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Artificial Intelligence-Driven Physiotherapy: Transforming Personalized Rehabilitation Through Wearable Technology and Smart Exercise Monitoring

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Abstract

Artificial intelligence (AI) and wearable technologies are reshaping physiotherapy by enabling continuous measurement of movement, objective assessment of exercise performance, and more responsive rehabilitation planning. Wearable inertial measurement units, surface electromyography, pressure sensors, and camera-based systems can capture biomechanical and physiological information during therapeutic activity, and machine-learning algorithms can interpret these signals to classify exercises, estimate joint motion, identify movement deviations, and quantify adherence. When combined with clinician-supervised feedback and remote monitoring, these tools may extend rehabilitation beyond the clinic and support individualized home programs. This narrative review examines the technological foundations, clinical applications, potential benefits, and implementation challenges of AI-driven physiotherapy, drawing on evidence published between 2016 and 2025. Current literature supports the feasibility of wearable-supported monitoring and suggests that feedback can increase

physical activity in selected populations. However, evidence for durable improvements in patient-important outcomes is less mature than evidence for technical performance. Key barriers include sensor error, algorithmic bias, limited external validation, privacy risks, cost, digital exclusion, and uncertain workflow integration. AI should therefore be regarded as a decision-support and monitoring resource rather than a replacement for physiotherapists. Future research should prioritize adequately powered pragmatic trials, transparent algorithms, clinically meaningful outcomes, interoperable systems, and equitable implementation.

INTRODUCTION

Physiotherapy is a core component of care for people recovering from musculoskeletal injury, surgery, neurological disorders, cardiopulmonary illness, and age-related functional decline. Effective rehabilitation depends not only on selecting appropriate exercises but also on ensuring that patients perform them with suitable technique, dose, intensity, and progression. Conventional care commonly relies on periodic clinical assessments, patient-reported adherence, and therapist observation during scheduled sessions. Although these approaches remain essential, they provide only intermittent information about performance between appointments. Travel, workforce constraints, geographical barriers, and limited access to supervised services can further restrict continuity of care.

Digital health technologies offer opportunities to address some of these limitations, and international policy increasingly frames digital tools as a means of strengthening health systems when they are implemented equitably and safely World Health Organization, (2021). Wearable devices can record activity and movement outside the clinic, while AI can convert large streams of sensor data into interpretable indicators. In physiotherapy, these indicators may

include repetition counts, joint-angle estimates, gait characteristics, postural stability, muscle activation patterns, exercise quality, and changes in activity over time. The combination of sensing, algorithmic interpretation, and feedback creates the possibility of rehabilitation programs that adapt to an individual's changing capacity rather than following a fixed schedule.

The clinical promise of AI-driven rehabilitation must, however, be distinguished from proven clinical effectiveness. A model that accurately recognizes a movement in a laboratory dataset does not necessarily improve pain, disability, participation, or long-term recovery in routine practice. Recent reviews describe rapid growth in AI and wearable applications but also identify weaknesses in validation, reporting, dataset diversity, and clinical translation Latif et al., (2024) and Senadheera et al., (2024). This review discusses the field from a physiotherapy perspective and considers how smart monitoring can be incorporated safely into individualized rehabilitation (Wei & Wu, 2023.

Review Approach

This article is a narrative review rather than a registered systematic review or meta-analysis, and it was not conducted or reported according to the PRISMA 2020 guideline, which is designed for systematic reviews Page et al., (2021). The literature base was informed by searches of PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Google Scholar using combinations of the term's artificial intelligence, machine learning, physiotherapy, physical therapy, rehabilitation, wearable sensors, inertial measurement unit, electromyography, exercise monitoring, biofeedback, and telerehabilitation. Priority was given to peer-reviewed publications from 2016 through 2025, including clinical studies and recent systematic, scoping, and narrative reviews. Reference lists of relevant reviews were used to identify additional publications. The literature was synthesized thematically according to sensing technologies, AI methods, clinical applications, personalization, outcomes, and implementation considerations.

Because selection was purposive and no formal duplicate screening, risk-of-bias assessment, or quantitative synthesis was undertaken, the findings should be interpreted as a narrative synthesis and not as an exhaustive estimate of treatment effect.

Technological Foundations of AI-Driven Physiotherapy

Sensing Technologies

Inertial measurement units (IMUs), typically incorporating accelerometers and gyroscopes and sometimes magnetometers, are among the most widely used wearable technologies for movement monitoring Wei & Wu, (2023). Attached to the trunk or limbs, IMUs can estimate segment orientation, acceleration, angular velocity, step characteristics, and movement timing. They are relevant to gait analysis, balance assessment, upper-limb training, sit-to-stand tasks, and lower-limb exercise monitoring. Their portability makes them attractive for home-based programs, although sensor placement, calibration, soft-tissue movement, and accumulated orientation drift can affect measurement accuracy. Surface electromyography (sEMG) measures electrical activity associated with skeletal muscle activation. In rehabilitation, it can help characterize muscle recruitment, timing, co-contraction, and fatigue-related changes. However, readings are influenced by electrode location, skin preparation, adipose tissue, cross-talk, and movement artifact. Pressure-sensitive insoles, force platforms, and instrumented mats provide complementary information about plantar loading, weight distribution, and balance. Smartwatches and activity trackers can provide step counts, activity duration, heart rate, and other physiological or behavioral indicators, but consumer-grade measurements should not automatically be treated as equivalent to validated clinical instruments.

Camera-based systems, including RGB and depth cameras, provide marker less estimates of body pose and joint position. These systems may be easier for

some patients to use because they do not require multiple body-worn sensors. Their performance can be affected by lighting, camera angle, occlusion, clothing, background complexity, and the range of body types represented in training data. A review of lower-limb telerehabilitation technologies identified vision-based, wearable, and pressure-sensing approaches as common technical pathways, while highlighting inconsistent evaluation methods and limited testing across patient groups Ettefagh & Roshan Fekr, (2024). However, the below mention Table 1 summarizes the main sensing modalities and their principal limitations.

Table 1

Sensing Technologies Used in AI-Supported Rehabilitation

Technology	Typical outputs	Main limitations
Inertial measurement units	Segment orientation, acceleration, angular velocity, step timing, joint excursion	Placement sensitivity, calibration needs, soft-tissue artifact, orientation drift
Surface electromyography	Muscle activation, timing, co-contraction, fatigue-related change	Electrode location, skin preparation, cross-talk, movement artifact
Pressure insoles and mats	Plantar loading, weight distribution, balance	Hardware cost, limited task range, calibration
Smartwatches and activity trackers	Step count, activity duration, heart rate	Proprietary algorithms; not equivalent to validated clinical instruments
RGB and depth cameras	Marker less pose and joint position	Lighting, camera angle, occlusion, limited diversity in training data

Note: Summary based on Ettefagh and Roshan Fekr (2024) and Wei and Wu (2023). sEMG = surface electromyography.

Artificial Intelligence and Machine-Learning Methods

AI is a broad term covering computational approaches that perform tasks commonly associated with human reasoning or perception. Machine learning (ML), a major subset of AI, uses data to identify patterns and generate predictions or classifications. Supervised learning models, including support vector machines, random forests, gradient-boosting methods, and neural networks, can classify exercise types, distinguish correct from incorrect movement, or estimate clinical outcomes when trained on labeled examples Sengupta et al., (2024). Deep-learning methods such as convolutional and recurrent neural networks can learn complex patterns from time-series sensor signals, video, or combinations of data modalities (Wei & Wu, 2023).

A typical smart rehabilitation pipeline includes sensor acquisition, signal preprocessing, feature extraction or representation learning, model inference, feedback generation, and clinician review. Preprocessing may involve filtering noise, segmenting repetitions, synchronizing sensors, and normalizing signals. Models can then estimate movement variables or identify deviations from a prescribed pattern. The output should be translated into clinically meaningful feedback. As cue to reduce trunk compensation or improve knee alignment rather than an unexplained numerical score.

Wearable sensing combined with ML has been reviewed as a means of improving the measurement and interpretation of rehabilitation activity Wei & Wu, (2023). In stroke rehabilitation, wearable data and ML have been explored for assessment, training support, and remote monitoring Senadheera et al., (2024) and Sengupta et al., (2024). Yet model performance reported in development datasets may overestimate real-world utility if training and test

data contain participants or sessions that are not truly independent. Subject-wise and external validation are therefore critical (Senadheera et al., 2024).

Personalized Rehabilitation Through Smart Monitoring

Baseline Assessment and Individualized Targets

Personalized rehabilitation begins with a clinically grounded assessment of impairment, activity limitation, participation goals, comorbidities, environmental context, and patient preference. Wearable measurements can supplement not replace standardized clinical tools by documenting how a person moves in everyday settings. For example, baseline gait speed, step symmetry, walking duration, joint excursion, balance behavior, and daily activity may provide information that is not captured during a brief clinic visit. The physiotherapist can use these data to set realistic targets and determine whether the prescribed program is being completed at an appropriate dose.

Individualization should not mean allowing an algorithm to prescribe treatment without clinical reasoning. Exercise selection and progression require consideration of diagnosis, tissue healing, contraindications, pain response, fatigue, cognition, falls risk, and patient goals. AI outputs are best used to identify trends or prompt reassessment. The clinician remains responsible for interpreting measurements in context and deciding whether to progress, regress, or modify an intervention.

Real-Time Exercise Recognition and Movement-Quality Feedback

Smart exercise monitoring can identify which exercise a patient is performing, count repetitions, estimate range of motion, measure tempo, and detect selected compensatory movements. Camera-based pose estimation and wearable IMUs can provide complementary information about joint trajectories and segment motion. A system may compare the observed movement with a

therapist-defined target and provide visual, auditory, or vibrotactile feedback. Such feedback can help patients recognize errors while exercising independently and may improve consistency between supervised sessions.

However, movement quality is multidimensional. A single joint-angle threshold may not adequately represent safe or effective performance because acceptable movement varies with anatomy, diagnosis, stage of recovery, symptoms, and task demands. Algorithms should therefore be designed around clinically meaningful criteria and allow the therapist to adjust thresholds. A recent systematic review of depth-camera assessment illustrates the growing role of ML in marker less exercise evaluation, while also underscoring the need to evaluate robustness beyond controlled environments (Zhou et al., 2025).

Adaptive Exercise Progression and Adherence

Wearable monitoring can help distinguish between prescribed activity and completed activity. Data on repetitions, duration, step count, movement quality, and symptom reports may reveal barriers to adherence or signs that a program is too demanding. A clinician-facing dashboard can summarize trends and flag clinically relevant changes for review. In principle, adaptive systems could adjust reminders, exercise difficulty, or feedback frequency according to performance and recovery. Any automated change to exercise intensity or complexity should operate within clinician-defined safety boundaries.

Adherence is influenced by more than reminders. Pain, fear of movement, low confidence, competing responsibilities, poor connectivity, and limited health literacy can all reduce participation. Feedback should therefore be supportive, understandable, and proportionate. Gamification may improve engagement for some individuals, but competitive scoring or excessive alerts may discourage others. The best design is one that supports self-efficacy and shared decision-making rather than simply maximizing app usage.

Clinical Applications

Musculoskeletal and Postoperative Rehabilitation

In musculoskeletal rehabilitation, wearable systems may monitor range of motion, exercise repetitions, gait, loading, and activity after conditions such as knee or hip surgery, ligament injury, and lower-back disorders. Following joint replacement, for example, activity trackers may support monitoring of walking volume and recovery milestones, while IMUs or camera systems may assess functional tasks such as sit-to-stand and step-ups. These measures can complement pain scales, patient-reported outcome measures, strength testing, and clinician examination.

Evidence from commercially available wearables is encouraging but should be interpreted cautiously. A systematic review of 18 studies involving 1,754 patients reported that all six included randomized trials found increased physical activity with wearable-driven feedback, and two orthopedic trials reported non-inferiority of wearable-supported self-directed rehabilitation compared with traditional physiotherapy for the outcomes studied (Latif et al., 2024). These findings support wearables as potential adjuncts or, in selected pathways, components of self-directed care. They do not establish that all wearable applications are equivalent to supervised physiotherapy or that activity gains necessarily translate into superior long-term function.

Neurological Rehabilitation

Stroke, Parkinson's disease, spinal cord injury, and other neurological conditions can produce complex impairments in strength, coordination, balance, gait, and upper-limb function. Wearable sensors can capture movement frequency, symmetry, velocity, and activity in the home or community. ML may support

classification of movement patterns, quantify use of an affected limb, and track changes across repeated sessions Sengupta et al., (2024).

. For stroke rehabilitation, the combination of wearable devices and ML has been investigated for motor assessment, training, and remote monitoring (Senadheera et al., 2024).

These applications are particularly relevant because recovery is dynamic and often requires high-repetition practice. Nonetheless, systems must accommodate heterogeneous impairment profiles, including spasticity, apraxia, sensory loss, cognitive impairment, and fatigue. Algorithms trained predominantly on healthy participants may not reliably interpret atypical movement. Clinical validation in representative patient cohorts is essential before feedback is used to guide treatment.

Gait, Balance, and Falls Prevention

Wearable accelerometers, gyroscopes, pressure insoles, and smartphone sensors can support gait and balance assessment outside specialist laboratories (Ettefagh & Roshan Fekr, 2024). Potential variables include cadence, step time, stride variability, turning, trunk sway, and left right loading. AI models may combine these features to identify changes associated with mobility decline or increased falls risk. Such information can help physiotherapists target balance, strength, gait, and environmental interventions (Wei & Wu, 2023). However, falls prediction is a high-stakes task: false reassurance and false alarms can both cause harm. Models should be validated prospectively and used alongside clinical assessment rather than as stand-alone screening tools.

Home-Based Rehabilitation and Telerehabilitation

Telerehabilitation connects patients and clinicians through video consultations, digital exercise programs, remote monitoring, and asynchronous feedback. AI-

enabled virtual physiotherapy assistants may guide exercise execution, deliver reminders, and summarize performance for the treating professional. A recent narrative review describes the potential of virtual assistants to support home rehabilitation while identifying sensor precision, user engagement, affordability, and accessibility as continuing challenges (Olawade et al., 2025).

Remote care can reduce travel and improve access for people living far from rehabilitation services or facing mobility barriers. It may also allow clinicians to observe activity across a longer period rather than relying exclusively on clinic-based snapshots. Nevertheless, remote delivery is not suitable for every patient or every stage of recovery. Initial assessment, complex neurological presentations, severe pain, unstable medical conditions, significant falls risk, and situations requiring hands-on examination may still require in-person care. Hybrid models that combine face-to-face assessment with remote follow-up are often a more defensible approach than universal substitution.

Potential Benefits and Clinical Value

The main potential benefit of AI-driven physiotherapy is the ability to make rehabilitation more measurable and responsive. Continuous or repeated monitoring can reveal changes in activity and performance that might otherwise remain unnoticed. Objective feedback may improve exercise awareness and support adherence, Latif et al., (2024). Remote dashboards can help clinicians prioritize follow-up, identify stalled progress, and tailor consultations. Automated measurement may also reduce some repetitive administrative tasks, allowing physiotherapists to devote more time to complex clinical reasoning and therapeutic interaction.

Wearables may support continuity between appointments by making home exercise performance more visible. In a patient who is recovering from surgery, for example, a combination of activity data, functional task performance, pain reports, and clinician assessment may provide a more complete picture than

step count alone. In neurological rehabilitation, repeated sensor measurements may help quantify changes in movement that are difficult to capture through occasional observation, Sengupta et al., (2024). The value of these systems depends on whether the information changes decisions and improves outcomes, not merely on the volume of data collected.

Limitations, Risks, and Implementation Challenges

Measurement Validity and Algorithmic Generalizability

Sensor outputs are estimates and are affected by device placement, calibration, sampling frequency, battery status, environmental conditions, and user behavior. Consumer devices may use proprietary algorithms that are not fully disclosed. A measurement validated for step counting may not be valid for estimating joint kinematics or movement quality. Clinicians should examine the intended use, reliability, validity, responsiveness, and known error of each device before incorporating its output into care.

Algorithmic generalizability is another concern. Models may perform differently across age groups, body sizes, skin tones, disability profiles, assistive-device users, and movement patterns. Datasets may be small, collected in laboratories, or dominated by healthy volunteers. Reviews of AI in rehabilitation have identified limited external validation and explainability as important weaknesses in the evidence base, Senadheera et al., (2024). Performance should be reported using clinically relevant measures and tested in independent populations and real-world settings (Zhou et al., 2025).

Privacy, Cybersecurity, and Informed Consent

Wearable rehabilitation systems can collect sensitive information about location, activity, sleep, heart rate, movement, and health status. Data collection should be proportionate to the clinical purpose, and patients should understand what

is collected, who can access it, how long it is retained, and whether it is shared with third parties. Secure transmission, encryption, role-based access, data minimization, and clear retention policies are necessary. Consent should be meaningful and revisited when the purpose or use of data changes.

Patients should also be informed when an AI system contributes to assessment or recommendations. They need an opportunity to question automated outputs and request human review. A clinician should be able to override a recommendation and document the rationale. Responsibility for monitoring alerts, responding to abnormal data, and managing technical failures must be clearly assigned.

Digital Equity, Affordability, and Usability

The benefits of smart rehabilitation may be distributed unevenly. Patients may lack smartphones, reliable internet, digital literacy, language-compatible interfaces, or the financial resources to purchase devices Olawade et al., (2025) Some people may find wearable devices uncomfortable or difficult to don, particularly when they have cognitive, sensory, or dexterity limitations. Systems should be designed for accessibility, provide low-bandwidth options, support relevant languages, and avoid making access to essential rehabilitation dependent on personal ownership of expensive technology.

Implementation also requires workflow integration. A dashboard that produces excessive alerts or poorly prioritized data can increase clinician workload rather than reduce it. Services need training, technical support, clear protocols, and reimbursement models that recognize remote monitoring work. The evidence base should include cost-effectiveness and implementation outcomes, not only technical accuracy (World Health Organization, 2021.

The Role of the Physiotherapist

AI does not replace the therapeutic relationship, clinical reasoning, or hands-on skills of physiotherapy. Rehabilitation decisions require interpretation of symptoms, examination findings, patient goals, psychosocial factors, and changing clinical circumstances. Algorithms can support measurement and pattern recognition, but they cannot independently establish the meaning of a patient's pain, understand all contextual barriers, or assume professional accountability.

The physiotherapist's role is therefore evolving toward the integration of digital measurements with clinical assessment. Practitioners need sufficient digital and data literacy to understand sensor limitations, interpret dashboards, explain AI-generated feedback, and recognize when outputs are unreliable. Patients should remain active participants in decisions about goals, exercise selection, and progression. A human-in-the-loop model, in which AI supports but does not autonomously determine care, is currently the most appropriate framework for routine clinical use.

Future Directions and Research Priorities

Future research should move beyond proof-of-concept systems and evaluate whether AI-enabled monitoring improves outcomes that matter to patients. Trials should include adequate sample sizes, clinically representative populations, appropriate comparators, and follow-up long enough to assess sustained function and participation Latif et al., (2024) Outcomes should include pain, disability, mobility, quality of life, adherence, adverse events, health service use, and cost-effectiveness. Technical outcomes such as classification accuracy should be reported alongside clinical outcomes (Senadheera et al., 2024).

Multimodal systems that combine IMUs, sEMG, pressure sensors, video, and patient-reported symptoms may provide richer context than any single sensor. However, greater data complexity increases demand for calibration, synchronization, interpretability, and governance. Researchers should prioritize

transparent reporting, subject-independent validation, external testing, and open or well-documented datasets where privacy permits. Explainable AI may help clinicians understand why a system has flagged a movement or recommended reassessment.

Personalized systems should also be evaluated for unintended consequences, including excessive monitoring, anxiety, reduced autonomy, and inappropriate exercise progression. Co-design with patients, caregivers, physiotherapists, and service managers can improve relevance and usability Olawade et al., (2025). Finally, implementation studies should examine how these technologies function in low-resource settings and whether they reduce or widen existing disparities in access to rehabilitation (World Health Organization, 2021).

Conclusion

Artificial intelligence and wearable technology are creating new opportunities for personalized physiotherapy through continuous movement measurement, smart exercise monitoring, remote feedback, and data-informed treatment review. Current evidence supports technical feasibility and indicates that wearable feedback can increase activity in selected rehabilitation populations Latif et al., (2024). AI-enabled systems may help extend care into the home, improve visibility of exercise performance, and support more timely clinical decisions. However, the evidence for broad, sustained improvements in patient-important outcomes remains developing. Measurement error, limited external validation, privacy concerns, cost, digital exclusion, and workflow demands must be addressed before widespread adoption. The most clinically appropriate model is one in which validated digital tools augment physiotherapists' expertise and preserve individualized, person-centered care.

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