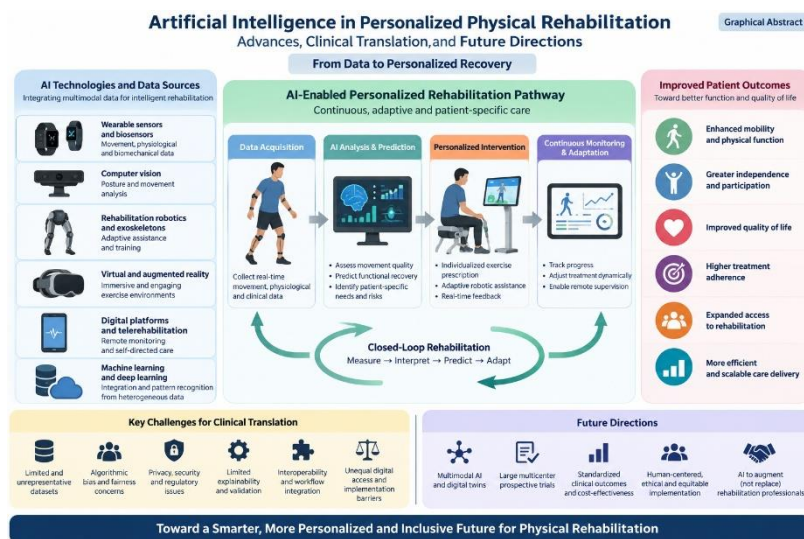


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KEYWORDS	ABSTRACT
Artificial intelligence; Personalized rehabilitation; Physical rehabilitation; Machine learning; Telerehabilitation; Rehabilitation robotics	Artificial intelligence (AI) is rapidly transforming physical rehabilitation by enabling more personalized, adaptive, data-driven, and accessible approaches to patient assessment and therapeutic intervention. This systematic review critically synthesizes advances in AI-enabled personalized physical rehabilitation, with particular emphasis on technological development, clinical translation, and future implementation. Following PRISMA 2020 principles, evidence was examined across machine learning, deep learning, computer vision, wearable and biosensor technologies, rehabilitation robotics and exoskeletons, virtual and augmented reality, digital platforms, and telerehabilitation. Current applications demonstrate substantial potential for automated functional and movement assessment, patient-specific outcome prediction, individualized exercise prescription, adaptive robotic assistance, continuous monitoring, and real-time therapeutic feedback. Clinical translation is most developed in neurological and stroke rehabilitation, while growing applications are evident across musculoskeletal and orthopedic, geriatric, and cardiopulmonary rehabilitation. Collectively, these technologies support a transition from episodic and standardized therapy toward closed-loop rehabilitation in which patient performance is continuously measured, interpreted, predicted, and used to adapt treatment. However, clinical effectiveness remains heterogeneous, and strong algorithmic performance does not necessarily translate into meaningful improvements in mobility, independence, participation, quality of life, or treatment adherence. Major barriers include small and unrepresentative datasets, algorithmic bias, limited external validation, insufficient explainability, privacy and regulatory concerns, poor interoperability, workflow integration challenges, and unequal digital access. Emerging multimodal AI and patient-specific digital twins may further strengthen precision rehabilitation by integrating diverse clinical, biomechanical, physiological, and behavioral information. Future progress requires multicenter prospective validation, standardized clinically meaningful outcomes, fairness assessment, cost-effectiveness evaluation, and human-centered implementation. AI should ultimately augment rather than replace rehabilitation professionals, combining computational intelligence with clinical judgement to deliver safe, equitable, trustworthy, and genuinely personalized rehabilitation.
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Graphical abstract



Introduction

Physical rehabilitation is a fundamental component of contemporary healthcare, aiming to restore or optimize physical functioning, mobility, independence, and participation among individuals affected by injury, disease, disability, or age-related functional decline. Growing population ageing, increased survival after severe illness and injury, and the rising prevalence of chronic neurological and musculoskeletal disorders have intensified global demand for effective rehabilitation services. These pressures have exposed persistent limitations in conventional rehabilitation delivery, including restricted access to therapists, resource-intensive treatment models, inconsistent follow-up, and difficulties in providing continuous individualized care. Artificial intelligence (AI) has consequently emerged as a potentially transformative technology capable of improving the accessibility, efficiency, and personalization of physical rehabilitation, although evidence of its clinical effectiveness remains heterogeneous (Sumner et al., 2023). Conventional physical rehabilitation depends heavily on clinical assessment, standardized functional measures, therapist expertise, and repeated observation of patients' responses to intervention. Although these approaches remain essential, rehabilitation outcomes vary substantially even among patients with similar diagnoses because recovery is influenced by disease severity, baseline functional status, comorbidities, biomechanical characteristics, motivation, environment, treatment adherence, and individual biological responses. Personalized rehabilitation therefore requires methods capable of integrating heterogeneous patient information and dynamically adapting interventions as recovery progresses. Machine-learning approaches have demonstrated the capacity to model complex clinical datasets and predict post-stroke functional recovery, illustrating their potential to support individualized prognostic reasoning and rehabilitation planning (Campagnini et al., 2022). AI encompasses machine learning, deep learning, computer vision, natural language processing, reinforcement learning, and related computational approaches capable of identifying complex patterns and generating predictions or decisions from data. Within physical rehabilitation, these techniques are

increasingly integrated with sensors, mobile applications, robotics, virtual environments, and movement-analysis systems. Computer vision is particularly relevant because it can automatically analyze human posture and exercise performance from skeletal or image-based movement data, potentially enabling objective assessment of rehabilitation exercises outside continuous therapist supervision (Sardari et al., 2023). Such capabilities can transform rehabilitation assessment from periodic clinical observation toward continuous and quantitatively informed evaluation.

The expansion of wearable technologies has further strengthened this transformation. Wearable inertial sensors, accelerometers, gyroscopes, electromyographic devices, and other sensing systems can continuously collect movement and physiological information during rehabilitation. Machine-learning algorithms can convert these high-dimensional data into clinically meaningful measures of movement quality, functional performance, and recovery progression, thereby supporting individualized feedback and rehabilitation adjustment (Wei & Wu, 2023). Commercial wearable devices are also increasingly being evaluated as rehabilitation adjuncts, with evidence suggesting their feasibility for promoting physical activity and supporting self-directed rehabilitation in selected clinical populations (Latif et al., 2024). Collectively, these developments are changing the conceptual basis of physical rehabilitation. Rather than relying exclusively on predetermined protocols and intermittent face-to-face assessments, AI-supported systems create opportunities for rehabilitation that is predictive, responsive, continuously monitored, and increasingly adapted to individual patients. Nevertheless, technological capability should not be equated with clinical effectiveness. The central challenge is therefore to determine whether these rapidly developing technologies can progress beyond algorithmic performance and experimental feasibility to produce reliable, safe, clinically meaningful, and patient-centered improvements in rehabilitation practice.

Personalized rehabilitation involves tailoring therapeutic decisions to the specific characteristics, functional limitations, preferences, responses, and recovery trajectory of each patient. AI is particularly suited to this objective because it can analyze multidimensional information that may exceed the practical processing capacity of conventional clinical assessment. In stroke rehabilitation, for example, machine-learning models have been developed to predict treatment outcomes and identify factors associated with functional recovery, potentially enabling clinicians to stratify patients and establish more individualized rehabilitation strategies (Zu et al., 2023). The value of such models lies not simply in predicting outcomes but in translating predictions into clinically actionable treatment decisions. Gait assessment represents another important application. Traditional instrumented gait analysis can generate large volumes of biomechanical and kinematic data that require specialized interpretation. Machine-learning techniques can identify patterns within these datasets and have been increasingly applied to gait abnormalities associated with stroke and cerebral palsy. However, current evidence highlights continuing challenges concerning clinical suitability, feasibility, reliability, dataset quality, and methodological standardization, demonstrating that predictive performance alone does not guarantee clinical usefulness (Samadi Kohnehshahri et al., 2024).

Rehabilitation robotics provides another pathway toward individualized treatment. Robotic devices and exoskeletons can deliver intensive, repetitive, task-specific movement training while collecting detailed information on patient performance. When combined with AI, robotic rehabilitation can move beyond fixed assistance toward adaptive human–robot interaction, in which assistance, resistance, movement trajectories, and feedback are modified according to patient performance. AI-based methodologies for lower-limb exoskeleton rehabilitation increasingly employ machine learning, neural networks, support vector machines, and reinforcement learning to facilitate personalized robotic control and therapeutic feedback (Coser et al., 2024). This integration offers particular potential for neurological rehabilitation, where the level of motor impairment and rate of recovery vary markedly among individuals. Virtual rehabilitation provides a complementary approach by extending individualized rehabilitation beyond conventional clinical environments. AI-enabled virtual systems can combine movement tracking, automated assessment, interactive exercise, and adaptive feedback to support rehabilitation in community and home settings. A scoping review of AI-driven virtual rehabilitation demonstrated the expanding application of intelligent virtual systems for community-dwelling populations while emphasizing the need for stronger evaluation of usability, effectiveness, and implementation (Abedi et al., 2024). Such systems could be particularly important for patients facing geographic, mobility, transportation, or workforce-related barriers to conventional therapy. Virtual reality (VR) also offers the ability to create immersive and adjustable therapeutic environments in which task difficulty, sensory feedback, and exercise complexity can be adapted to patient capabilities. Evidence from post-stroke rehabilitation indicates that immersive VR may provide additional benefits for upper-limb function, gait, dynamic balance, independence, and patient engagement when incorporated into rehabilitation programs (Demeco et al., 2023). Although VR is not inherently an AI technology, its integration with intelligent movement recognition and adaptive algorithms creates opportunities for increasingly responsive and individualized therapeutic environments.

Telerehabilitation further extends the digital rehabilitation continuum by enabling therapeutic exercise and professional supervision at a distance. Evidence comparing telerehabilitation with face-to-face physiotherapy suggests that remotely delivered therapeutic exercise can achieve comparable outcomes for several physical conditions, although effectiveness varies according to population, intervention design, and outcome measure (Muñoz-Tomás et al., 2023). When integrated with AI-driven monitoring, wearables, and automated exercise assessment, telerehabilitation could evolve from simple video-based care into an intelligent remote rehabilitation ecosystem capable of continuously monitoring performance and adapting treatment recommendations. Emerging generative AI technologies may broaden this ecosystem further. Large language models have potential applications in physical therapy education, clinical documentation, communication, information retrieval, and decision support, while also presenting concerns involving accuracy, hallucination, privacy, professional accountability, and inappropriate substitution for clinical judgement (Nagvi et al., 2024). Consequently, the transition toward personalized AI-supported rehabilitation should be understood as augmentation rather than replacement of therapists. Human clinical expertise remains essential

for interpreting patient context, establishing therapeutic goals, managing risk, and determining whether algorithmic recommendations are clinically appropriate.

Despite rapid technological development, an important gap persists between AI innovation and routine clinical implementation. Existing research encompasses heterogeneous technologies, populations, algorithms, outcomes, and validation strategies, making it difficult to determine which approaches are sufficiently mature for clinical adoption. Recent mapping of AI applications in rehabilitation has shown substantial growth in the field while also revealing methodological weaknesses, including limited external validation, inconsistent comparator use, and insufficient explainability in many studies (Maccarone et al., 2026). This fragmentation creates a need for an integrated review that evaluates not only technological advances but also their capacity to support genuinely personalized and clinically translatable rehabilitation. Accordingly, this review aims to critically synthesize current advances in AI-enabled personalized physical rehabilitation and evaluate their progression from technological development toward clinical implementation. It addresses three principal research questions: (1) How are AI technologies being applied to personalize assessment, prediction, monitoring, and therapeutic intervention in physical rehabilitation? (2) What evidence supports the clinical translation of these technologies across rehabilitation populations and delivery settings? and (3) What methodological, technological, clinical, ethical, and implementation barriers must be addressed to enable safe, effective, equitable, and scalable AI-supported rehabilitation? These questions are particularly important because clinical translation requires more than demonstrating technical accuracy. For example, machine-learning analysis of gait data has considerable potential, yet clinically meaningful adoption requires models that are feasible, reliable, interpretable, and relevant to actual therapeutic decisions (Samadi Kohneshahri et al., 2024). More broadly, digital interventions must demonstrate that technological improvements translate into functional benefits meaningful to patients and therapists. Evidence from VR rehabilitation following stroke illustrates the importance of assessing not only technology performance but also motor function, balance, gait, and activities of daily living as clinically meaningful outcomes (Zhang et al., 2023).

This review adopts an interdisciplinary perspective encompassing machine learning, deep learning, computer vision, wearable sensing, rehabilitation robotics, virtual rehabilitation, telerehabilitation, and emerging generative AI applications relevant to personalized physical rehabilitation. It considers applications across major rehabilitation populations, particularly neurological, musculoskeletal, orthopedic, and age-related conditions. This breadth is necessary because contemporary rehabilitation increasingly operates through interconnected digital ecosystems rather than isolated technologies. For example, physiotherapist-led telerehabilitation for older adults has demonstrated potential improvements in physical and health-service outcomes, highlighting how digitally delivered rehabilitation may address both individual functional needs and broader healthcare accessibility challenges (Wicks et al., 2023). The review also emphasizes clinical translation by distinguishing technological feasibility from evidence sufficient for routine practice. In musculoskeletal rehabilitation, internet-based telerehabilitation has demonstrated promising clinical potential, but evidence concerning cost-effectiveness,

implementation, and applicability across heterogeneous musculoskeletal disorders remains important when determining broader adoption. Similarly, advanced virtual rehabilitation approaches following stroke demonstrate therapeutic promise, yet the quality and certainty of evidence across systematic reviews remain variable, emphasizing the need for rigorous clinical evaluation before widespread implementation (Barger et al., 2023).

A further contribution is the explicit consideration of emerging AI modalities alongside established rehabilitation technologies. Recent developments suggest that AI is increasingly shifting rehabilitation from fragmented technology-assisted interventions toward interactive systems integrating real-time assessment, adaptive intervention, and continuous feedback (Zhang et al., 2025). At the same time, contemporary computer-vision research is moving beyond simple motion recognition toward integrated frameworks involving perception, assessment, and automated coaching, potentially enabling more sophisticated personalized home-based rehabilitation (Ye et al., 2026). Therefore, the principal contribution of this review is to connect AI advancement, rehabilitation personalization, and clinical translation within a unified conceptual framework. Rather than evaluating innovation primarily through algorithmic accuracy, the review examines whether AI can provide clinically actionable assessment, individualized prediction, adaptive treatment, meaningful functional improvement, and sustainable integration into therapist-led care. By synthesizing current evidence and identifying methodological and translational gaps, this review seeks to establish priorities for developing explainable, externally validated, interoperable, equitable, and patient-centered AI systems capable of supporting the next generation of personalized physical rehabilitation.

Methodology

Review design and protocol

This review was designed as a systematic review with narrative evidence synthesis to examine the development, application, and clinical translation of artificial intelligence (AI) in personalized physical rehabilitation. The methodological framework was structured according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) shown in [Figure 1](#), which provides standardized guidance for transparent identification, selection, appraisal, and synthesis of evidence (Page et al., 2021). The review protocol predefined the research questions, information sources, eligibility criteria, screening procedures, data-extraction variables, quality-appraisal approach, and synthesis strategy to minimize methodological bias. The review was further informed by established evidence-synthesis principles emphasizing alignment among the research question, eligibility criteria, evidence searching, study selection, extraction, and presentation of findings (Aromataris et al., 2024).

Literature search strategy and databases

A comprehensive literature search was undertaken to identify peer-reviewed studies addressing AI-enabled personalized physical rehabilitation. Electronic searches covered PubMed, Scopus, Web of Science Core Collection, IEEE Xplore, Embase, and the Cochrane Library. These

databases were selected to provide complementary coverage of clinical rehabilitation, medicine, physiotherapy, biomedical engineering, computer science, robotics, and digital health. Searches were designed to maximize sensitivity while retaining sufficient specificity to identify clinically relevant AI applications. Search development and reporting followed PRISMA-S principles, which emphasize reproducible documentation of databases, search strategies, limits, and information sources in systematic reviews (Rethlefsen et al., 2021). Reference lists of eligible studies and relevant systematic reviews were additionally screened to identify potentially overlooked publications, consistent with supplementary-search approaches recommended for comprehensive evidence retrieval (Cooper et al., 2018).

Search terms and Boolean combinations

Search terms were organized around three principal conceptual domains: artificial intelligence, personalization, and physical rehabilitation. AI-related terms included “artificial intelligence,” “machine learning,” “deep learning,” “neural network,” “computer vision,” “generative AI,” and “predictive model.” Rehabilitation terms included “physical rehabilitation,” “physical therapy,” “physiotherapy,” “rehabilitation,” “motor rehabilitation,” “neuromuscular rehabilitation,” and “musculoskeletal rehabilitation.” Technology-specific terms such as “rehabilitation robotics,” “wearable sensors,” “virtual reality,” “digital rehabilitation,” and “telerehabilitation” were incorporated where appropriate. Personalization terms included “personalized,” “individualized,” “adaptive,” “patient-specific,” and “precision rehabilitation.” Boolean operators AND and OR, phrase searching, truncation, and database-specific subject headings were applied. Search strings were adapted to each database rather than using an identical syntax across platforms, reflecting recommended systematic-search practices (Bramer et al., 2018).

Eligibility and exclusion criteria

Eligibility was established using a Population–Concept–Context-oriented framework adapted to the interdisciplinary nature of the review. Studies were eligible when they involved human participants receiving physical rehabilitation; investigated an AI-based or AI-integrated technology; and reported outcomes related to assessment, prediction, monitoring, personalization, functional recovery, treatment adaptation, or clinical implementation. Randomized controlled trials, non-randomized intervention studies, prospective or retrospective observational studies, feasibility studies, and clinically relevant technology-validation studies were considered. Only peer-reviewed articles published in English were included. Conference abstracts without sufficient methodological information, editorials, commentaries, protocols, animal studies, purely engineering simulations without patient-related rehabilitation outcomes, and studies unrelated to physical rehabilitation were excluded. Explicit a priori eligibility criteria were used to improve consistency and reduce subjective study selection (Munn et al., 2018).

Study screening and selection

All retrieved records were exported to reference-management software, and duplicate records were removed before screening. Selection proceeded through two stages: title screening followed

by full-text assessment. Two reviewers independently evaluated potentially eligible studies against the predefined criteria, with disagreements resolved through discussion and, where necessary, consultation with a third reviewer. Reasons for full-text exclusion were documented. The complete identification and selection process was summarized using a PRISMA flow diagram to report records identified, duplicates removed, studies screened, full texts assessed, exclusions, and final inclusions transparently (McKenzie et al., 2021).

Data extraction and quality assessment

A standardized data-extraction form was developed and pilot-tested before full extraction. Extracted variables included author, publication year, country, study design, sample characteristics, clinical condition, rehabilitation setting, AI technique, input data, rehabilitation technology, personalization mechanism, comparator, outcome measures, model performance, clinical outcomes, validation approach, and reported implementation barriers. Particular attention was given to whether AI generated clinically actionable information or adapted rehabilitation to individual patients. Methodological quality and risk of bias were assessed using design-appropriate validated appraisal tools rather than applying a single instrument to heterogeneous study designs. Randomized studies were assessed using the revised Cochrane Risk of Bias tool (RoB 2), which evaluates bias arising across key domains of randomized trials (Sterne et al., 2019). Relevant non-randomized studies were appraised using established critical-appraisal criteria appropriate to their methodological design (Ma et al., 2020).

Evidence synthesis and analysis

Because substantial heterogeneity was anticipated across patient populations, AI architectures, rehabilitation technologies, intervention protocols, comparators, and outcome measures, findings were synthesized primarily through structured narrative and thematic analysis. Studies were categorized according to AI modality, rehabilitation technology, clinical population, personalization function, and stage of clinical translation. Evidence was synthesized around four functional domains: AI-enabled assessment and monitoring, outcome prediction, personalized intervention, and clinical implementation. Patterns in clinical effectiveness, model validation, usability, explainability, and barriers to translation were compared across studies. Where sufficiently homogeneous quantitative evidence was available, effect estimates were reported descriptively rather than pooled automatically. This approach recognizes that statistical aggregation should be undertaken only when clinical and methodological comparability permits meaningful synthesis (Campbell et al., 2020). The final synthesis therefore integrated technological performance with clinical outcomes and implementation evidence to identify current advances, translational gaps, and priorities for future AI-enabled personalized rehabilitation.

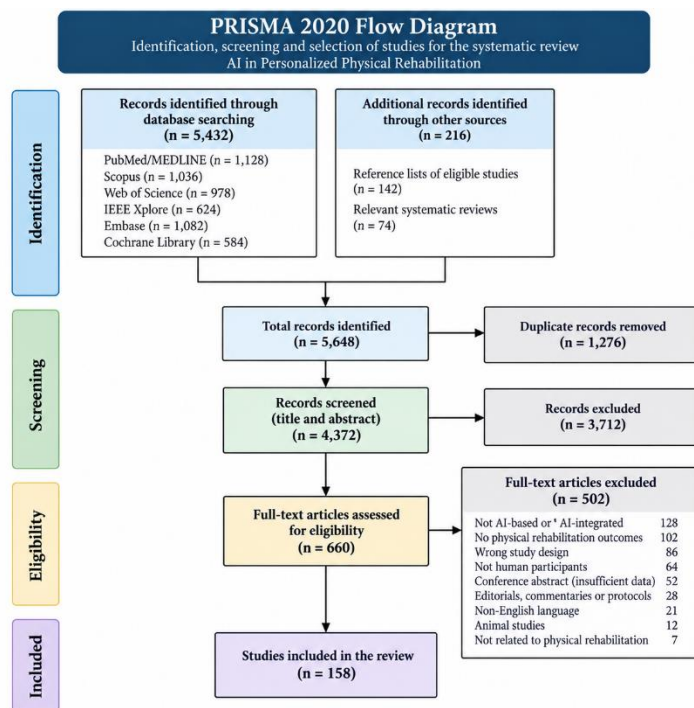


Figure 1. PRISMA 2020 flow diagram of study identification, screening, eligibility assessment, and final inclusion in the systematic review

AI Technologies and Digital Ecosystems for Personalized Physical Rehabilitation

Machine learning and deep learning

Machine learning (ML) and deep learning (DL) constitute the computational foundation of many emerging applications in personalized physical rehabilitation. ML algorithms can identify relationships within complex clinical and biomechanical datasets and use these patterns to classify functional impairment, predict rehabilitation outcomes, recognize movement patterns, and support individualized therapeutic decisions. Common approaches include support vector machines, decision trees, random forests, k-nearest-neighbor algorithms, artificial neural networks, and ensemble-learning methods. Systematic evidence indicates that AI-supported physical rehabilitation has increasingly incorporated these techniques for movement evaluation, prediction, clinical decision support, and treatment delivery, although substantial heterogeneity remains in clinical populations, algorithms, and outcome measures (Sumner et al., 2023).

DL extends conventional ML through multilayer neural architectures capable of learning complex representations directly from large-scale and high-dimensional data. Convolutional neural networks, recurrent neural networks, long short-term memory networks, and increasingly transformer-based architectures can process images, sequential movement signals,

electromyographic data, and other multimodal rehabilitation information. Such methods are particularly relevant when temporal and spatial relationships within human movement must be identified without extensive manual feature engineering. In lower-limb rehabilitation, integration of ML with robotic systems has demonstrated potential for optimizing therapeutic protocols, predicting outcomes, and providing real-time feedback tailored to individual performance (Zhang et al., 2024). However, limited training datasets, model overfitting, inadequate external validation, poor interpretability, and differences between laboratory and clinical populations remain major barriers to dependable clinical translation mentioned in Figure 2. ML can also contribute to precision rehabilitation by continuously updating predictions as new patient information becomes available. Rather than assigning patients to fixed rehabilitation pathways solely according to diagnosis, intelligent models could integrate baseline impairment, treatment response, movement characteristics, adherence, and longitudinal recovery data to estimate individualized trajectories. In post-stroke rehabilitation, machine-learning models have already demonstrated potential for predicting functional outcomes, although systematic evaluation has identified substantial methodological variation and risks of bias that currently constrain their routine clinical use (Zu et al., 2023).

Computer vision and motion analysis

Computer vision (CV) provides an increasingly important interface between AI and objective physical-function assessment. Conventional movement assessment often depends on therapist observation or specialized laboratory systems requiring force platforms, marker-based motion capture, and trained personnel. CV-based approaches can instead derive information about posture, joint positions, range of motion, gait, exercise execution, and movement quality from video or depth-camera data. Advances in pose estimation and skeleton-based activity recognition have consequently created opportunities for automated rehabilitation assessment in both clinical and home environments.

AI-based skeleton analysis is particularly promising for evaluating whether patients perform prescribed exercises correctly. A systematic review of skeleton-based physical rehabilitation demonstrated that combinations of vision sensors, skeletal representations, and DL methods can support automated evaluation of rehabilitation activities, potentially providing patients with feedback when therapists are not physically present (Sardari et al., 2023). Markerless motion-capture approaches may additionally reduce the cost and infrastructure requirements associated with conventional biomechanical laboratories, thereby facilitating repeated assessments and remote monitoring. Nevertheless, clinical adoption requires algorithms that remain accurate under real-world variations in camera positioning, lighting, clothing, body morphology, assistive devices, and compensatory movements. Computer-vision systems must therefore progress from simple recognition of whether an exercise has occurred toward clinically meaningful assessment of how well, how safely, and with what compensatory strategies it has been performed.

Wearable and biosensor technologies

Wearable sensors provide continuous physiological and biomechanical data that can complement AI-based assessment. Common technologies include inertial measurement units incorporating accelerometers and gyroscopes, electromyography sensors, pressure sensors, smart insoles, heart-rate sensors, and other body-worn devices. Unlike periodic clinical assessments, wearables can capture functional behavior during daily activities and repeated rehabilitation sessions, generating longitudinal information about movement quality and recovery. Combining wearable sensing with ML is particularly valuable because algorithms can transform large quantities of raw sensor signals into interpretable indicators of gait, posture, muscular activation, exercise performance, and disease-related movement patterns. A systematic review found that wearable sensors combined with ML can facilitate rehabilitation assessment and optimization across multiple clinical conditions and may be especially useful for extending intelligent rehabilitation into home environments (Wei & Wu, 2023). Wearable technology has also shown potential for remotely quantifying mobility and supporting rehabilitation monitoring, although differences among devices, outcome definitions, and validation procedures remain important limitations (Prill et al., 2022).

Biosensors may further expand personalization by integrating movement information with physiological responses such as muscle activation, cardiovascular load, fatigue, and potentially stress-related signals. Multimodal sensor fusion could therefore allow an AI system to determine not merely whether an exercise was completed but whether its intensity and biomechanical execution were appropriate for a particular patient. However, sensor accuracy, calibration, battery life, data interoperability, adherence, privacy, and the clinical interpretability of continuously generated information remain significant implementation challenges.

Rehabilitation robotics and exoskeletons

Rehabilitation robotics represents one of the most advanced intersections between AI and physical therapy. Robotic systems can provide intensive, repetitive, task-oriented training while recording detailed information about movement trajectories, forces, joint angles, and patient-robot interaction. Upper-limb robots, gait-training systems, and wearable exoskeletons are particularly relevant to neurological rehabilitation, including stroke and spinal cord injury. AI has the potential to transform these systems from devices executing predetermined movement trajectories into adaptive therapeutic partners. ML, neural networks, support vector machines, decision trees, and reinforcement-learning approaches have been investigated for robot control, locomotion classification, intention detection, and prediction of human joint trajectories. A dedicated review of lower-limb exoskeleton rehabilitation demonstrated that AI can improve personalized control, patient-state recognition, and adaptive feedback, while emphasizing that many proposed algorithms still require validation in representative clinical populations (Coser et al., 2024). Robot-assisted gait training may provide structured opportunities for high-intensity practice after neurological injury, although effectiveness varies with patient characteristics, device type, treatment intensity, and comparator therapy (Mehrholz et al., 2020). Emerging soft

robotic exosuits and wearable robots may further improve portability and naturalistic human–robot interaction compared with rigid systems (Di Natali et al., 2021). The future emphasis should therefore move from maximizing robotic repetition toward patient–responsive assistance, in which AI continuously determines how much support is required and progressively modifies assistance as functional capacity improves.

Virtual augmented reality and digital platforms

Virtual reality (VR), augmented reality (AR), and digital rehabilitation platforms provide interactive environments in which therapeutic tasks can be adapted, monitored, and gamified. VR can simulate real-life functional activities while systematically controlling task complexity, sensory feedback, repetition, and environmental demands. Evidence from stroke rehabilitation suggests that VR interventions can positively influence motor function, gait, balance, and activities of daily living, although effects vary across technologies and treatment protocols (Demeco et al., 2023). More recent umbrella evidence similarly indicates that VR has considerable potential in stroke rehabilitation but highlights variability in methodological quality and certainty across existing systematic reviews (Hao et al., 2024). AR differs from fully immersive VR by superimposing digital information on the patient's physical environment, potentially allowing real-world therapeutic movements to be combined with visual instructions, performance cues, and feedback (Postolache et al., 2023).

Digital platforms further extend rehabilitation beyond institutional settings through mobile applications, web-based exercise programs, remote monitoring, and telerehabilitation. Evidence suggests that therapeutic exercise delivered through telerehabilitation can achieve outcomes comparable to face-to-face physiotherapy for selected conditions, supporting its potential as an alternative or complementary model of care (Muñoz-Tomás et al., 2023). Integration with AI can move these platforms beyond conventional video consultation by enabling automated movement recognition, adherence monitoring, risk detection, progression recommendations, and personalized feedback. AI-driven virtual rehabilitation systems are consequently emerging as potentially scalable approaches for community-based care, although stronger evidence regarding effectiveness, usability, equity, and real-world implementation remains necessary (Abedi et al., 2024). Collectively, ML, computer vision, wearable sensing, robotics, and immersive digital technologies are converging toward an interconnected rehabilitation ecosystem. Their greatest clinical value may arise not from any individual technology but from their integration: wearable and visual sensors capture patient behavior, AI interprets these data, predictive models estimate progress, and robotic or digital platforms adapt therapy accordingly. Such integration provides the technological foundation for a transition from standardized rehabilitation toward continuous, data-driven, and genuinely personalized physical rehabilitation.

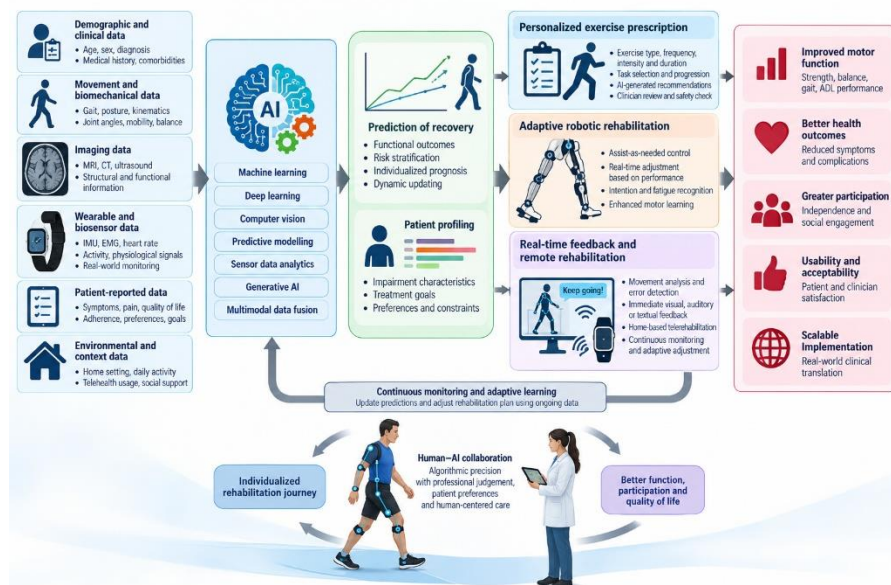


Figure 2. AI-enabled framework for personalized physical rehabilitation.

AI-Driven Assessment, Prediction, and Personalized Rehabilitation Interventions

Automated functional and movement assessment

Accurate assessment of physical function is fundamental to rehabilitation because therapeutic decisions depend on identifying movement limitations, compensatory strategies, functional capacity, and changes during recovery. Conventional assessments rely heavily on therapist observation, standardized clinical scales, and laboratory-based biomechanical measurements. Although clinically valuable, these methods may be time-intensive, episodic, and influenced by inter-rater variability. Artificial intelligence (AI) provides an opportunity to automate portions of functional assessment by integrating computer vision, wearable sensors, and machine-learning algorithms to quantify movement continuously and objectively. Computer-vision systems can estimate joint positions, body segments, posture, and movement trajectories from conventional or depth-camera recordings. Skeleton-based AI methods have demonstrated particular potential for evaluating rehabilitation exercises by comparing patient movements with reference actions and automatically identifying deviations in execution (Sardari et al., 2023). These approaches can quantify joint angles, range of motion, repetition quality, gait characteristics, and compensatory movements without requiring sophisticated marker-based motion laboratories. Wearable sensors provide complementary information through accelerometers, gyroscopes, inertial measurement units, pressure sensors, and electromyography. Combining these signals with machine learning enables recognition and classification of movement patterns during both supervised therapy and daily activities are illustrated in Figure 3. Evidence indicates that wearable sensors coupled with ML algorithms can facilitate objective rehabilitation assessment

while extending monitoring beyond clinical environments (Wei & Wu, 2023). The resulting longitudinal datasets may allow therapists to assess not only performance during scheduled appointments but also functional behavior throughout recovery.

Patient-specific outcome prediction

Prediction of recovery is central to personalized rehabilitation because patients with similar diagnoses can follow markedly different functional trajectories. AI models can integrate demographic, clinical, neurological, biomechanical, imaging, and treatment-related variables to identify complex relationships associated with rehabilitation outcomes. Such information can potentially assist clinicians in estimating prognosis, identifying patients at risk of poor recovery, setting realistic goals, and allocating rehabilitation intensity according to individual needs. This approach is particularly developed in stroke rehabilitation. Machine-learning methods have been applied to predict motor recovery, activities of daily living, functional independence, and discharge outcomes. A systematic review demonstrated that ML can provide promising predictions of post-stroke functional recovery, while also identifying substantial methodological limitations related to small datasets, variable feature selection, model validation, and risk of bias (Campagnini et al., 2022). Similar evidence suggests that predictive models may support individualized rehabilitation planning, but their clinical utility depends on external validation and demonstration that predictions meaningfully improve therapeutic decision-making (Zu et al., 2023). Patient-specific prediction could ultimately evolve from a single baseline prognosis toward a dynamic process. Data collected during rehabilitation sessions, through wearables, or in home environments could continuously update predicted recovery trajectories. Such adaptive prediction would allow rehabilitation plans to respond to actual progress rather than relying primarily on initial assessment.

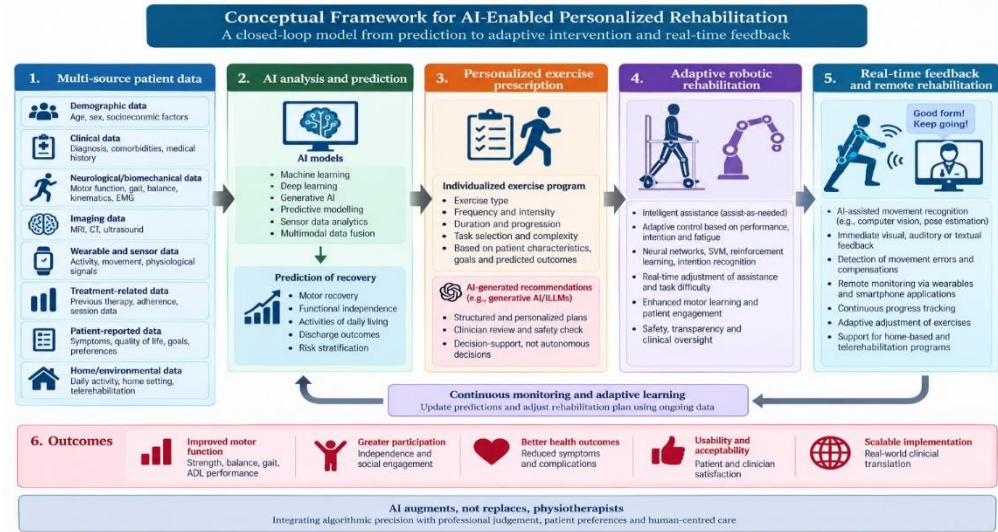


Figure 3. Closed-loop AI framework for personalized and adaptive physical rehabilitation

Personalized exercise prescription

Exercise prescription traditionally involves selecting exercise type, frequency, intensity, duration, progression, and therapeutic goals based on clinical assessment and professional judgement. AI creates opportunities to supplement this process by integrating patient characteristics, functional measurements, physiological responses, previous performance, and treatment goals to generate individualized exercise recommendations. Generative AI and large language models have recently expanded interest in automated exercise prescription. Evaluation of GPT-4-generated exercise programs for hypothetical individuals with different health conditions demonstrated that AI can generate structured and personalized recommendations but also identified limitations requiring professional oversight, particularly when complex health considerations affect exercise safety (Washif et al., 2024). Therefore, AI-generated prescriptions should currently function as decision-support tools rather than autonomous replacements for physiotherapists.

More advanced systems can move beyond generating an initial prescription by modifying exercises according to patient performance. AI-enabled rehabilitation applications can adjust exercise intensity, repetitions, progression, and task complexity using functional assessments and ongoing monitoring. Recent clinical research using AI recognition-based telerehabilitation illustrates this model: patient risk stratification was used to generate individualized exercise prescriptions, while movement performance and follow-up information informed subsequent program adjustment (Li et al., 2026). The increasing sophistication of automated prescription also creates a need to evaluate whether AI-generated programs are clinically appropriate has demonstrated in Figure 4. Emerging work on AI-assisted evaluation frameworks emphasizes objective assessment of personalized exercise prescriptions against established professional guidelines rather than assuming that algorithm-generated recommendations are inherently safe or effective (Huang et al., 2026).

Adaptive robotic rehabilitation

Rehabilitation robots and exoskeletons can deliver intensive, repetitive, task-specific therapy while simultaneously collecting detailed biomechanical information. Traditional robotic devices frequently operate through predetermined trajectories or fixed levels of assistance. AI provides a pathway toward adaptive robotic rehabilitation, in which robotic behavior changes dynamically according to movement capability, muscle activation, intention, fatigue, or treatment progress. For lower-limb rehabilitation, AI techniques including neural networks, support vector machines, reinforcement learning, and intention-recognition algorithms have been incorporated into exoskeleton systems to improve movement classification and individualized assistance (Coser et al., 2024). Instead of completing movements for the patient, an intelligent robotic system could provide only the level of assistance required to accomplish a therapeutic task, reducing support as voluntary motor capacity improves. This approach is consistent with an “assist-as-needed” rehabilitation philosophy, potentially encouraging active patient participation and motor learning. However, adaptive systems introduce important safety challenges because incorrect estimation of patient intention or capability could generate inappropriate robotic responses.

Evidence concerning human–robot interaction therefore emphasizes the importance of reliable sensing, real-time responsiveness, user trust, transparency, and continued clinical oversight before AI-controlled rehabilitation robots can operate with greater autonomy (Patel et al., 2026).

Real-time feedback and remote rehabilitation

Real-time feedback represents one of the most clinically relevant applications of AI because rehabilitation effectiveness depends partly on performing therapeutic movements correctly and consistently. In conventional home programs, patients may unintentionally use compensatory strategies or discontinue exercises without therapists being aware. AI systems can analyze movements during exercise and immediately provide visual, auditory, or textual feedback concerning posture, joint position, repetition quality, range of motion, and task completion. AI-assisted telerehabilitation can combine markerless pose estimation with real-time movement recognition to detect movement errors and deliver corrective guidance remotely. A recent randomized controlled trial demonstrated the practical application of this approach using smartphone-based recognition of skeletal key points to calculate movement angles and displacement while providing immediate feedback during remotely delivered exercise (Li et al., 2026).

More broadly, AI-driven virtual physiotherapy assistants can integrate wearable sensing, automated monitoring, personalized guidance, and feedback to support rehabilitation in the patient's home. Such systems may improve continuity of care and reduce dependence on frequent clinic attendance, although sensor reliability, affordability, engagement, digital literacy, and access remain significant barriers (Agarwal et al., 2025). AI-enabled telerehabilitation may similarly support continuous progress monitoring and adaptive therapy, but implementation requires careful attention to data security, algorithmic bias, accessibility, and preservation of meaningful therapist–patient interaction (Abbas et al., 2025). Collectively, these applications illustrate a transition from episodic rehabilitation toward a closed-loop personalized rehabilitation model in which patient movement is measured, AI interprets functional performance, outcomes are predicted, therapy is adapted, and feedback is delivered continuously. The most clinically valuable future systems are therefore likely to augment rather than replace physiotherapists, combining algorithmic precision and continuous monitoring with professional judgement, patient preferences, safety assessment, and human-centered therapeutic care.

Clinical Translation Across Physical Rehabilitation Populations

Neurological and stroke rehabilitation

Neurological rehabilitation represents one of the most developed clinical areas for artificial intelligence (AI)-enabled physical rehabilitation. Stroke, spinal cord injury, Parkinson's disease, multiple sclerosis, and other neurological disorders frequently produce heterogeneous motor impairments, making standardized rehabilitation protocols insufficient for addressing individual recovery trajectories. AI can support personalization by integrating clinical, biomechanical, neurophysiological, imaging, and longitudinal performance data to characterize impairment,

predict recovery, and adapt therapeutic interventions. In post-stroke rehabilitation specifically, machine-learning models have been investigated for predicting motor recovery, functional independence, activities of daily living, and discharge outcomes. Systematic evidence indicates promising predictive performance but also substantial methodological heterogeneity, small datasets, and insufficient external validation, which currently limit routine clinical implementation (Campagnini et al., 2022).

AI is also increasingly integrated with wearable sensors, computer vision, robotic devices, and virtual environments to provide intensive and adaptive motor training. Robotic systems can quantify movement trajectories and deliver repetitive task-oriented therapy, while AI algorithms can adjust assistance according to patient performance. Similarly, computer-vision systems can monitor upper- and lower-limb exercises and identify movement deviations without requiring continuous therapist observation. Virtual reality (VR) adds interactive and task-specific training environments that may promote repetition and engagement. Evidence from post-stroke rehabilitation suggests that immersive VR can improve upper-limb function, gait, dynamic balance, independence, and participation when appropriately integrated with conventional rehabilitation (Demeco et al., 2023). Despite these advances, neurological rehabilitation illustrates the broader translational challenge facing AI. Algorithms developed in controlled research environments may not generalize to patients with different impairment severity, comorbidities, cognitive limitations, or sociocultural characteristics. Clinically useful AI must therefore complement therapist judgement, accommodate neurological heterogeneity, and demonstrate that improvements in prediction or movement recognition translate into meaningful functional recovery.

Musculoskeletal and orthopedic rehabilitation

Musculoskeletal and orthopedic conditions constitute another important area for AI-supported rehabilitation because they represent a major source of pain, disability, and reduced mobility. Applications extend across low-back and neck pain, osteoarthritis, sports injuries, fractures, joint replacement, and postoperative rehabilitation. AI can support these populations through movement assessment, exercise recognition, risk stratification, outcome prediction, and individualized progression of therapeutic exercise. Wearable technologies are particularly relevant because recovery after orthopedic injury or surgery frequently depends on restoring joint mobility, gait, strength, and functional activity. Wearable movement sensors have demonstrated potential for quantifying knee-joint function and rehabilitation outcomes, although systematic evidence identifies considerable variability in sensor placement, algorithms, validation procedures, and reported clinical measures (Prill et al., 2021). Such systems could nevertheless allow clinicians to assess real-world mobility between appointments rather than relying exclusively on clinic-based testing and patient-reported adherence.

Digital and remotely delivered rehabilitation also has substantial relevance to musculoskeletal care because many interventions involve progressive therapeutic exercise that can be performed outside hospitals. Telerehabilitation can provide exercise instruction, monitoring, education, and

professional follow-up while reducing travel requirements. Evidence comparing telerehabilitation with face-to-face physiotherapy indicates that remotely delivered therapeutic exercise can achieve comparable outcomes for several musculoskeletal conditions, although effects vary according to diagnosis, intervention characteristics, and treatment duration (Muñoz-Tomás et al., 2023). Integration with AI could further enhance these models by automatically assessing exercise technique, detecting compensatory movement, monitoring adherence, and recommending progression while maintaining therapist oversight.

Geriatric rehabilitation

Population ageing is increasing demand for rehabilitation addressing mobility impairment, frailty, falls, sarcopenia, balance deficits, and loss of functional independence. Older adults frequently present with multiple interacting conditions rather than isolated impairments, making personalized rehabilitation especially important. AI-enabled systems may integrate movement, physiological, clinical, and behavioral information to identify changes in functional capacity and tailor rehabilitation according to individual risk and response. Wearable sensors and AI-based activity recognition can facilitate continuous assessment of walking, balance, physical activity, and daily functioning. Such monitoring could help identify deterioration that is not apparent during episodic clinic assessments and support earlier modification of rehabilitation programs. Telerehabilitation additionally offers a mechanism for maintaining access among older adults who face transportation or mobility barriers. A systematic review and meta-analysis found that physiotherapist-led, exercise-based telerehabilitation for older adults can improve physical outcomes and may provide benefits for healthcare utilization, supporting its potential as an alternative or adjunct to conventional rehabilitation services (Wicks et al., 2023).

However, digital rehabilitation for older adults introduces specific implementation challenges. Sensory impairment, cognitive decline, low digital literacy, difficulties operating wearable devices, internet accessibility, and concerns regarding privacy may influence adoption. Technology must therefore be designed around the capabilities and preferences of older users rather than assuming uniform digital competence. Human support remains particularly important because rehabilitation also provides motivation, reassurance, social interaction, and professional interpretation that cannot be reduced to algorithmic recommendations.

Cardiopulmonary rehabilitation

Cardiopulmonary rehabilitation aims to improve exercise tolerance, functional capacity, symptom management, and quality of life among people with cardiovascular and respiratory disease. Traditional programs commonly combine supervised exercise, education, risk-factor management, and behavioral support. However, participation can be restricted by geographic distance, limited program availability, transportation difficulties, and long-term adherence challenges. Digital technologies and AI offer opportunities to extend monitoring and personalized exercise beyond institutional settings. Wearable devices can continuously capture heart rate, activity, exercise intensity, oxygen-related variables, and other physiological indicators. When

integrated with AI, these data may facilitate individualized exercise prescription, early identification of abnormal responses, and adaptive progression according to physiological tolerance. Recent randomized evidence has demonstrated the feasibility of AI recognition-based telerehabilitation for patients with hypertension, in which individualized exercise prescription and remote monitoring were integrated within a digitally delivered intervention (Yao et al., 2026).

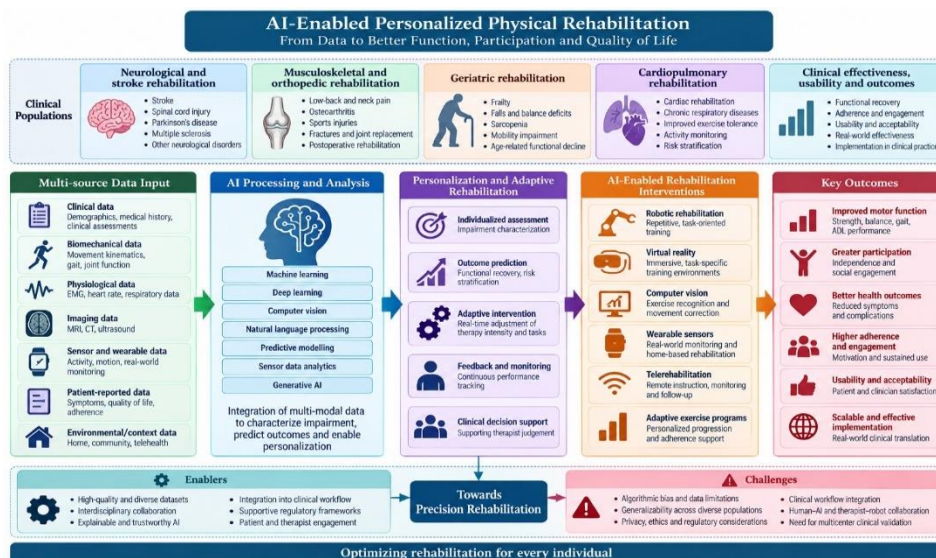


Figure 4. Conceptual framework of AI-enabled personalized physical rehabilitation integrating multimodal data, adaptive interventions, and clinical outcomes

The broader evidence base for remotely delivered cardiac rehabilitation is also encouraging. Systematic evidence suggests that telerehabilitation can improve functional capacity and other clinically relevant outcomes in patients with coronary artery disease while providing an alternative pathway for individuals unable to participate consistently in center-based programs (Ramachandran et al., 2022). Nevertheless, cardiopulmonary applications demand particularly rigorous safety mechanisms because inappropriate exercise intensity or failure to identify clinical deterioration could have serious consequences. AI-supported systems should therefore incorporate validated physiological thresholds, escalation pathways, and professional supervision.

Clinical effectiveness, usability, and patient outcomes

Successful clinical translation depends ultimately on whether AI-enabled rehabilitation improves outcomes that matter to patients rather than merely demonstrating high algorithmic accuracy. Relevant outcomes include mobility, strength, balance, pain, independence, participation, exercise capacity, quality of life, treatment adherence, and patient satisfaction. A systematic review of AI in physical rehabilitation found substantial growth in AI applications but

reported inconsistent evidence of clinical effects, highlighting the gap between technological innovation and demonstrated patient benefit (Sumner et al., 2023). Usability is equally important because even technically accurate systems have little clinical value if patients or therapists find them burdensome, confusing, unreliable, or incompatible with routine practice. AI-driven virtual rehabilitation may improve accessibility and enable individualized remote support, but successful implementation depends on user-centered interfaces, digital literacy, reliable connectivity, clinician acceptance, and appropriate integration into existing healthcare pathways (Abedi et al., 2024). Patient trust is particularly relevant when algorithms generate therapeutic recommendations or monitor sensitive health information.

Clinical effectiveness must therefore be considered alongside safety, feasibility, engagement, accessibility, and equity. AI-enabled telerehabilitation offers substantial potential for increasing personalization and continuity of rehabilitation, yet ethical concerns involving privacy, algorithmic bias, transparency, professional accountability, and preservation of the therapeutic relationship remain important barriers to implementation (Calabrò & Mojdehdehbaher, 2025). Furthermore, emerging AI applications across rehabilitation suggest that the most sustainable model is likely to involve human-AI collaboration, in which algorithms support continuous measurement and data-driven decision-making while therapists retain responsibility for contextual interpretation, goal setting, safety, and patient-centered care (Alshami et al., 2025).

Overall, clinical translation is progressing at different rates across rehabilitation populations. Neurological rehabilitation currently demonstrates particularly extensive integration of AI with prediction, robotics, and virtual environments, while musculoskeletal, geriatric, and cardiopulmonary applications are increasingly benefiting from wearables and remote rehabilitation. Future clinical adoption should prioritize externally validated technologies, comparative clinical trials, meaningful functional outcomes, usability testing, and equitable access. The objective should not simply be to introduce more AI into rehabilitation, but to determine where, for whom, and under what clinical conditions AI meaningfully improves personalized physical rehabilitation.

Challenges, Research gaps, and Future directions

Algorithmic bias and data limitations

Despite rapid advances in artificial intelligence (AI)-enabled rehabilitation, the quality and representativeness of training data remain fundamental barriers to reliable clinical translation. Rehabilitation datasets are frequently small, single-center, retrospective, and concentrated on selected populations, particularly patients with stroke and other neurological disorders. Such datasets may inadequately represent variation in age, sex, ethnicity, disability severity, comorbidities, socioeconomic circumstances, and rehabilitation environments. Consequently, models trained on restricted populations may perform well internally but deteriorate when applied to clinically different groups. Recent systematic mapping of AI in rehabilitation identifies dataset bias and inadequate external validation among the principal barriers preventing

translation from experimental research into routine rehabilitation practice (Maccarone et al., 2026).

Data heterogeneity creates an additional problem. Rehabilitation information may originate from electronic health records, clinical scales, imaging, wearable sensors, electromyography, motion-capture systems, smartphones, robotic devices, and patient-reported outcomes. Differences in measurement protocols, sensor configurations, sampling frequencies, missing-data patterns, and outcome definitions can reduce interoperability and reproducibility. AI-driven virtual rehabilitation research similarly remains heterogeneous in-patient populations, technologies, assessment methods, and study designs, complicating comparison and generalization across clinical settings (Abedi et al., 2024). Future research should therefore prioritize representative datasets, standardized outcome definitions, transparent preprocessing procedures, and systematic evaluation of model performance across clinically relevant subgroups.

Explainable and trustworthy AI

High predictive accuracy alone is insufficient for rehabilitation applications because clinicians must understand whether an algorithmic recommendation is clinically plausible and appropriate for an individual patient. Complex deep-learning architectures can function as “black boxes,” making it difficult to determine which variables drive predictions or why particular therapeutic recommendations are generated. This becomes especially important when AI influences exercise intensity, prognosis, assistive robotic control, or decisions regarding progression of treatment. Explainable AI (XAI) approaches, including feature-attribution and interpretable modeling techniques, may improve transparency by showing which clinical or biomechanical factors contribute most strongly to algorithmic outputs. However, explainability remains underused in rehabilitation AI research. Recent mapping evidence indicates that only a minority of rehabilitation AI studies explicitly incorporated explainability, despite its importance for clinical trust and decision support (Maccarone et al., 2026). [In the final manuscript, this source should be cited only at its first occurrence above.] Trustworthy rehabilitation AI should therefore extend beyond accuracy to encompass robustness, calibration, interpretability, fairness, reproducibility, uncertainty estimation, and mechanisms that allow clinicians to challenge or override inappropriate recommendations.

Privacy, ethics, and regulatory considerations

Personalized rehabilitation increasingly depends on continuous collection of sensitive information from cameras, wearable sensors, mobile applications, connected robots, and home-monitoring platforms. These data may reveal not only medical status but also mobility patterns, behaviors, and activities within private environments. Consequently, informed consent, cybersecurity, data ownership, secondary data use, anonymization, and access control require explicit governance. More broadly, healthcare AI creates ethical and regulatory concerns surrounding accountability, transparency, autonomy, fairness, privacy, and responsibility when algorithm-supported decisions contribute to adverse outcomes. Existing regulatory structures must simultaneously protect

patients and accommodate rapidly evolving AI systems, including technologies whose performance may change after deployment (Alowais et al., 2024). Rehabilitation systems should consequently incorporate privacy and safety requirements from the design stage rather than treating them as post-development compliance exercises.

Clinical workflow integration

A technically successful algorithm has limited value if it cannot be incorporated efficiently into clinical practice. Rehabilitation professionals already manage substantial documentation, assessment, treatment-planning, and communication responsibilities. AI systems that require duplicate data entry, complex interfaces, separate software environments, or lengthy interpretation may increase rather than reduce workload. Integration should therefore focus on interoperability with electronic health records, rehabilitation equipment, sensor platforms, and existing clinical decision processes. Research examining the convergence of machine learning and rehabilitation robotics similarly identifies clinical integration, interpretability, economic feasibility, and regulatory constraints as important obstacles to translation (Zhang et al., 2024). Co-design involving physiotherapists, rehabilitation physicians, occupational therapists, engineers, patients, caregivers, and health-service managers should begin during technology development rather than after algorithms have been finalized.

Human-AI and therapist-robot collaboration

AI should not be conceptualized primarily as a replacement for rehabilitation professionals. Rehabilitation involves therapeutic alliance, motivation, communication, contextual interpretation, shared goal setting, and adaptation to psychological and social factors that are difficult to capture computationally. The more clinically appropriate model is therefore collaborative intelligence, where AI provides continuous measurement, pattern recognition, prediction, and decision support while clinicians retain responsibility for contextual interpretation and treatment decisions. This principle is particularly important in rehabilitation robotics and exoskeletons. AI-based control methods can estimate movement intention and adapt robotic assistance according to patient performance, potentially allowing more personalized training (Coser et al., 2024). However, safe therapist-robot collaboration requires predictable device behavior, appropriate assistance levels, emergency override mechanisms, and clear allocation of clinical responsibility. Human oversight should therefore remain integral to increasingly autonomous rehabilitation technologies.

Multimodal AI and digital twins

A major future direction is the transition from isolated data streams toward multimodal AI capable of integrating clinical records, imaging, biomechanics, wearable signals, physiological measurements, patient-reported outcomes, environmental information, and treatment history. Such integration may generate a more comprehensive representation of the patient than models relying on a single modality. Digital twins extend this concept by creating dynamic computational representations of individual patients that can be continuously updated using

real-world information. Healthcare digital twins could potentially simulate disease progression and compare alternative interventions before they are applied clinically (Katsoulakis et al., 2024). In rehabilitation specifically, AI-based patient digital twins could combine multimodal information to simulate rehabilitation scenarios, predict patient-specific responses, and dynamically modify treatment as recovery progresses (Kaczmarek et al., 2024). Nevertheless, digital twins remain an emerging rather than established clinical technology. Current challenges include incomplete data, interoperability, computational requirements, model updating, privacy, biological complexity, and clinical validation. Systematic evidence suggests considerable potential for precision health but emphasizes that effectiveness and implementation evidence remain insufficient (Shen et al., 2024). Accordingly, future rehabilitation digital twins should be evaluated according to demonstrable clinical benefit rather than technological sophistication alone.

Priorities for multicenter clinical validation

The decisive research priority is to move from proof-of-concept development toward rigorous multicenter validation. Many rehabilitation AI studies emphasize algorithmic metrics such as accuracy, sensitivity, specificity, F1 score, or area under the curve, whereas clinicians and patients require evidence of improved mobility, independence, participation, safety, quality of life, adherence, and treatment efficiency. AI systems should therefore be evaluated prospectively against appropriate clinical comparators and across diverse healthcare settings. Multicenter studies are especially important because they test whether algorithms remain reliable when patient demographics, rehabilitation protocols, clinicians, devices, and healthcare environments change. Broader healthcare digital-twin research similarly identifies technical, biological, and ethical heterogeneity as important obstacles to generalizable clinical implementation (Sun et al., 2024). Evaluation should additionally examine usability, cost-effectiveness, implementation burden, health equity, and unintended consequences rather than focusing exclusively on predictive performance.

Future trials should employ transparent reporting, preregistered protocols, clinically meaningful endpoints, independent external validation, subgroup fairness analyses, and sufficiently long follow-up periods. Conceptual work on healthcare digital twins further emphasizes the need for structured evaluation of functional, technological, and operational characteristics when translating these systems into healthcare environments (Pellegrino et al., 2025). Ultimately, the next phase of personalized rehabilitation AI should be defined not by increasingly complex algorithms, but by trustworthy, explainable, interoperable, clinically validated, and human-centered systems that demonstrably improve rehabilitation outcomes across diverse patient populations.

Conclusion

Artificial intelligence is reshaping physical rehabilitation by creating opportunities to move beyond standardized and episodic treatment toward continuous, adaptive, and patient-specific

care. This review demonstrates that machine learning, deep learning, computer vision, wearable sensing, rehabilitation robotics, virtual environments, and AI-enabled telerehabilitation can support multiple stages of the rehabilitation pathway, including functional assessment, recovery prediction, exercise prescription, treatment adaptation, remote monitoring, and real-time feedback. Their convergence provides the foundation for closed-loop rehabilitation systems capable of continuously interpreting patient performance and adjusting interventions according to individual recovery trajectories.

Despite these advances, the transition from technological innovation to routine clinical practice remains incomplete. Evidence is particularly promising in neurological and stroke rehabilitation, with expanding applications in musculoskeletal, orthopedic, geriatric, and cardiopulmonary populations. However, improvements in algorithmic accuracy cannot alone establish clinical value. AI-enabled interventions must demonstrate meaningful benefits in mobility, functional independence, participation, safety, adherence, quality of life, and patient experience. Current limitations involving small and heterogeneous datasets, algorithmic bias, inadequate external validation, limited explainability, privacy, interoperability, regulatory uncertainty, digital inequality, and workflow integration continue to constrain widespread implementation.

Future research should therefore prioritize prospective multicenter trials, diverse and representative datasets, standardized rehabilitation outcomes, independent external validation, subgroup fairness analyses, cost-effectiveness, usability, and long-term clinical evaluation. Multimodal AI and digital twins offer important opportunities for integrating clinical, biomechanical, physiological, behavioral, and longitudinal data into dynamic patient-specific rehabilitation models, but their value must be established through demonstrable clinical benefit. Ultimately, the future of AI in rehabilitation should be based on collaborative intelligence rather than professional replacement. Trustworthy AI should strengthen therapists' capacity for objective assessment, prediction, monitoring, and personalization while preserving human judgement, therapeutic relationships, patient preferences, safety, and professional accountability. Such an approach offers the strongest pathway toward scalable, equitable, and clinically meaningful personalized physical rehabilitation.

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reviewed and edited the content to ensure accuracy and integrity, taking full responsibility for the final version.

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