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Remote patient-targeted health monitoring to reduce clinical workload

Deliverable 1.3

State of the Art (SotA) Updated

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Management Summary

This deliverable provides an updated and expanded State of the Art (SoTA) analysis for the REMO project. It covers the two clinical use cases addressed in the project: UC1 SPIDA, focusing on monitoring systems for spinal disorders rehabilitation, and UC2 MIND-SLEEP, focusing on integrated monitoring of sleep and mental well-being for preventive and supportive care.

For each use case, the document reviews recent scientific and technological developments, identifies emerging trends, and refines the challenges and gaps previously identified, taking into account progress made during the first phase of the project.

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1. Introduction

1.1. Purpose of the document

This document provides an updated and expanded State of the Art (SoTA) analysis for the REMO project, building upon the preliminary SoTA presented in Deliverable D1.1. It covers the two clinical use cases addressed in the project: UC1 SPIDA, focusing on monitoring systems for spinal disorders rehabilitation, and UC2 MIND-SLEEP, focusing on integrated monitoring of sleep and mental well-being for preventive and supportive care.

The purpose of this deliverable is to consolidate recent scientific and technological developments relevant to each use case, refine the challenges and gaps previously identified, and provide an updated evidence base to support subsequent technical and clinical work within the consortium.

1.2. Related documents

The following project deliverables are directly related to the present document:

- D1.1 – Use case descriptions, initial State of the Art (SoTA) and demonstrator specifications
- D1.4 – Patient and clinical requirements
- D2.1 – Conceptual Architecture, Technical Requirements and Functional Use Cases
- D3.1 – Comprehensive list of features to extract and use in downstream analysis steps & Risk register and validation plan
- D4.4 – Demonstrators description and results

2. UC1 (SPIDA) Monitoring system for spinal disorders rehabilitation

2.1. State of the Art

The State-of-the-Art analysis conducted as part of this work has demonstrated that while wearable sensors (EMG, HR), optical motion sensors, and telemedicine platforms are increasingly common, their application in rehabilitation is often fragmented and lacks integration. This creates a unique opportunity for REMO to introduce an advanced, evidence-based solution that not only meets a clear clinical need but also positions Lithuania at the forefront of digital rehabilitation innovation.

The Lithuanian use case is a technological solution that connects wearable sensor technologies and optical motion analysis sensor solutions with intelligent software to replicate and augment the in-clinic rehabilitation experience. Specifically, it monitors four key data streams: kinematic, internal load, external load, and subjective feedback. For example, in this system, kinematic aspects might be tracked by optical motion sensors recording how far and how fast the patient bends or lifts (*Tan et al., 2023*), whereas internal load is captured via devices like surface electromyography (EMG) or heart rate monitors, which gauge muscle activation and psychophysiologic effort (*Afsharipour et al., 2016; Kim et al., 2018*). External load is quantified through parameters such as movement quality, range of motion, or mechanical work, providing a biomechanical perspective on tissue demands (*Grenier et al., 2004; Flaxman et al., 2019*). In addition, patients regularly input subjective measures such as pain levels, fatigue, or a rating of perceived exertion after exercises, which complement objective data (*Coyne et al., 2022; Gabbett & Oetter, 2025*). Capturing all four aspects – what the patient did, how their body reacted, the mechanical demands, and how they felt – allows a multifaceted view of training load progressions. Research emphasizes that monitoring both external and internal loads, alongside subjective feedback, is essential for a complete understanding of exercise impact, since no single metric can capture the complexity of human response and individual variability (*Lancere et al., 2023*). By employing this multivariate approach, the system can more precisely tailor exercise intensity to the patient's capacity, optimizing the training stimulus while mitigating risk of overexertion or injury.

The conceptual framework of motor coordination (Safavynia, Torres-Oviedo, & Ting, 2011) highlights that while the nervous system itself is not directly measurable, its output can be observed through muscle activation patterns, which in turn generate forces, kinematics, and ultimately behavior. Traditional clinical tests often emphasize functional behaviour or kinematic outcomes (e.g., sit-to-stand, gait analysis). However, such measures may mask important neural-level differences: similar behaviors can be produced by distinct neuromuscular coordination patterns.

Muscle activation, assessed through surface electromyography (sEMG), provides direct insight into motoneuron activity and muscle synergies—patterns of coordinated recruitment across muscles that reflect underlying neural strategies for movement. At the same time, kinematic analysis captures the quality, amplitude, and control of movement, providing an objective measure of external load and mechanical execution. By combining muscle activation and kinematic assessment, clinicians in a clinical environment can:

- differentiate whether movement limitations are due to neuromuscular deficits or compensatory strategies;
- tailor exercise selection and progression more precisely, based on both internal load (effort, agonist activation) and external load (movement quality, range of motion);
- provide feedback-driven training (EMG and optical motion sensors) that supports patient engagement in both in-clinic and remote environments.

This integrated approach is especially relevant for chronic non-specific low back pain (CLBP), where movement alterations may reflect subtle deficits in trunk muscle coordination, endurance, or compensatory activation. Remote rehabilitation platforms leveraging EMG and kinematic feedback thus align with current neuroscience evidence and international rehabilitation guidelines, ensuring that exercise prescriptions address both neural control and mechanical execution.

Recent studies further support this rationale. Hodges & Tucker (2011) showed that pain induces redistribution of trunk muscle activity, leading to altered coordination that is not always detectable through gross kinematic outcomes. Similarly, van Dieën, Reeves, Kawchuk, van Dillen, & Hodges (2019) emphasized that CLBP is associated with maladaptive motor control changes and compensatory strategies, requiring multidimensional assessment combining EMG and movement analysis. Dankaerts et al. (2006) demonstrated distinct movement patterns and muscle activation profiles in CLBP patients during functional tasks, suggesting that both EMG and kinematics are needed to tailor rehabilitation effectively.

Importantly, this methodological approach is also consistent with international clinical guidelines. The NICE guideline NG59 recommends exercise, patient education, and function-focused assessment for persistent low back pain (NICE, 2016). The WHO guideline for the non-surgical management of chronic primary low back pain underscores the importance of non-invasive, active, and personalized rehabilitation strategies (WHO, 2023). Similarly, the American College of Physicians (ACP) and JOSPT Clinical Practice Guidelines stress active treatments and standardized assessment of pain, function, and movement (Qaseem et al., 2017; Delitto et al., 2012).

AI-Powered Analysis and Personalization. Another major innovation in this system is the incorporation of Artificial Intelligence (AI) algorithms to analyse the technological data and assist both patients and clinicians. These AI components are being developed to perform several critical functions: (i) Exercise Quality Assessment, (ii) Adaptive Progression, and (iii) Pattern Recognition and Risk Detection. For instance, deep learning frameworks have shown promising results in quantifying rehabilitation exercise quality and correcting execution errors in real time (*Liao et al., 2020; Karlov et al., 2025*). AI-driven adaptive systems can adjust exercise difficulty dynamically, ensuring progression tailored to individual recovery trajectories (*Cunha et al., 2023; Moccardi et al., 2025*). Moreover, pattern recognition models applied to gait, posture, and muscle activation data support early detection of compensatory movements or injury risk factors (*Taylor et al., 2024; Rahman et al., 2022; Alfahad & Alothaim, 2025*). Recent reviews emphasize that AI-powered personalization enhances both patient engagement and clinical decision support, accelerating functional recovery and reducing risk of relapse (*Sumner et al., 2023; Jawed et al., 2025*).

2.2. UC1 (SPIDA): Challenges and Gaps

Many existing tele-rehabilitation solutions are limited to video consultations or unsupervised exercise applications that provide generic guidance without accounting for individual variability. Very few systems integrate objective biomechanical measurements with internal physiological responses and subjective patient input, and fewer still employ artificial intelligence to support clinicians in tailoring rehabilitation dynamically. In Lithuania, telemedicine solutions are still in their infancy, with most developments concentrated in emergency medicine rather than rehabilitation.

3. UC2 (MIND SLEEP): Integrated Monitoring of Sleep and Mental Well-being for Preventive and Supportive Care

3.1. State of the Art

Sleep and mental well-being are deeply interconnected, yet manifestations such as anxiety, fatigue, cognitive decline, and sleep disturbances remain substantially under-monitored, particularly outside controlled clinical environments and especially among older adults living with multimorbidity and frailty. The current literature consistently highlights the multidimensional nature of this relationship and the need for more integrated monitoring solutions, with recent reviews underscoring links among sleep disturbances, cardiovascular risk, and affective and cognitive dysregulation [Jaspan et al 2024, Thompson et al 2022].

Poor sleep quality has been consistently linked to increased risk of cardiovascular disease, emotional dysregulation, and cognitive impairments, reinforcing the importance of reliable monitoring of sleep patterns in everyday contexts [Paiva & Penzel 2011].

Psychosocial factors such as stress, social isolation, and mood disorders also exert a direct influence on sleep architecture and overall sleep patterns, contributing to a bidirectional cycle between disturbed sleep and symptoms of anxiety and depression across the life course [Lin et al 2021]. Evidence from population-level studies conducted during the COVID-19 confinement period illustrates significant changes in sleep and awakening quality associated with lifestyle disruptions and increased psychosocial burden [Paiva et al 2025].

Despite advances in digital health, existing technological solutions frequently address sleep and mental well-being in isolation, for example, through stand-alone sleep-tracking applications, consumer wearables, or mental health apps that seldom share data or clinical context [Andrews et al 2019, Aziz et al 2025, Schäfer et al 2024]. This separation limits the potential for integrated and synergistic care pathways capable of providing a unified and clinically meaningful view of an individual's physical and psychological status [Faustino et al 2024], particularly when long-term trajectories in older adults with multiple chronic conditions need to be monitored [Wilson et al 2021].

Although remote monitoring systems and AI-based healthcare solutions are becoming more widespread, they often lack key properties such as non-intrusiveness, continuous data acquisition, contextual awareness, and clinical interoperability within Internet of Medical Things (IoMT) architectures [Batista et al 2021, Jayousi et al 2025]. Reviews of context-aware health sensing technologies highlight persistent gaps in security, interoperability, and real-world deployment capabilities [Batista et al 2021].

Among older adults, short or fragmented sleep, insomnia symptoms, and altered sleep architecture are associated with accelerated accumulation of chronic conditions, greater frailty, worse self-rated health, and poorer cognitive performance [Sindi et al 2020, Carvalhas-Almeida et al 2023]. Population-based data indicate that sleep disturbances frequently co-occur with late-life depression and anxiety, amplifying functional decline and the risk of loss of independence. At the same time, age-related conditions such as chronic pain, nocturia, cardiopulmonary disease, and polypharmacy further disrupt sleep, creating a complex, bidirectional relationship between sleep, multimorbidity, and

emotional well-being that is rarely captured in routine, time-limited clinical consultations [Sindi et al 2020].

A wide range of digital tools has emerged to monitor and support sleep and mental health, including home-based actigraphy, under-mattress or radar sensors, mobile applications for sleep diaries and cognitive-behavioural therapy for insomnia, and online programmes designed to sustain emotional well-being. Scoping reviews show that objective sleep monitoring at home in older adults is feasible but currently relies predominantly on wearables that provide limited information on sleep architecture and are variably accepted in the presence of frailty, multimorbidity or cognitive impairment [Ghazi et al 2025].

In parallel, older adults express clear interest in using digital technologies to maintain good mental health, while simultaneously reporting concerns about usability, trust, and the perceived relevance of generic applications to their everyday lives [Andrews et al 2019]. Real-world evaluations of digital well-being and resilience-building interventions suggest that engagement typically wanes over time and that benefits are greater when interventions are personalised, interactive, and embedded in ongoing care relationships [Boucher et al 2022, Schäfer et al 2024].

However, the routine implementation of digital sleep and mental health tools in geriatric care remains limited. Barriers include low digital literacy, lack of tailored interfaces for sensory and cognitive impairments, concerns about privacy and autonomy, and insufficient technical support for older users and caregivers [Wilson et al 2021]. From a systems perspective, data on sleep, symptoms, mood, and daily functioning are often fragmented across devices and platforms, with limited semantic interoperability and minimal integration into electronic health records and decision-making workflows. Analyses of context-aware smart healthcare and IoMT infrastructures emphasise that secure, interoperable, and contextually rich sensing solutions are still the exception rather than the norm, particularly outside specialist centres and research settings [Batista et al 2021, Jayousi et al 2025].

In addition to scientific developments, the market for digital sleep and mental-wellbeing solutions has expanded rapidly over the past decade, dominated by consumer-oriented platforms such as Fitbit, Apple Watch, Garmin, and Samsung Health. These ecosystems provide large-scale passive sensing of sleep duration, sleep stages, activity and heart-rate variability, often combined with app-based interfaces for mood tracking, mindfulness and stress-reduction content. Despite their wide adoption, independent evaluations show substantial variability in accuracy, particularly for sleep staging, alongside limited transparency regarding algorithms and data governance [Birrer et al 2024]. Commercial mental-wellbeing apps represent another fast-growing segment, offering meditation, Cognitive Behavioral Therapy informed modules and automated conversational agents. However, most lack robust clinical validation, and reviews consistently report insufficient and heterogeneous engagement in real-world settings, with additional usability and accessibility barriers for older adults [Yin et al 2024- Lipschitz et al 2023].

Market analyses highlight that although consumer products achieve scale, they rarely provide interoperable, clinically actionable data, reinforcing the gap between high user adoption and low clinical integration. This reinforces the need for platforms capable of linking objective sleep-sensing, contextual behavioural information and mental-health indicators within secure, interoperable and clinically meaningful architectures.

In addition to wearable-based approaches, recent developments in contactless sensing technologies, such as radar-based systems, enable unobtrusive monitoring of user activity and physiological signals in natural environments. These technologies support continuous data acquisition without requiring active user interaction, making them particularly relevant for long-term monitoring scenarios.

However, challenges remain regarding robustness, environmental variability, and integration with other sensing modalities. Combining contactless sensing with wearable technologies is therefore considered a promising approach to improve reliability and coverage in remote monitoring systems.

3.2. Challenges and Gaps

The main challenges associated with this use case include insufficient monitoring outside the hospital environment and the difficulty of correlating physiological, behavioral, and emotional data in a continuous and clinically meaningful way. User adherence is also a concern, as wearable devices are often poorly accepted or inconsistently used by older or frail individuals. Economic and regulatory barriers may further limit adoption, particularly in contexts where reimbursement schemes for remote monitoring remain unclear or where organisational processes and staffing models are not yet adapted to remote, data-driven workflows. To ensure clinical trust, the system must incorporate explainable AI techniques that allow healthcare professionals to understand and validate model outputs. Limited or absent internet connectivity may also hinder the reliability of data transmission and remote supervision, especially in rural or under-resourced settings.

A dedicated database will be developed to support the storage and retrieval of all relevant information, enabling users and caregivers to access a clear visual history of sleep patterns, daily activity, self-reported mood and cognition, and coaching interactions. Additionally, ethical and legal considerations must be fully addressed, particularly regarding privacy, the handling of personal data, and the use of technologies such as imaging or environmental sensing. This requires strong governance mechanisms, granular consent and access control, auditable data flows, and transparent communication to users about what is being measured, why, and with whom it is shared. Robust security and privacy measures will be implemented to ensure that personal information is protected and accessible only to authorized individuals.

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