigue caused by too intensive training. It might be that they believe that three hours of training during the week will suffice and that they can take a step back in their other activities. Detailed information on real-time activity patterns will give insight that might lead to adjustment. We also wonder whether patients will increase their activities progressively during the training period which could demonstrate the success of the lifestyle changes of the program.

Furthermore, evaluation of activity patterns after surgery by real-time data will give insight into the recovery process and potentially detect deviations triggering specific interventions.

3.7.1.3 The role of mental support

There is a pillar in the prehabilitation program that aims on optimal patient information and anxiety reduction. There is no possibility to support patients to be compliant to the training program. Potentially feedback on their progress in fitness can be presented by hand held tools/smartphones with specific applications.

3.7.1.4 The role of feedback to health care professionals.

Digital transmission to data to health care professionals will enable tele-monitoring and distant supervision.

3.7.2 Challenges

3.7.2.1 Monitoring functional capacity

An inventory should be made to identify potential variables for real-time measurements. The measurements should aim at daily life registration of functional capacity and improving patient safety. The second step should be to select appropriate wearables to record the data. Criteria for these wearables could be data content, location on the body, durability, exchange of data, battery time, measurement interval.

Next, data registration should take place in patients that participate in the prehabilitation program and probably also patients that do not participate but still undergo surgery, although it may be challenging to recruit patients in the latter category.

Finally, interpretation of real-time data and in-hospital measurements should be made available.

3.7.2.2 Registration of activity patterns

Real-time measurements should cover both the preoperative phase (prehabilitation) and the postoperative period (rehabilitation).

Based on real-time data activity patterns will be investigated. Outcomes will potentially give better insight into the individual effects of the prehabilitation program. Both in monitoring activity patterns and functional capacity AI can play an important role in making use of all available raw data.

AI can also play an important role in finding correlations between separate measurements or changes over time on surgical outcomes and recovery.

3.7.2.3 The role of mental support

Selection of tools to bring data from wearables to the patient. Applications should support patients in their compliance with the program and stimulate them to adjust their goals. We hypothesize that if patients are aware of their daily activity patterns, they will be more willing to change their activity patterns. Also, we would like to investigate the role of the motivational support of wearables if they give acknowledgments to the patients if daily targets are surpassed. Other options include possibilities to reward patients for their efforts with social benefits. Wouldn't it be nice to offer a patient a free ticket to some event together with their grandchildren if they met their set goals?

The optimal solution will include prehabilitation or revalidation data in more comprehensive patient pathway support programs.

3.7.2.4 the role of feedback to health care professionals.

Selection of tool for data transmission and application to distantly monitor the patients' progress. The ultimate goal is to include the data into comprehensive pathway care delivery systems. A true challenge will be to integrate these data into existing digital hospital support systems such as the electronic patient file.

3.8 Disease Prevention by Big Data Aggregation

Personal health and wellness monitoring and self-assessment for health prevention, empowerment and management

The overall goal is to enable Users within a defined community to have a common aggregated health and wellness dashboard to empower health self-monitoring and assessment for health prevention, management, and tracking. Users will actively link their consumer wearable device account to a common community platform. The system will allow the user to share their data and aggregate anonymized data will be available for platform owners to proactively improve community health strategies, outreach, programming and messaging.

Further, the application will offer the option of providing AI based feedback to the User based on their recorded activity to support improved personal health and wellness. Two-factor authentication will be utilized in the application.

This use case will be demonstrated by the following scenarios:

- Personal health and wellness improvement
- Community health and wellness improvement. Community is defined as the 'group' of users participating within a defined community-based platform. A community consists of a public platform offered to all users within a defined geographical area, and/or a platform offered to employees, students, staff/faculty within a specific organization or institution.
- Big data aggregation will be used to further empower personal health and wellness monitoring and self-assessment for disease prevention, health empowerment and management.

3.8.1 State of the art

Personal health and wellness is currently focused on the individual, and/or within the wearable device global community. A harmonized health and wellness platform that enables people within their work or residential community to connect disparate wearable devices within a harmonized platform offers the opportunity for broader-based public health interventions. They key elements in this use case consist of the following:

1. **Gathering raw data via diverse consumer wearable devices (e.g. Fitbit, Garmin, Polar) and potentially XCO health patch and Philips ePatch individually**
   Data from each wearable device individually will be connected to the RideShark platform.
   .
2. **Developing a harmonized common user health dashboard that displays the live data of integrated systems for continuous health and fitness monitoring**
   Data from all wearable devices will be harmonized to develop an integrated common health dashboard that displays harmonized common metrics, using advanced statistical analysis, AI and ML.

3. **Developing an Aggregate Anonymized Administration dashboard for use by community platform owners (public or private sector).**
   Protecting user data from a privacy and security perspective is a key element of this use case.

4. **Incorporation of AI-based User feedback**

   Metrics based on big data aggregation will be visualized on dashboards to provide the individual user with trends, progress and comparisons.

RideShark configurable custom-labelled platform overview

The RideShark platform currently provides many of the core technological components necessary for the delivery of a customer-based health and wellness platform. Extensive data security and privacy elements are already in the core multitenant platform. In addition, the platform allows for each customer to have a distinct, unique and configurable private network that includes only their stakeholders. This allows for functional module and content-driven customizations by client, for their end-users. Extensive data access authority permissions ensure data access levels is restricted to authorized users.

The core RideShark modular platform is available to users on desktop, mobile and via custom-branded iOS and Android apps. RideShark's current modules consist of multimodal trip planning, booking and payments, trip logging (including active modes such as walking, cycling, stationary bike, hiking, etc.), incentives and rewards, as well as other modules such as challenges, parking management, vanpool management and more. The proposed RideShark health module will be provide integrated modular functionality within the entire RideShark portfolio or will be offered as a stand-alone service.

RideShark's existing integration with transportation data allows for the continuous data integration via real time APIs for such elements as transit GTFS-RT data, or transportation data from wearable devices (for active transportation modes). RideShark's existing GIS-based trip tracking can automatically and dynamically record active transportation activity.

The extensive database reporting and visualization for transportation data will be expanded to include a health/wellness dashboard as well as AI-based feedback derived from big data aggregation.

This project includes the essential activities required to complete key strategic goals within the project timelines. These activities include:

- R&D activities develop and implement an enhanced data network
- R&D activities to integrate wearable health and wellness data
- R&D activities to harmonize health and wellness data from different providers
- R&D activities to develop an AI based user feedback loop
- Dynamic health and wellness dashboard development for the individual and community, including available information such as:
  - Temperature

- Blood oxygenation
- Heart rate
- Respiration Rate
- Blood Pressure
- Physical Activity indicators

Fundamentally, the RideShark Health AI functionality will result in new communities of users being better able to proactively improve health prevention, empowerment and management, while the individual will be better able to improve their personal health and wellness monitoring and self-assessment.

3.8.2 Challenges

Technical Challenges:

- Enhanced core data network that allows for extensive permission and data access authority levels to maintain protection of personal data
- Wearable device integration. Each consumer wearable device offers differing APIs, timing of data availability and datasets
- Development of a harmonized dynamic health and wellness dashboard (for users and community owners or authorized stakeholders) that can accommodate data from different providers.
- Development of AI based user feedback loop

Technical challenge will be resolved through extensive database configuration, technical analysis and testing.

Usability Challenges:

- User population testing (obtaining a critical mass for analytical purposes)
- User sharing information auditing

Usability challenges will be addressed by piloting the technology within a core group of users with predetermined stakeholders from both a public and private sector community group.

4 References

[1] Norgren L, Hiatt WR, Dormandy JA, et al. Inter-society consensus for the management of peripheral arterial disease (TASC II). Eur J Vasc Endovasc Surg. 2007;33(Suppl 11):S1–S75.

[2] Fowkes FGR, Aboyans V, Fowkes FJI, McDermott MM, Sampson UKA, Criqui MH. Peripheral artery disease: epidemiology and global perspectives. Nat Rev Cardiol 2017;14:156e70.

[3] Peripheral arterial disease: diagnosis and management. NICE. Available at:https://www.nice.org.uk/guidance/cg147.

[4] Gardner AW, Parker DE, Montgomery PS, et al. Efficacy of quantified homebased exercise and supervised exercise in patients with intermittent claudication: a randomized controlled trial. Circulation. 2011;123:491–498.

[5] Chan, C., Sounderajah, V., Normahani, P., Acharya, A., Markar, S. R., Darzi, A., Bicknell, C., & Riga, C. (2021). Wearable Activity Monitors in Home Based Exercise Therapy for Patients with Intermittent Claudication: A Systematic Review. European journal of vascular and endovascular surgery : the official journal of the European Society for Vascular Surgery, 61(4), 676–687. https://doi.org/10.1016/j.ejvs.2020.11.044

[6] Nicolaides, A. N., & Labropoulos, N. (2019). Burden and Suffering in Chronic Venous Disease. Advances in therapy, 36(Suppl 1), 1–4.

[7] V. Rajathi, R. R. Bhavani & G. Wiselin Jiji (2019) Varicose ulcer(C6) wound image tissue classification using multidimensional convolutional neural networks, The Imaging Science Journal, 67:7, 374-384

[8] Anusha DN, Bhavani RR. Classification of varicose ulcer tissue images. Adv Nat Appl Sci. 2016 April; 4:227–232.

[9] Li, R., Nie, B., Zhai, C., Cao, J., Pan, J., Chi, Y. W., & Pan, T. (2016). Telemedical Wearable Sensing Platform for Management of Chronic Venous Disorder. Annals of biomedical engineering, 44(7), 2282–2291.

[10] Abbott, C. A., Chatwin, K. E., Foden, P., et al. (2019). Innovative intelligent insole system reduces diabetic foot ulcer recurrence at plantar sites: a prospective, randomised, proof-of-concept study. The Lancet Digital Health, 1(6), e308–e318.

[11] Cavanagh PR, Lipsky BA, Bradbury AW, Botek G. Treatment for diabetic foot ulcers. Lancet 2005; 366: 1725–35.

[12] Armstrong DG, Boulton AJM, Bus SA. Diabetic foot ulcers and their recurrence. N Engl J Med 2017; 376: 2367–75.

[13] Pham H, Armstrong DG, Harvey C, Harkless LB, Giurini JM, Veves A. Screening techniques to identify people at high risk for diabetic foot ulceration: a prospective multicenter trial. Diabetes Care 2000; 23: 606–11.

[14] Crawford F, Cezard G, Chappell FM. The development and validation of a multivariable prognostic model to predict foot ulceration in diabetes using a systematic review and individual patient data meta-analyses. Diabet Med 2018; 35: 1480–93.

[15] Bus SA, van Deursen RW, Armstrong DG, Lewis JE, Caravaggi CF, Cavanagh PR. Footwear and offloading interventions to prevent and heal foot ulcers and reduce plantar pressure in patients with diabetes: a systematic review. Diabetes Metab Res Rev 2016; 32 (suppl 1): 99–118.

[16] S. A. Bini, R. F. Shah, I. Bendich, J. T. Patterson, K. M. Hwang, and M. B. Zaid, “Machine Learning Algorithms Can Use Wearable Sensor Data to Accurately Predict Six-Week Patient-Reported Outcome Scores Following Joint Replacement in a Prospective Trial,” J. Arthroplasty, vol. 34, no. 10, pp. 2242–2247, Oct. 2019, doi: 10.1016/j.arth.2019.07.024.

[17] S. Díaz, J. B. Stephenson, and M. A. Labrador, “Use of wearable sensor technology in gait, balance, and range of motion analysis,” Applied Sciences (Switzerland), vol. 10, no. 1. MDPI AG, p. 234, Jan. 01, 2020, doi: 10.3390/app10010234.

[18] C. Kokkotis, S. Moustakidis, E. Papageorgiou, G. Giakas, and D. E. Tsaopoulos, “Machine learning in knee osteoarthritis: A review,” Osteoarthr. Cartil. Open, vol. 2, no. 3, p. 100069, Sep. 2020, doi: 10.1016/j.ocarto.2020.100069.

[19] A. Saeed, F. D. Salim, T. Ozcelebi, and J. Lukkien, “Federated Self-Supervised Learning of Multisensor Representations for Embedded Intelligence,” IEEE Internet Things J., vol. 8, no. 2, pp. 1030–1040, Jan. 2021, doi: 10.1109/JIOT.2020.3009358.

[20] D. Spathis, I. Perez-Pozuelo, S. Brage, N. J. Wareham, and C. Mascolo, “Self-supervised transfer learning of physiological representations from free-living wearable data,” in ACM CHIL 2021 - Proceedings of the 2021 ACM Conference on Health, Inference, and Learning, Apr. 2021, pp. 69–78, doi: 10.1145/3450439.3451863.

[21] C. I. Tang, I. Perez-Pozuelo, D. Spathis, and C. Mascolo, “Exploring Contrastive Learning in Human Activity Recognition for Healthcare,” Nov. 2020, Accessed: Jun. 28, 2021. [Online]. Available: http://arxiv.org/abs/2011.11542.

[22] C. I. Tang, I. Perez-Pozuelo, D. Spathis, S. Brage, N. Wareham, and C. Mascolo, “SelfHAR: Improving Human Activity Recognition through Self-training with Unlabeled Data,” Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol., vol. 5, no. 1, Mar. 2021, doi: 10.1145/3448112.

[23] M. O. Yerebakan, X. Zhong, H. K. Parvataneni, C. F. Gray, and B. Hu, “Use of Wearable Sensors and Machine Learning Methods in Promoting Total Joint Replacement Treatment Outcomes: A Survey,” Proc. Hum. Factors Ergon. Soc. Annu. Meet., vol. 64, no. 1, pp. 627–631, 2020, doi: 10.1177/1071181320641142.

[24] Kida, N., Oda, S., & Matsumura, M. (2005). Intensive baseball practice improves the Go/Nogo reaction time, but not the simple reaction time. Cognitive Brain Research, 22(2), 257–264. doi:10.1016/j.cogbrainres.2004.09.003

[25] Mori, S., Ohtani, Y., & Imanaka, K. (2002). Reaction times and anticipatory skills of karate athletes. Human Movement Science, 21(2), 213–230. doi:10.1016/s0167-9457(02)00103-3

[26] Nathanael Chong Hao Ong (2015) The use of the Vienna Test System in sport psychology research: A review, International Review of Sport and Exercise Psychology, 8:1, 204-223, DOI: 10.1080/1750984X.2015.1061581

[27] MPU easy. https://www.mpu-easy.de/files/MPU%20easy%20Handbuch.pdf