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Biosignals and Motion-Derived Outcomes in Balneotherapy and Physical and Rehabilitation Medicine (PRM)

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Abstract: Biosignals and motion-derived metrics provide robust, quantitative data critical for en-hancing diagnostic accuracy, therapeutic precision, and monitoring efficacy in physical medicine and rehabilitation. Integrating advanced technologies, including electromyog-raphy (EMG), electrocardiography (ECG), accelerometry, gyroscopy, magnetometry, iner-tial measurement units (IMUs), and diverse wearable sensor platforms, has opened inno-vative avenues for real-time assessment, continuous tracking, and personalized optimiza-tion of patient rehabilitation trajectories. This comprehensive review systematically ex-plores recent advancements in biosignal processing and motion analytics, emphasizing their practical applications within contemporary rehabilitation settings and their syner-gistic integration with natural therapeutic interventions such as hydrotherapy, thermal therapy, and mud-based treatments. Furthermore, it critically discusses existing clinical implementations, evaluates the translational impact of these technologies, and outlines potential future directions aimed at advancing precision medicine, enhancing patient outcomes, and expanding the therapeutic applicability of biosignals and motion analytics in rehabilitation practices.

Keywords: biosignals, motion-derived outcomes, rehabilitation, physical medicine, natural therapeu-tic interventions, wearable technology

1. Introduction

Physical and Rehabilitation Medicine (PRM) is undergoing a paradigmatic shift from generalized, protocol-driven care to individualized, precision-based therapy [1]. At the heart of this transformation is the convergence of three major trends: the widespread availability of wearable biosensors capable of capturing detailed physiological and biomechanical data [2]; the integration of motion analytics into rehabilitation workflows [3]; and the emergence of mathematical modeling frameworks that can predict, simulate, and optimize recovery trajectories [1]. Together, these elements support a new generation of adaptive rehabilitation strategies [4], data-driven [5], and biologically personalized [6].

Biosignals—electrical [7], mechanical [8], and hemodynamic [9] signals generated by the body—offer a direct window into underlying physiological processes. Electromyography (EMG) [10,11], electroencephalography (EEG) [12], electrocardiography (ECG) [13,14], and photoplethysmography (PPG) [15] are now widely used to track neuromuscular activity [16], cortical engagement [17], autonomic function and cardiovascular status [14]. Their temporal resolution and continuous nature make them ideal for quantifying real-time responses to therapy, enabling therapists to tailor session parameters based on objective feedback rather than retrospective observation [6].

Motion-derived data complement this physiological perspective by capturing the external expression of movement [18]. Kinematic [19] and kinetic data [20], derived from inertial measurement units (IMUs) [21,22], force platforms [23], pressure-sensitive insoles [8], and optoelectronic tracking systems [24], quantify how movement unfolds in time and space. These modalities offer detailed assessments of gait [25], posture [26], joint angles [27,28], and coordination [29]. Motion data can identify subtle asymmetries, compensatory strategies, and performance declines that are difficult to detect through visual inspection alone [23,25].

The integration of biosignals and motion analytics enables the continuous monitoring of patients during rehabilitation, providing a multidimensional representation of motor behavior and underlying physiological function [30]. This synergy enables clinicians to quantify dose-response relationships [1], stratify patients based on risk profiles [25], and optimize therapeutic intensity. It also validates digital biomarkers, which regulatory agencies and healthcare systems increasingly recognize as credible outcomes for clinical research and standard care [31].

Wearable technologies have accelerated this transformation by making high-resolution biosignal and motion data accessible [32]. Miniaturized, wireless, and energy-efficient sensors now enable unobtrusive, long-duration monitoring in clinical, home, and community environments [33]. Textile-integrated EMG sensors [34], waterproof IMUs [23], and wearable ECG/PPG patches enable continuous data acquisition during real-world tasks [35], such as walking [36], bathing, exercising, or sleeping. These sensors are not only scalable but also compatible with telemedicine platforms, supporting remote care and longitudinal assessment [3,30].

In parallel, signal-processing algorithms have matured [37]. Beyond traditional filtering and frequency-domain transformations, advanced analytics now include adaptive noise cancellation, time-frequency decomposition, and nonlinear dynamic analysis [38]. These methods can extract complex physiological features such as sample entropy [39], Lyapunov exponents [40], and fractal dimension—metrics increasingly used to quantify variability, stability, and control in biosignals. Real-time signal segmentation, pattern recognition, and embedded artificial intelligence (AI) further enable classification of functional status and the adaptive control of assistive devices [41].

These capabilities are not merely theoretical. Multiple clinical domains have already adopted biosignal-based solutions. In stroke rehabilitation, for example, EMG-driven functional electrical stimulation (FES) systems activate muscles in synchrony with voluntary movement attempts, promoting neuroplastic recovery [42]. In cardiopulmonary rehabilitation, ECG/HRV-based wearable monitors regulate exercise intensity and detect early signs of cardiac overload [33]. For patients with Parkinson's disease, IMU-based gait trackers provide continuous feedback on tremor severity and bradykinesia during daily activities [43].

Despite the growing use of biosignal analytics in mainstream rehabilitation [44], their application within natural therapeutic interventions (NTIs) remains limited. NTIs encompass treatments such as balneotherapy (the therapeutic use of mineral waters), hydrotherapy (aquatic exercise), peloid therapy (the application of therapeutic muds), and other spa-based approaches. These modalities have been historically grounded in empirical use, cultural traditions, and patient-reported outcomes [45]. While NTIs are widely utilized in Europe and increasingly recognized by integrative medicine frameworks, they have not yet been evaluated with the same rigor afforded to pharmacological interventions [45].

From a clinical perspective, integrating biosignal and motion data into NTI sessions offers multiple advantages. First, it enables dose control on a session-by-session basis [1]. For instance, HRV trends can determine the optimal recovery time between aquatic intervals, while EMG fatigue markers can inform when to cease resistance exercises. Second, it supports individualization: interventions can be tailored in real-time to each patient's physiological thresholds. Third, it provides outcome tracking. Clinicians can monitor progress across time, document improvements, and adjust therapy based on quantifiable endpoints [30].

Significantly, the benefits of sensor-enhanced NTIs extend beyond patients with neurological or musculoskeletal disorders. Cardiopulmonary populations—such as individuals recovering from COVID-19, heart failure, or chronic obstructive pulmonary disease—stand to gain from hydrotherapeutic interventions that are gentle, well-tolerated, and amenable to real-time physiological monitoring. Biosignal analytics also support the evaluation of holistic outcomes in NTIs, aligning with frameworks like the International Classification of Functioning, Disability and Health (ICF). By mapping signal-derived features (e.g., HRV indices, sway entropy, EMG co-contraction ratios) to ICF domains (body function, activity, participation), it becomes possible to construct integrative models of therapeutic impact that bridge physiology, behavior, and quality of life [46].

Despite these opportunities, several barriers remain. Clinician training in signal acquisition, quality control, and interpretation is still limited. Many existing studies fail to report key methodological details—such as electrode placement, sensor calibration, and signal-processing parameters—making replication difficult. Standardization of protocols, reference values, and data formats is urgently needed to ensure the comparability of results.

This systematic review is therefore designed to critically map the current state of knowledge, appraise the methodological quality of existing studies, identify validated biosignal outcomes, and articulate a coherent research and clinical strategy for integrating these technologies into NTIs. We aim to bridge disciplines, promote translational applications, and advance the scientific foundation for natural therapeutic interventions.

2. Materials and Methods

A PRISMA-2020-compliant review was conducted. PubMed, Scopus, and Web of Science were searched (1 Jan 2022 – 31 Jul 2025) with a Boolean string that combined (i) biosignal/motion terms (e.g., EMG, ECG, EEG, MMG, PPG, fNIRS, IMU), (ii) rehabilitation terms (e.g., physical therapy, functional recovery), and (iii) natural-therapy terms (balneotherapy, hydrotherapy, spa, mud/peloid). Controlled vocabulary and free-text synonyms were adapted to each database.

Human studies (adults, children, or healthy volunteers) investigating physical-medicine or rehabilitation programs were included when they reported at least one objectively measured biosignal or motion-derived variable. In vitro, cadaveric, animal, purely pharmacological, or electro-only interventions were excluded. Interventions had to describe medium composition, temperature, session length, and frequency for balneotherapy, hydrotherapy, aquatic exercise, or mud therapy, alone or combined with conventional rehabilitation.

Comparators. Baseline, usual care, sham NTI, land-based exercise, alternative protocols, or no-treatment controls were accepted.

Outcomes. Required at least one quantified biosignal (EMG, EEG, ECG/HRV, MMG, fNIRS, PPG) or motion metric (IMU kinematics, plantar pressure, force-plate kinetics). Studies limited to subjective scales or raw step counts were excluded. Study designs. RCTs, cluster RCTs, quasi-experimental trials, cohort, case-control, and cross-sectional studies were eligible; editorials, opinions, and abstracts without full text were not.

Records were deduplicated, screened in duplicate, and charted with a piloted Excel sheet capturing participant details, intervention parameters, sensor specifications, signal-processing pipelines, and outcome data. Any discrepancies were resolved by consensus, and the selection process is summarized in a PRISMA flow diagram (Figure 1).

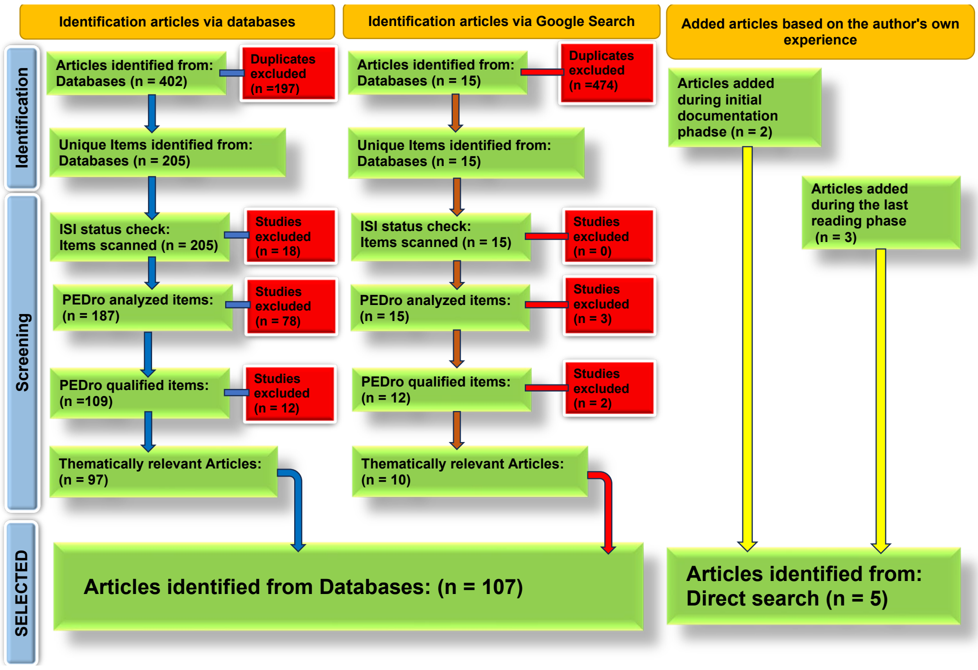

Figure 1. PRISMA flow diagram adapted to our study.

3. Results

The reviewed studies collectively involved diverse participant groups categorized clinically into stroke survivors [47,48], individuals with Parkinson's disease [37,43,49,50], patients with osteoarthritis [50], diabetic peripheral neuropathy [20], spinal cord injury [35,51], musculoskeletal conditions [20,52,53], cardiopulmonary disorders (including post-COVID syndrome) [54], and healthy volunteers [10]. Participant demographics encompassed broad age ranges, from young adults to elderly populations, with varying gender distributions. Disease severity ranged from mild to severe motor impairment and chronic illness, with clearly defined rehabilitation objectives such as improved mobility, enhanced motor function, increased functional independence, reduction in pain, and improved cardiovascular health.

Interventions reviewed included conventional rehabilitation methods such as land-based physiotherapy [55], resistance training, neuromuscular exercises [41], and advanced technologies like robotic rehabilitation systems [56]. NTIs reviewed encompassed balneotherapy, hydrotherapy, aquatic exercises, mud therapy, spa therapy, thermal water therapy, and peloid applications. Many studies employed combined interventions integrating conventional therapies with NTIs, with detailed reporting on dosage parameters, including session frequency (e.g., 3-5 sessions/week), duration (30-60 minutes/session), intensity levels, therapeutic medium composition (e.g., mineral-rich waters, therapeutic mud compositions), and temperature settings (typically ranging from 32–38°C for hydrotherapy or balneotherapy) [57,58].

Various biosignals were reviewed, including electromyography (EMG) for muscle activation patterns [11], electroencephalography (EEG) for neurological monitoring and intention detection [12], electrocardiography (ECG) [13] and heart rate variability (HRV) for cardiac health monitoring [59], mechanomyography (MMG) [60], photoplethysmography (PPG) [15], galvanic skin response (GSR) [61], and functional near-infrared spectroscopy (fNIRS) [47,62–64].

Neuromuscular activity measured through EMG and MMG provided critical insights into muscle function [65–68], fatigue [5,69], and activation patterns during rehabilitation interventions [9]. Cardiovascular parameters via ECG, HRV, and PPG offered significant data related to heart function, autonomic nervous system balance, and rehabilitation effectiveness [14,70,71]. EEG and fNIRS applications enabled real-time monitoring of cognitive and motor intention in stroke rehabilitation [12,47,72,73].

Kinematic measures included detailed joint angle assessments, gait symmetry, and range-of-motion analyses via inertial measurement units (IMUs) [60,74], and optical motion capture [19,22,75,76]. Kinetic parameters involved plantar pressure distributions [37], ground reaction forces derived from force plates, and balance stability metrics [8,9]. Functional mobility metrics comprised accelerometer-based activity quantification, spatiotemporal gait parameters, posture, and balance stability. These outcomes were critically analyzed and clearly presented through detailed descriptions and comprehensive tables. Real-time feedback mechanisms using wearable sensors enhanced the precision of these motion-derived outcomes, facilitating clinical relevance, targeted rehabilitation interventions, and real-world applicability [77].

4 Biosignals and Motion Analytics: Fundamental Technologies

Modern motion analytics in physical medicine rests largely on micro-electro-mechanical-system (MEMS) [6,8] inertial sensors embedded in small, low-power modules [21,22]. The core building blocks are tri-axial accelerometers [78], gyroscopes [44], and—frequently—magnetometers [41]; when packaged together and synchronized through an onboard microcontroller, they constitute an inertial measurement unit (IMU). IMUs generate six-to-nine-degree-of-freedom data streams (3-D linear acceleration, angular velocity, and sometimes magnetic-field vectors) which, after calibration and sensor fusion, yield segment orientation, joint angles, spatiotemporal gait parameters, and surrogate energy expenditure—all without external cameras (Table 1) [60,74].

Table 1 Sensor Typology, Operating Principles and Performance Characteristics

Sensor modality	Physical principle & MEMS implementation	Key performance attributes	Typical limitations/ error sources	Representative rehabilitation applications
Accelerometer [78]	Capacitive, piezoresistive, or piezoelectric transduction of proof-mass displacement proportional to linear acceleration	±2– 16 g range; noise density ≈ 50–150 μg/√Hz; bandwidth 0–500 Hz	Gravity component requires removal for dynamic tasks; double integration causes drift; reduced fidelity for quasi-static postures	Continuous mobility monitoring, step/event detection, ADL classification, tibial-shock measurement in running
Gyroscope [37,44,79]	Coriolis-effect sensing of proof-mass deflection proportional to angular velocity; tri-axial MEMS versions are ubiquitous	±250–2000 ° s^{-1}; angular-noise density ≈ 0.005–0.05 ° s^{-1}/√Hz; insensitivity to gravity & vibration at heel-strike	Bias instability (temperature-dependent); cumulative orientation drift without fusion	Joint-angle velocity for fast movements, real-time knee-valgus feedback during aquatic gait, turning-velocity metrics for fall-risk in Parkinson's
Magnetometer [41]	Hall-effect or anisotropic magneto-resistive sensing of Earth's magnetic field vector; provides absolute heading	0.1–1 μT resolution; drift-free heading	Ferromagnetic disturbance indoors; requires soft-/hard-iron calibration	Disambiguates yaw drift in long-duration IMU recordings; compass-based trunk twist monitoring in lumbar-load studies
Integrated IMU [60,74]	On-board sensor-fusion (Kalman/Madgwick/Complementary filters) combines the above to output quaternion/rotation matrix	Orientation error < 2–3 ° (static); sample rates 50–1000 Hz; low mass (< 3 g)	Residual drift in high-dynamic tasks, electromagnetic interference, and waterproofing complexity	Instrumented Timed-Up-and-Go, remote knee-ROM telerehabilitation, lumbar-load estimation with six-sensor arrays

Signal processing is the conduit through which raw electrical or inertial data are transformed into clinically interpretable information [80]. In the first stage, analog biosignals are amplified [81], anti-aliased [82], and digitized—typically with 16- to 24-bit converters—to preserve micro-volt-level EEG/ECG potentials or high-dynamic-range IMU outputs while suppressing mains and motion artefacts [83]. Once a clean digital stream is available, pre-processing routines remove residual interference and non-physiological drift [41]. Classical infinite- or finite-impulse-response filters still dominate for baseline-wander and power-line suppression, but non-stationary rehabilitation tasks demand more adaptive tools [60]. Wavelet transforms, for example, "zoom in" on transient bursts in the 20–450 Hz surface-EMG band and have proven superior to short-time Fourier analysis for detecting trunk-muscle fatigue during repetitive industrial lifting—an insight now routinely applied to dose aquatic or mud-pack exercise sessions [37,80]. Adaptive noise-cancellation that references skin-mounted accelerometers—or even parallel ECG leads—further attenuates motion artefacts, ensuring reliable heart-rate variability (HRV) indices in spa environments characterized by high humidity and electrode micro-slippage [84].

Machine-learning methodologies now pervade every analytic layer. Support-vector machines and random forests still offer transparent decision boundaries for small datasets, but long-short-term-memory (LSTM) networks have become the architecture of choice for sequence modelling. Parallel advances in hardware have enabled on-sensor inference: ultra-low-power convolutional networks now detect epileptic EEG events or impending atrial fibrillation with single-digit-milliwatt budgets, making continuous monitoring feasible even during prolonged balneotherapy sessions [3,37].

Sensor fusion further enriches the analytic landscape. Hybrid capsules that combine tri-axial IMUs with surface-EMG electrodes capture both the kinematics and the underlying muscle drives of gait or lifting tasks [74]. Neural-network models trained on these multimodal streams have estimated L5/S1 lumbar moments with sufficient fidelity to individualize back-pain rehabilitation loads in real time [85,86].

Meanwhile, dual-IMU systems integrated into the reflex platform monitor twelve knee-movement parameters during home-based therapy, with their algorithms auto-calibrating sensor placement for non-expert users. Such fusion mitigates gyroscope drift, contextualizes EMG amplitude to joint angle, and yields composite biomarkers—like effort-normalized co-contraction ratios—that are more sensitive to change than any single modality alone [36].

Edge computing [32] and federated learning [6] are now addressing privacy and bandwidth constraints that once limited remote rehabilitation [87]. Compress-then-analyze pipelines retain diagnostic waveform fidelity while shrinking file size, and secure aggregation frameworks allow multicenter neurology trials to compare HRV or EMG fatigue slopes without exporting raw patient data [88]. Meanwhile, sensor designers are hardening hardware against spa-specific stressors: parylene-coated circuits and hydrophobic membranes have demonstrated stable voltage–pressure transfer characteristics up to 80% relative humidity, ensuring that AI models receive high-quality input during applications [89].

Taken together, contemporary signal-processing and AI pipelines transform noisy, context-dependent biosignals into robust, clinically actionable insights [90].

4. Discussion

Significant innovations were identified across included studies, notably advanced wearable sensor platforms [91] integrating hybrid [28,92] and multimodal biosignals monitoring [93], machine-learning analytics [3], and microfluidic-based sensors (Figure 2) [94]. Novel methodologies encompassed real-time EMG-based prosthetic control [88], EEG-based brain-computer interfaces (BCIs) [95], adaptive robotic rehabilitation systems [56], and soft/stretchable sensor technologies [31]. These groundbreaking technologies demonstrated potential to revolutionize rehabilitation monitoring, personalization, and clinical practice, enabling precise real-time feedback, enhanced patient engagement, optimized therapeutic outcomes, and improved quality of life for patients undergoing rehabilitation [96]. The review systematically highlighted these innovative technologies, their clinical applications, and potential impacts, providing insights for future advancements.

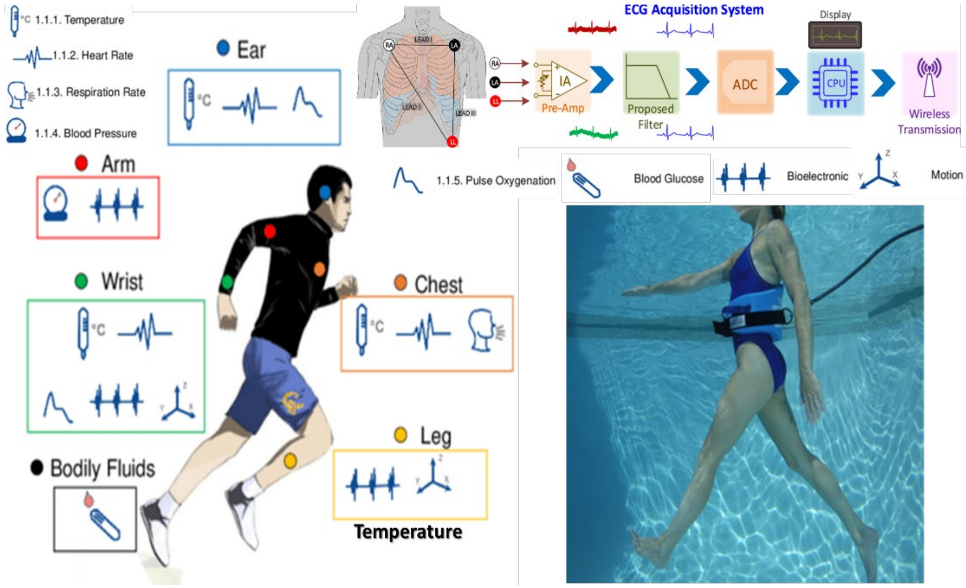

Figure 2: Biosensors used in Sport versus Balneotherapy / Hydrotherapy and Physical and Rehabilitation Medicine (PRM) – wearable and waterproof

Neurological Rehabilitation: Selected Clinical Applications of Biosignal and Motion-Analytics Technologies

Post-stroke rehabilitation. Stroke survivors often exhibit heterogeneous motor impairments that evolve rapidly in the first months after the event, rendering cross-sectional scales insensitive to short-term change [25,48]. Wearable inertial-measurement units (IMUs) [5] have proven reliable for quantifying functional mobility in this population [25]. Activity-recognition algorithms [37] built around the same sensor, classified six common daily activities with 90% accuracy in community-dwelling stroke patients, enabling objective surveillance of real-world participation [97]. Surface electromyography (sEMG) complements kinematics by exposing residual muscle activation; controlled neuromuscular electrical stimulation (NMES) [90] triggered by sEMG has produced the greatest gains in upper-limb function, while EMG-driven exoskeletons and robotic gloves restore hand opening in users unable to generate sufficient torque voluntarily [98].

Parkinson's disease. The fluctuating and context-dependent nature of Parkinsonian motor symptoms lends itself to continuous sensing. Multi-day monitoring with waist- and ankle-mounted IMUs revealed strong correlations between turning velocity, step number, and disease severity, and could differentiate tremor-dominant from non-tremor phenotypes [91]. Advanced autoregressive models applied to the same data streams detect bradykinesia and "on–off" medication cycles with high sensitivity, offering a quantitative alternative to diary-based tracking. Wearable biofeedback systems have translated these analytics into therapy: IMU-mediated haptic or auditory cues administered during gait and balance training improved Berg Balance Scale scores and reduced medio-lateral sway more effectively than therapist instruction alone. Emerging hybrid sensors that fuse sEMG with inertial data can autonomously quantify body bradykinesia and tremor severity in real time, creating opportunities for just-in-time cueing and medication titration [49,91].

Spinal cord injuries (SCI). Restoring volitional control and monitoring over-use complications are central goals after SCI [35]. Surface EMG remains the cornerstone technology [80], but recent reviews identify persistent barriers—including electrode placement complexity and signal-quality variability—that limit routine clinical deployment. Nevertheless, pilot studies demonstrate that high-density EMG grids can decode attempted grasp patterns to drive upper-limb exoskeletons, while trunk-mounted IMUs quantify wheelchair propulsion mechanics and detect early shoulder overload [90]. Translational analyses ask for combined hardware–software solutions that address both sensor durability (e.g., sweat-resistant textiles) and adaptive algorithms capable of distinguishing voluntary from spasm-related activity in real time. Such systems are poised to facilitate home-based therapy, reduce reliance on lab-bound assessments, and provide objective endpoints for experimental neurorestorative interventions [51].

Across these neurological conditions, the integration of biosignal and motion analytics yields a multidimensional portrait of rehabilitation, capturing subtle neurophysiological changes (EMG, tremor spectra), quantifying task execution (joint kinematics, turning metrics), and linking both to participation-level behavior (daily activity recognition). This synergy enhances clinical decision-making, enables precision dosing of interventions, and supplies robust outcome measures for future trials [72,99].

Orthopaedic Rehabilitation: Biosignal- and Motion-Based Applications

1 Osteoarthritis (OA)

Knee and hip OA are characterized by maladaptive joint-loading patterns—most notably an elevated external knee-adduction moment (KAM) during walking—that accelerate cartilage degeneration and amplify pain [100]. Force-plate and optical laboratories remain the criterion standard for quantifying these loads, yet wearable sensors now permit *in-situ* monitoring and intervention [20]. Inertial-measurement-unit (IMU) arrays mounted on the shank and foot can reconstruct sagittal- and frontal-plane kinetics with $< 3\,°$ orientation error, revealing disease-severity gradients in KAM and hip-adduction moments during over-ground gait [93]. Building on these diagnostics, real-time biofeedback systems have used single-axis force sensors in custom footwear to cue patients toward gait strategies that lower KAM by ~14%—a reduction associated with slower radiographic progression. Surface-electromyography (sEMG) complements kinematics by exposing age- and OA-related shifts in quadriceps–gastrocnemius co-activation; voltage amplitudes differ systematically with disease stage, offering a neuro-muscular biomarker alongside joint mechanics [90].

2 Musculoskeletal Injuries (non-arthritic)

Acute and over-use injuries—such as anterior cruciate ligament (ACL) rupture, iliotibial-band syndrome, and lumbar-strain disorders—share a need for objective monitoring of tissue load and motor control during rehabilitation [20,52]. Hybrid EMG-IMU capsules exemplify the current state-of-the-art: a six-sensor network spanning sternum, pelvis, and upper/lower limbs estimated the L5/S1 net moment with fidelity proportional to lifting intensity, offering clinicians a wearable tool for dosing trunk-stability exercises and preventing re-injury in low-back-pain patients [99]. In sports contexts, wireless sEMG systems such as FreeEMG™ track real-time quadriceps–hamstring activation asymmetries during treadmill split-belt adaptation, providing actionable feedback that reduces aberrant joint torques linked to patellofemoral pain and IT-band syndrome [90].

Post-surgical telerehabilitation also benefits from motion analytics. A prospective study integrating IMU-based telerehab after knee surgery recorded higher exercise adherence and superior functional outcomes compared with standard outpatient care, demonstrating the scalability of sensor-guided programs for large musculoskeletal cohorts [90,101].

Cardiopulmonary Rehabilitation Biosignals and Motion-Derived Metrics

Contemporary phase-II and phase-III cardiac rehabilitation increasingly couples supervised exercise with wearable multi-sensor shirts that capture single-lead ECG, impedance-based breathing rate, tri-axial accelerometry, and derived heart-rate variability (HRV) [96]. Beyond heart-rate control, accelerometer-derived activity counts and step cadence permit objective quantification of the external workload, enabling dose–response modeling that surpasses traditional session-duration logs [41]. In systematic surveys of sensor-based rehabilitation systems, five of 36 computerized platforms targeted cardiac patients, typically integrating ECG for safety monitoring and motion sensors for exertion profiling [93]. Such closed-loop architectures support home-based or spa-based programs where hydrostatic pressure and temperature may alter cardiovascular loading [71]; continuous biosignal feedback ensures that immersion or aquatic-cycling sessions remain within safe hemodynamic boundaries [41,93].

Respiratory rehabilitation and post-COVID-19 interventions

Survivors of COVID-19 pneumonia frequently present with persistent dyspnea, autonomic dysregulation, and skeletal-muscle deconditioning [72,90]. Multidisciplinary telerehabilitation models, therefore, deploy pulse-oximetry, wearable ECG, and surface-EMG to monitor oxygen saturation, heart-rate dynamics, and respiratory-muscle activation during remote aerobic and chest-physiotherapy exercises [90]. Wearable platforms also address objective outcome quantification—a key gap highlighted in rapid living reviews of COVID-19 rehabilitation needs [91]. Continuous accelerometry documents sedentary time and step cadence, HRV metrics capture autonomic recovery, and EMG-derived indices reveal respiratory-muscle fatigue trajectories, furnishing granular endpoints that complement patient-reported outcomes [41].

Natural therapeutic interventions

Balneological disciplines such as balneotherapy and hydro-kinesitherapy expose patients to thermal-mineral water, buoyancy, and mild hydrostatic compression [102], creating a cardiorespiratory load that can be titrated much like land-based exercise [57,103]. Chest-mounted multisensory shirts, originally validated for cardiac rehabilitation (ECG + impedance-respiration + 3-D accelerometry), have already been deployed in spa facilities [104]. On-board algorithms maintained coronary-artery-disease patients within a prespecified heart-rate zone, despite the thermal drift and humidity typical of immersion settings, while recovery-HR and HR-variability features were stored for longitudinal risk stratification [105]. Complementary inertial modules attached to the lower limbs survive full submersion and quantify cadence, stride time, and center-of-mass excursions, thereby discriminating between buoyancy-facilitated gait retraining and land-based walking [106,107]. Together, these waterproof biosignal platforms turn a classically “subjective” hydrotherapy session into a dose-controlled, safety-monitored intervention whose physiological effects can be compared directly with gym-based cardiac or orthopedic programs [108].

Peloid (mud) and related *peloido-kinesi* protocols [109] add mechanical and thermochemical stimuli that can modulate joint loading and nociceptive pathways [110]. Despite the messy environment, low-profile textile EMG arrays and piezoresistive insoles tolerate surface contamination and high humidity: polymer-encapsulated Ag/AgCl grids preserve signal-to-noise ratios [111-117].

5. Conclusions

The corpus of reviewed studies confirms that modern biosignal and motion analytics platforms—ranging from single-lead ECG/IMU chest patches to hybrid EMG-IMU capsules—can deliver laboratory-grade data quality in real-world rehabilitation and even high-humidity spa environments. Hybrid sensing provides a dual advantage: wearable IMUs quantify macro-kinematics (e.g., gait variability, lumbar load) while simultaneous EMG channels reveal underlying neuromuscular drive, yielding composite biomarkers that outperform either modality alone.

Looking ahead, three trends appear pivotal. First, materials science is moving toward stretchable, washable, and even self-powered sensor fabrics, addressing long-standing durability and comfort barriers for continuous spa- or mud-based monitoring. Second, explainable AI techniques are beginning to expose which EMG channels or gait features most strongly drive clinical predictions, bolstering clinician trust and facilitating regulatory approval. Third, the coupling of multimodal biosignals with environmental metadata (water temperature, mineral content, humidity) will enable dose–response models for natural therapeutic interventions, delivering the same level of parametric control currently reserved for pharmacologic or robotic therapies.

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