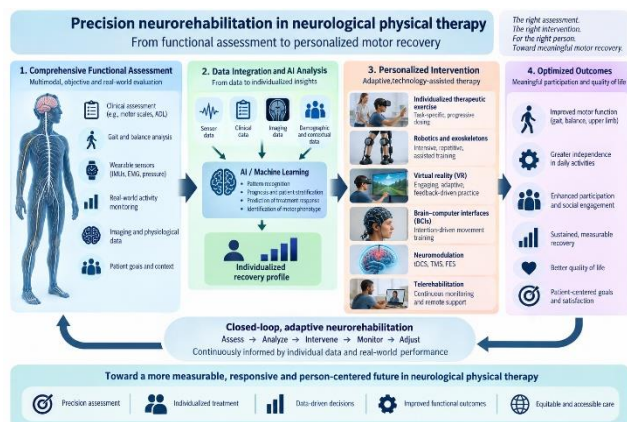


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KEYWORDS	ABSTRACT
Precision neurorehabilitation; Neurological physical therapy; Motor recovery; Artificial intelligence; Wearable sensors; Personalized rehabilitation	Neurological disorders produce heterogeneous motor impairments and recovery trajectories, challenging standardized approaches to neurological physical therapy. Precision neurorehabilitation offers a patient-specific framework that integrates objective functional assessment, predictive analytics, and adaptive interventions to optimize motor recovery. This review synthesizes current advances in precision neurorehabilitation across the continuum from functional assessment to individualized therapeutic decision-making. Particular attention is given to digital and sensor-based assessment, quantitative gait and balance analysis, wearable movement biomarkers, artificial intelligence (AI)-assisted prediction, individualized therapeutic exercise, robotics and exoskeletons, virtual reality (VR), brain-computer interfaces (BCIs), neuromodulation, and telerehabilitation. Digital technologies enable continuous and objective characterization of motor behavior beyond episodic clinical assessment, while wearable sensors and machine-learning approaches facilitate longitudinal monitoring and identification of patient-specific recovery patterns. AI-based models further support prognosis, patient stratification, and potentially dynamic adaptation of rehabilitation strategies. Robotics, VR, and BCIs provide opportunities for intensive, repetitive, feedback-driven, and increasingly individualized motor training. Collectively, these technologies support a transition toward closed-loop rehabilitation in which patient performance is continuously measured, interpreted, and used to modify therapeutic interventions. However, clinical translation remains constrained by heterogeneous protocols, small study populations, limited external validation, inconsistent outcomes, cost, interoperability, usability, digital accessibility, and uncertainties regarding long-term effectiveness. Patient safety, algorithmic transparency, clinician oversight, and meaningful patient goals remain fundamental to responsible implementation. Future precision neurorehabilitation should therefore prioritize multicenter validation, standardized outcomes, explainable AI, cost-effectiveness, equitable access, and human-technology collaboration. Integrating multidimensional assessment with adaptive treatment may ultimately enable neurological physical therapy to become more measurable, responsive, patient-centered, and capable of optimizing meaningful motor recovery and functional participation across diverse neurological populations.
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Graphical abstract



Introduction

Neurological disorders are a major cause of long-term motor disability and frequently impair mobility, balance, coordination, upper-limb function, gait, and independence in activities of daily living. Stroke, Parkinson's disease, spinal cord injury, multiple sclerosis, traumatic brain injury, and other neurological conditions can produce highly heterogeneous functional consequences, even among individuals with apparently similar diagnoses. Neurological physical therapy therefore plays a central role in restoring movement, maximizing functional independence, preventing secondary complications, and facilitating participation in everyday life. However, conventional rehabilitation frequently relies on standardized assessments and broadly prescribed interventions that may not fully account for differences in neurological impairment, recovery potential, treatment responsiveness, environmental context, and patient goals. Precision rehabilitation has emerged as an alternative framework that seeks to optimize function by matching assessment and intervention strategies to the characteristics, needs, and recovery trajectories of individual patients (French et al., 2022).

Motor recovery is inherently complex because it reflects interactions among neural repair, neuroplasticity, motor learning, compensatory strategies, physical capacity, task practice, treatment intensity, and individual biological and behavioral factors. In neurological rehabilitation, improvement in clinical scores does not necessarily indicate restoration of premorbid movement patterns, as functional gains may also result from compensatory strategies. This distinction is particularly important when evaluating the mechanisms and quality of recovery. Contemporary analysis of post-stroke motor recovery highlights substantial conceptual variation in how recovery, compensation, motor control, and motor learning are defined and measured in clinical research, emphasizing the need for more precise characterization of changes in motor behavior (Favetta et al., 2023). Precision neurorehabilitation consequently requires more than diagnosis-based treatment selection; it requires detailed identification of the patient's motor phenotype and continuous assessment of how that phenotype changes during therapy.

Functional assessment is therefore the foundation of precision neurological physical therapy. Conventional measures such as clinical rating scales, observational gait analysis, balance tests, manual assessments, and functional independence measures remain essential, but they typically provide episodic snapshots of performance. They may also be insufficiently sensitive to subtle changes in movement quality or everyday functioning. Advances in wearable technologies are creating opportunities to complement conventional assessment with continuous and objective measurements of neurological function. Wearable-derived digital biomarkers can characterize gait, balance, upper-limb activity, movement smoothness, postural control, and real-world physical activity across clinical and community environments. Recent evidence across neurological populations indicates that such biomarkers may improve ecological assessment of physical function, although methodological heterogeneity and limited longitudinal validation continue to constrain their clinical implementation (Shalabi et al., 2026).

Wearable sensors are increasingly combined with machine-learning methods to convert high-dimensional movement data into clinically interpretable information. Inertial measurement units, accelerometers, gyroscopes, electromyography, pressure sensors, and other devices can capture movement and physiological signals during therapeutic exercises and daily activities. Machine-learning algorithms can subsequently recognize movement patterns, classify functional status, detect abnormalities, and potentially estimate rehabilitation progress. A systematic review of wearable sensors and machine learning in rehabilitation demonstrated their potential for optimizing assessment and creating more responsive home-based rehabilitation systems (Wei & Wu, 2023). Such developments are particularly relevant to precision neurorehabilitation because they shift assessment from intermittent observation toward longitudinal characterization of individual motor behavior.

Artificial intelligence (AI) further extends this transition by enabling complex relationships among clinical, biomechanical, demographic, imaging, sensor-derived, and treatment variables to be analyzed simultaneously. AI applications in physical rehabilitation increasingly include automated movement assessment, outcome prediction, exercise evaluation, patient monitoring, and decision support. Nevertheless, evidence concerning direct clinical effectiveness remains less developed than evidence concerning algorithmic performance, demonstrating an important gap between technological development and routine rehabilitation practice (Sumner et al., 2023). In precision neurological physical therapy, the value of AI therefore lies not merely in achieving high predictive accuracy but in generating information that improves clinical decisions and patient outcomes.

Prediction of individual recovery trajectories represents a particularly important component of precision neurorehabilitation. Patients with apparently comparable neurological lesions and baseline impairment may respond differently to the same rehabilitation program. Predictive models could help identify patients likely to recover rapidly, those requiring greater therapeutic intensity, and those at risk of persistent disability. Machine-learning approaches have already been investigated for predicting post-stroke motor and functional recovery using combinations of clinical and biomedical variables. Although promising results have been reported, limitations

including small datasets, heterogeneous outcomes, methodological bias, and insufficient external validation indicate that prediction models require further refinement before widespread clinical adoption (Campagnini et al., 2022). The future objective is therefore to move from population-level prognosis toward dynamic patient-specific prediction that can be updated as rehabilitation progresses.

Precision rehabilitation also requires interventions capable of adapting to individual motor capacity. Rehabilitation robotics represents one such approach because robotic devices can provide high-frequency, repetitive, task-specific training while objectively recording patient performance. Contemporary evidence indicates that robot-assisted upper-limb therapy after stroke can improve selected motor and functional outcomes, although effects vary according to intervention characteristics and patient populations (Park et al., 2025). For gait recovery, electromechanical and robot-assisted devices can facilitate repetitive stepping practice and may increase the probability of regaining independent walking when appropriately incorporated into post-stroke rehabilitation (Mehrholz et al., 2020). Rather than delivering fixed assistance, future precision systems may increasingly modify robotic support according to voluntary effort, movement quality, fatigue, and recovery stage.

Virtual reality (VR) provides another mechanism for delivering individualized, intensive, and engaging motor practice. Immersive environments can simulate functional tasks, manipulate task difficulty, provide immediate performance feedback, and increase the amount of repetitive practice without reproducing every physical environment clinically. Evidence from stroke rehabilitation indicates that immersive VR may provide additional benefits for upper-limb dexterity, gait performance, dynamic balance, independence, and treatment engagement when appropriately integrated with conventional therapy (Demeco et al., 2023). The ability to progressively modify virtual tasks according to performance makes VR particularly compatible with precision rehabilitation principles.

Brain-computer interfaces (BCIs) represent an emerging approach that extends personalization from observable movement toward neural activity. BCI systems can decode motor-related brain signals and translate them into feedback or commands for external devices, potentially creating a closed-loop connection between motor intention and sensory feedback. Evidence syntheses indicate that BCI-based rehabilitation may improve motor function following stroke, while highlighting variation in protocols, methodological quality, and safety reporting that requires further investigation (Liu et al., 2025). More recent evidence focusing on post-stroke lower-limb rehabilitation suggests that BCI-based training can influence motor function, balance, walking capacity, and activities of daily living, although optimal training dosage remains uncertain (Liu et al., 2026).

Precision neurorehabilitation is also expanding beyond the physical boundaries of rehabilitation centers. Telerehabilitation enables therapeutic exercise, movement monitoring, feedback, education, and professional supervision to be delivered in home and community settings. This is particularly important for patients with chronic neurological disability who require prolonged

rehabilitation but face geographical, transportation, financial, or mobility-related barriers. Evidence comparing telerehabilitation with face-to-face stroke rehabilitation suggests that remote approaches can support physical function and treatment adherence, although intervention design and outcomes remain heterogeneous (Sharififar et al., 2023). Combining telerehabilitation with wearables, computer vision, and adaptive algorithms could ultimately enable rehabilitation programs to respond continuously to real-world patient performance.

Importantly, precision neurorehabilitation extends beyond stroke. Exercise remains a fundamental component of physical therapy for Parkinson's disease, with evidence supporting improvements in motor function and mobility while also illustrating the importance of selecting appropriate exercise approaches for individual patients (Palm et al., 2024). In spinal cord injury, robot-assisted gait training is increasingly investigated as a means of enhancing locomotor practice and functional recovery, although clinical responses depend on neurological severity and training characteristics (Park et al., 2024). Similarly, technology-supported rehabilitation is expanding in multiple sclerosis, where virtual reality may improve balance, postural control, upper-limb function, participation, and quality of life, despite continuing uncertainty resulting from limited and heterogeneous evidence (De Keersmaecker et al., 2025). These differences across neurological populations reinforce the central premise that precision neurorehabilitation should be diagnosis-informed but ultimately patient-specific.

Against this background, the present review examines precision neurorehabilitation in neurological physical therapy across the continuum from functional assessment to personalized motor recovery. It evaluates advances in objective functional assessment, digital biomarkers, predictive analytics, AI, wearable technologies, robotics, virtual reality, brain-computer interfaces, and remote rehabilitation while considering their contribution to individualized therapeutic decision-making. Particular attention is given to how multidimensional patient information can be translated into adaptive interventions and clinically meaningful motor outcomes. By integrating assessment, prediction, intervention, and recovery within a unified precision framework, this review aims to clarify current evidence, identify barriers to clinical translation, and define future priorities for developing neurological physical therapy that is increasingly measurable, adaptive, patient-centered, and responsive to individual recovery trajectories.

Methodology

Review design and reporting framework

This review will adopt a systematic review design to synthesize evidence on precision neurorehabilitation in neurological physical therapy, with particular emphasis on the continuum from functional assessment to personalized motor recovery. A systematic rather than scoping approach was selected because the review aims not only to map available research but also to critically evaluate intervention effectiveness, assessment approaches, patient-specific rehabilitation strategies, and the methodological quality of the available evidence (Munn et al., 2018). The review will be conducted and reported according to the Preferred Reporting Items for

Systematic Reviews and Meta-Analyses 2020 (PRISMA 2020) statement (Page et al., 2021a). Additional methodological decisions and reporting details will follow the PRISMA explanation and elaboration guidance to enhance transparency and reproducibility (Page et al., 2021b). The review protocol and any subsequent amendments should be documented prospectively before formal screening begins.

Information sources and search strategy

A comprehensive electronic search will be conducted in PubMed/MEDLINE, Embase, Scopus, Web of Science Core Collection, CINAHL, PEDro, Cochrane CENTRAL, and IEEE Xplore from database inception to the final search date. This multidisciplinary combination is appropriate because precision neurorehabilitation intersects medicine, physical therapy, neuroscience, biomedical engineering, robotics, and digital health. Searching multiple complementary databases improves retrieval because no single bibliographic database provides complete coverage of the relevant biomedical literature (Bramer et al., 2017). Search procedures will be documented in accordance with PRISMA-S recommendations to permit reproducibility (Rethlefsen et al., 2021). Controlled vocabulary, including Medical Subject Headings (MeSH) and Emtree terms where applicable, will be combined with free-text keywords. The core search concepts will include terms related to neurological disorders, physical therapy/neurorehabilitation, functional assessment, precision or personalized rehabilitation, and motor recovery. Representative terms will include “neurorehabilitation,” “neurological physical therapy,” “stroke,” “Parkinson disease,” “multiple sclerosis,” “spinal cord injury,” “traumatic brain injury,” “motor recovery,” “gait,” “balance,” “functional assessment,” “precision rehabilitation,” “personalized rehabilitation,” “wearable sensor,” “artificial intelligence,” “machine learning,” “robotic rehabilitation,” “virtual reality,” and “brain-computer interface.” Boolean operators AND and OR, truncation, phrase searching, and database-specific subject headings will be applied. Search strategies should be independently checked before execution because structured peer review can identify errors and improve electronic search quality (McGowan et al., 2016). Reference lists of eligible studies and relevant systematic reviews will additionally be searched to identify potentially missed studies. The final search strategy, databases, dates, and number of retrieved records will be reported transparently.

Eligibility criteria

Eligibility will be structured around population, intervention/exposure, comparator, outcomes, and study design. Eligible populations will include adults with neurological conditions requiring physical rehabilitation, including stroke, Parkinson’s disease, multiple sclerosis, spinal cord injury, traumatic brain injury, and other acquired or progressive neurological disorders associated with motor impairment. Studies involving mixed populations will be included when neurological rehabilitation findings can be separately extracted. Overall methodology shown in [Figure 1](#).

Eligible studies must evaluate functional assessment or personalized neurorehabilitation approaches relevant to motor recovery. These may include clinical functional assessments, biomechanical and gait analysis, wearable sensors, digital biomarkers, AI-assisted prediction,

therapeutic exercise, robotic or exoskeleton-assisted therapy, virtual or augmented reality, brain-computer interfaces, neuromodulation integrated with physical rehabilitation, and telerehabilitation. Outcomes may include motor function, gait, balance, mobility, upper- or lower-limb function, activities of daily living, participation, functional independence, treatment response, and patient-reported outcomes. Eligibility will be defined before screening in accordance with established systematic-review principles to minimize post hoc selection decisions (Higgins et al., 2019). Randomized controlled trials, non-randomized controlled studies, prospective and retrospective cohort studies, diagnostic/measurement studies, and clinically relevant validation studies will be considered. Case reports, conference abstracts lacking sufficient data, editorials, letters, protocols, animal studies, purely technical simulations without patient-level rehabilitation outcomes, and studies unrelated to neurological physical therapy will be excluded.

Study selection

All retrieved records will be exported to reference-management software and duplicates removed before screening. Records may subsequently be managed using a systematic-review screening platform such as Rayyan, which supports independent and blinded screening decisions (Ouzzani et al., 2016). Two reviewers should independently screen titles and abstracts against the predefined criteria, followed by full-text assessment of potentially eligible articles. Disagreements will be resolved through discussion and, when necessary, consultation with a third reviewer. Reasons for full-text exclusion will be recorded. The complete identification, screening, eligibility, and inclusion process will be presented using a PRISMA 2020 flow diagram, ensuring transparent accounting of records throughout study selection.

Data extraction

A standardized data-extraction form will be developed and pilot-tested before full extraction. Information will include authors, publication year, country, study design, sample size, neurological diagnosis, participant characteristics, impairment severity, assessment technology, intervention characteristics, rehabilitation setting, treatment frequency and duration, personalization strategy, comparator, outcome measures, follow-up duration, and principal findings. For technology-enabled interventions, additional information will be extracted regarding sensors, algorithms, robotic systems, virtual environments, feedback mechanisms, and whether treatment was dynamically adapted to individual performance. Consistent extraction and explicit characterization of clinical and methodological heterogeneity will follow established evidence-synthesis principles (Ma et al., 2020).

Methodological quality and risk of bias

Risk of bias will be evaluated according to study design rather than applying a single instrument indiscriminately. Randomized controlled trials will be evaluated using Cochrane RoB 2, which assesses bias arising from randomization, deviations from intended interventions, missing outcome data, outcome measurement, and selective reporting (Sterne et al., 2019). Non-randomized intervention studies will be assessed using ROBINS-I, particularly for confounding, participant

selection, intervention classification, missing data, outcome measurement, and selective reporting (Sterne et al., 2016). Diagnostic or measurement-accuracy studies, where included, will be assessed using QUADAS-2, covering patient selection, index tests, reference standards, and flow and timing (Whiting et al., 2011). Two reviewers should conduct assessments independently, with disagreements resolved by consensus.

Evidence synthesis

Given the expected heterogeneity in neurological diagnoses, technologies, rehabilitation interventions, treatment doses, and outcome measures, findings will primarily be synthesized narratively and thematically. Studies will be grouped according to neurological condition and major precision-rehabilitation domains, including functional assessment, prediction of recovery, personalized therapeutic exercise, robotic rehabilitation, virtual rehabilitation, wearable/digital monitoring, and motor-recovery outcomes. Where statistical pooling is inappropriate, synthesis will follow the principles of Synthesis Without Meta-analysis to ensure that narrative conclusions remain systematic and transparent (Campbell et al., 2020). Where sufficiently homogeneous studies report comparable interventions and outcomes, quantitative pooling may be considered rather than assumed beforehand. The direction, magnitude, consistency, clinical relevance, and methodological quality of findings will be considered collectively. Certainty in major bodies of evidence may additionally be evaluated using GRADE principles, considering risk of bias, inconsistency, indirectness, imprecision, and publication bias (Balslem et al., 2011). Particular attention will be given to whether precision approaches demonstrate clinically meaningful improvements beyond conventional neurological physical therapy and whether benefits generalize across neurological populations. This framework will enable the review to distinguish technological feasibility from clinically validated personalization and identify priorities for future precision neurorehabilitation research.

Functional assessment and precision technologies in neurological physical therapy

Digital and sensor-based functional assessment

Digital technologies are changing functional assessment in neurological rehabilitation from episodic, observer-dependent evaluation toward continuous, quantitative, and patient-specific measurement. Conventional neurological physical therapy relies heavily on standardized clinical scales, therapist observation, manual range-of-motion assessment, timed mobility tests, and laboratory-based biomechanical evaluation. Although these approaches remain clinically essential, they may have limited sensitivity for detecting subtle changes in movement quality or fluctuations occurring between clinical visits. Digital assessment systems can complement these measures by continuously quantifying movement characteristics and generating objective longitudinal profiles of functional recovery. Computer vision, depth cameras, markerless motion capture, smartphones, pressure-sensing systems, and inertial measurement units (IMUs) are increasingly used to quantify posture, joint trajectories, range of motion, movement symmetry, exercise execution, and functional activities. Skeleton-based computer-vision approaches are

particularly promising because they can extract body-joint coordinates from images or video and automatically evaluate rehabilitation exercises. Sardari et al. (2023) demonstrated that the integration of vision sensors, skeleton representations, and AI algorithms provides a framework for automated rehabilitation activity recognition, performance evaluation, and feedback generation. Such technologies may extend objective assessment beyond specialized movement laboratories and enable repeated evaluation during supervised or home-based rehabilitation.

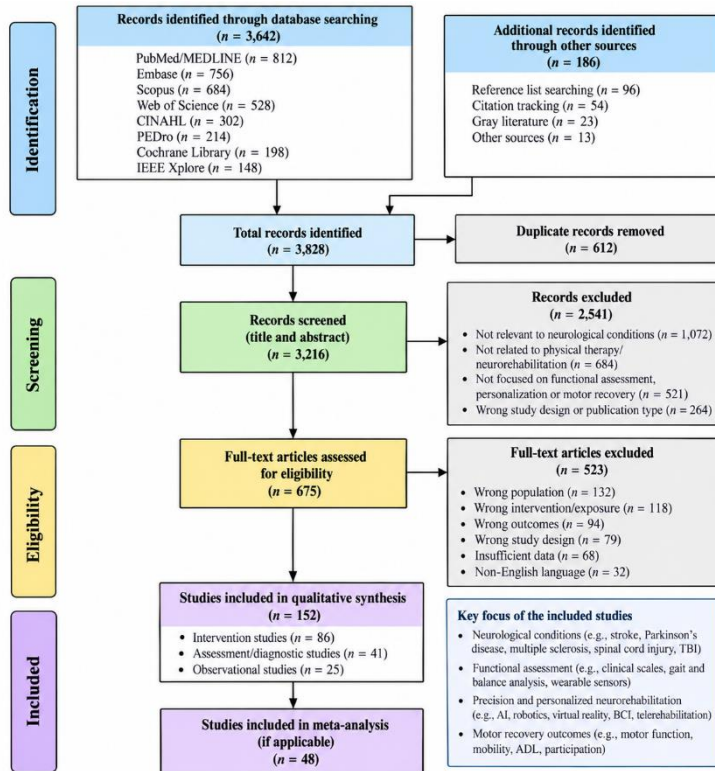


Figure 1. PRISMA flow diagram of study identification, screening, eligibility, and inclusion in the systematic review

Markerless motion capture is similarly emerging as a practical alternative to conventional marker-based systems. In neurological rehabilitation, markerless technologies have been used to assess and support functional movements in stroke and other neurological disorders, although considerable variability exists in devices, protocols, and clinical applications (Knippenberg et al., 2017). More recent evidence indicates that markerless full-body tracking can quantify gait and functional performance in Parkinson's disease, mild cognitive impairment, and dementia, but relatively few studies have rigorously compared these systems against established reference standards (Jeyasingh-Jacob et al., 2024). The principal advantage of digital assessment is therefore not simply automation but the creation of a richer functional phenotype. Repeated measurements can

reveal recovery trajectories, compensatory strategies, day-to-day variability, and deterioration that may be missed by isolated clinical examinations. Nevertheless, sensor accuracy, placement, calibration, environmental conditions, interoperability, clinical interpretability, and validation against established functional measures remain important prerequisites for translation into routine neurorehabilitation.

Gait, balance, and motor performance analysis

Gait and balance are central indicators of neurological function because impairments in walking speed, step length, cadence, symmetry, postural stability, coordination, and dynamic balance are strongly associated with mobility limitations and loss of independence. Instrumented gait analysis can provide detailed kinematic, kinetic, spatial, and temporal information; however, conventional laboratory systems require specialized equipment and expertise. The combination of digital sensing and AI provides an opportunity to perform increasingly objective gait and motor-performance assessments in clinics, homes, and community environments.

Machine learning has consequently attracted substantial interest for extracting clinically meaningful patterns from complex gait datasets. In cerebral palsy and stroke, ML methods have been applied to gait classification and analysis, but current evidence indicates that clinical suitability, feasibility, reliability, dataset selection, feature engineering, and methodological standardization remain substantial barriers to translation (Samadi Kohnehsahri et al., 2024). Rather than evaluating algorithms exclusively through classification accuracy, future studies should determine whether computational gait measures improve therapeutic decisions, intervention selection, and monitoring of meaningful functional recovery. Computer vision further enables gait assessment without requiring reflective markers or extensive body-worn instrumentation. Ng et al. (2020), for example, applied pose-estimation techniques to natural walking videos from older adults with dementia and extracted gait variables relevant to mobility and fall risk. Such unobtrusive assessment demonstrates how functional behavior can potentially be captured repeatedly in real-world environments rather than during a single structured examination. Markerless approaches have also been investigated for detecting gait deterioration, disease-related movement characteristics, and fall risk in neurodegenerative disorders (Jeyasingh-Jacob et al., 2024).

Balance assessment may similarly benefit from digital quantification of postural sway, trunk movement, weight transfer, stepping responses, and movement variability. When these parameters are combined with gait measures, clinicians may obtain a multidimensional motor profile that is more sensitive to neurological impairment than a single clinical score. Mehdizadeh et al. (2021) demonstrated the potential of markerless gait information within prognostic modelling of short-term falls among high-risk individuals with dementia, illustrating the potential progression from descriptive movement measurement toward clinically relevant risk estimation. These technologies are especially relevant to precision neurorehabilitation because patients sharing the same neurological diagnosis can exhibit substantially different motor phenotypes. Quantitative gait and

balance analysis can therefore contribute to patient stratification, individualized goal setting, identification of compensatory strategies, and monitoring of treatment response.

Wearable sensors and movement biomarkers

Wearable sensing provides an important bridge between controlled clinical assessment and patients' everyday functional behavior. IMUs containing accelerometers and gyroscopes, surface electromyography, pressure-sensitive insoles, smartwatches, and other body-worn devices can capture movement and physiological signals continuously or repeatedly during rehabilitation and daily activity. Unlike conventional assessments that provide a snapshot of performance, wearable technologies can generate longitudinal data reflecting how an individual actually moves across different environments. Clinically relevant features extracted from these signals may function as digital movement biomarkers. Potential biomarkers include gait speed, stride duration, cadence, step regularity, symmetry, variability, turning characteristics, postural transitions, activity intensity, joint motion, muscle activation, and movement smoothness. In neurological disorders, these measures may provide objective indicators of disease severity, functional capacity, treatment response, and recovery progression. Their longitudinal nature is particularly important because changes within an individual may be more informative for personalized rehabilitation than comparisons with population averages.

Wearable sensors become substantially more powerful when integrated with machine learning because raw multidimensional signals can be transformed into recognizable patterns of movement, impairment, or recovery. This enables algorithms to distinguish movement states, quantify exercise quality, identify abnormal motor patterns, and potentially detect clinically relevant changes before they become evident through conventional testing. Emerging systematic evidence indicates rapid growth in wearable sensor-based machine-learning approaches for human movement rehabilitation, while also highlighting continuing issues surrounding validation and clinical generalizability (Benachour et al., 2026). Wearables can also contribute to individualized rehabilitation dosage. Information about the amount, intensity, quality, and consistency of movement performed outside therapy sessions can reveal whether prescribed exercises are translating into real-world activity. Such information could allow physiotherapists to distinguish between inadequate treatment response, insufficient exercise exposure, poor adherence, or persistent biomechanical deficits and modify therapy accordingly.

However, a movement feature should not automatically be considered a clinically meaningful biomarker merely because it can be measured digitally. Candidate biomarkers require evidence of analytical validity, reliability, clinical validity, responsiveness, and relevance to outcomes meaningful to patients. Differences in sensor location, hardware, sampling frequency, algorithms, preprocessing, and outcome definitions currently limit comparisons between studies. Wearability, battery life, adherence, data privacy, comfort, cost, and digital literacy must also be considered before continuous sensing becomes a routine component of neurological physical therapy.

AI-assisted assessment and outcome prediction

Artificial intelligence provides the analytical layer capable of converting increasingly complex rehabilitation data into patient-specific assessment and prognostic information. Machine-learning and deep-learning models can integrate demographic characteristics, neurological impairment, baseline functional status, clinical scales, imaging, biomechanical variables, gait parameters, sensor signals, treatment exposure, and longitudinal responses. This creates the possibility of moving from descriptive assessment toward predictive rehabilitation in which likely recovery trajectories and treatment requirements are estimated for individual patients. Stroke rehabilitation provides one of the strongest examples. Machine-learning models have been investigated for predicting motor recovery, functional independence, activities of daily living, and rehabilitation outcomes. Campagnini et al. (2022) found considerable potential for ML-based prediction of post-stroke functional recovery, while also identifying methodological limitations affecting model reliability and translation. Prediction should therefore not be viewed as an end point; its clinical value depends on whether estimated prognosis leads to better goal setting, patient stratification, rehabilitation intensity, discharge planning, or selection of therapeutic interventions.

AI can additionally combine digital movement assessment with predictive modelling. For example, gait characteristics obtained from computer vision or wearable sensors may be used to identify fall risk, classify impairment, quantify disease severity, or predict rehabilitation status shown in Figure 2. Recent evidence in lower-extremity rehabilitation indicates that wearable sensor-based ML can achieve promising predictive performance, but limited external validation and methodological heterogeneity continue to restrict generalizability (Satija & Dkhar, 2026). This distinction between internal algorithmic performance and externally validated clinical utility is particularly important in neurological populations, where impairment severity, comorbidities, cognitive function, assistive-device use, and rehabilitation pathways vary substantially. The next stage should therefore involve dynamic prediction rather than one-time prognosis. A patient's predicted trajectory could be updated as new sensor, gait, functional, and treatment-response data become available. Such a model would establish a closed-loop pathway in which digital assessment identifies current status, AI estimates likely progression, therapy is individualized, subsequent performance is measured, and predictions are recalibrated according to actual response.

For this model to become clinically credible, AI systems must be externally validated, interpretable, calibrated, and evaluated in representative multicenter populations. Explainable AI is particularly important because clinicians need to understand which variables influence predictions before incorporating them into therapeutic decisions. Ultimately, AI-assisted assessment should function as clinical decision support rather than autonomous decision-making, combining computational recognition of complex patterns with physiotherapists' expertise, contextual judgement, patient goals, and safety assessment. Together, digital assessment, movement biomarkers, and AI prediction provide the foundation for a precision neurorehabilitation model in which treatment is continuously informed by objective and individualized evidence.

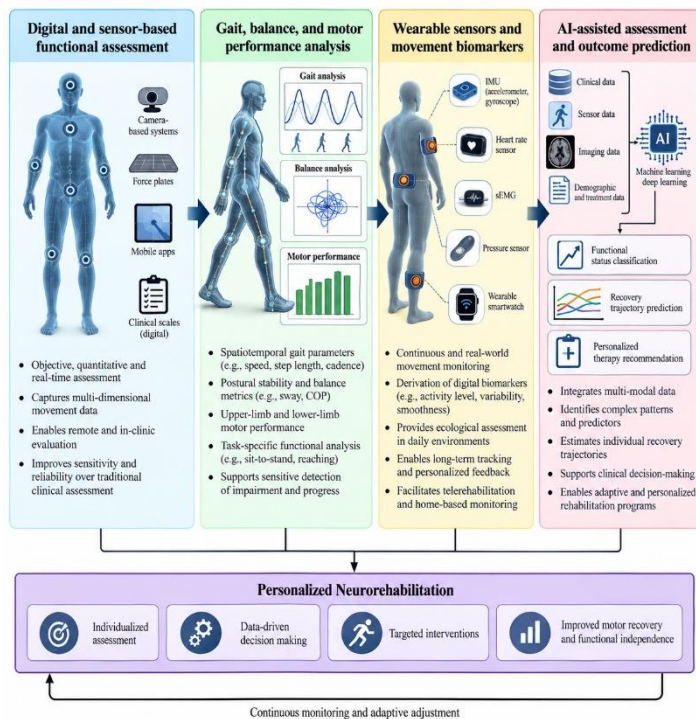


Figure 2. Integration of digital assessment, movement biomarkers, and AI for personalized neurorehabilitation and motor recovery

Personalized motor recovery and precision neurorehabilitation interventions

Individualized therapeutic exercise and motor learning

Therapeutic exercise remains a central component of physical rehabilitation, but precision rehabilitation shifts its emphasis from standardized exercise protocols toward interventions matched to individual impairment, recovery stage, functional goals, and response to training. Motor learning is particularly relevant because functional recovery depends not simply on completing exercises but on repeated, goal-directed practice that promotes acquisition or reacquisition of meaningful movement strategies. Important parameters include task specificity, repetition, intensity, progression, feedback, and the context in which movement is practiced. Evidence from stroke rehabilitation demonstrates considerable variation in the dose, content, and context of conventional upper-limb motor interventions, illustrating why identical prescriptions may produce different responses across patients (Newton et al., 2023).

Individualization should therefore involve continuous adjustment rather than a fixed prescription established at baseline. Initial impairment severity, fatigue, cognitive capacity, pain, cardiovascular tolerance, motivation, and rate of improvement can all influence the appropriate

training dose. Recent evidence evaluating task-specific training after stroke suggests that the relationship between greater training intensity and superior functional recovery is not straightforward; benefits may depend on the outcome, number of sessions, repetitions, and characteristics of the patient (Ibrahim et al., 2025). This supports a precision model in which clinicians progressively modify exercise complexity and practice conditions according to measured performance rather than assuming that increasing training volume alone will maximize recovery. Digital measurement may strengthen this approach by providing objective information on movement quality, repetitions, adherence, fatigue, and longitudinal improvement. These data could allow therapeutic exercise to operate as a closed-loop intervention: performance is measured, progress is evaluated, the therapeutic challenge is modified, and subsequent responses are reassessed. Such an approach retains the principles of motor learning while making exercise dosage increasingly patient-specific.

Robotics and exoskeleton-assisted rehabilitation

Robotic rehabilitation offers a technologically advanced mechanism for delivering intensive, repetitive, and quantifiable motor practice. Rehabilitation robots include upper-limb end-effector devices, powered orthoses, gait-training systems, wearable exoskeletons, and other assistive devices capable of measuring trajectories, forces, joint movements, and interaction between the patient and machine. A systematic review of physical rehabilitation robotics indicates that these technologies have considerable potential to support motor recovery and patient autonomy, while simultaneously highlighting continuing technical and clinical implementation challenges (Banyai & Brişan, 2024). The major development relevant to precision rehabilitation is the transition from predetermined robotic movement toward patient-responsive assistance. Instead of moving the limb through an identical trajectory for every patient, intelligent systems can potentially estimate voluntary effort and provide assistance according to the patient's residual motor capacity. Assistance-as-needed may preserve active participation while progressively reducing robotic support as function improves. Upper-limb assistive robotics similarly provide opportunities to combine intensive practice with quantitative assessment and personalized intervention, although device design, control architecture, clinical indication, and patient characteristics remain highly heterogeneous (Guatibonza et al., 2024).

For lower-limb recovery, robotic exoskeletons can facilitate repeated stepping and gait practice in individuals unable to perform sufficient independent walking. Meta-analytic evidence from randomized trials indicates that exoskeleton-based training can influence lower-limb function, activity, and participation following stroke, although outcomes vary according to intervention and patient characteristics (Yang et al., 2024). Future systems should therefore prioritize adaptive control, intention recognition, portability, comfort, safety, and clinically meaningful functional outcomes rather than maximizing robotic repetitions alone.

Virtual reality and technology-assisted training

Virtual reality (VR), augmented reality (AR), gaming systems, mobile applications, motion-tracking platforms, and telerehabilitation technologies extend motor rehabilitation into interactive environments in which therapeutic tasks can be manipulated systematically. VR is particularly suited to motor learning because task difficulty, visual feedback, repetition, environmental complexity, and motivational elements can be modified while performance is recorded continuously. This creates opportunities to deliver progressively challenging practice while maintaining patient engagement. The strongest evidence has emerged in neurological rehabilitation. An umbrella review of systematic reviews found substantial evidence supporting VR applications across multiple functional domains after stroke, although methodological quality and certainty differed among the underlying reviews (Hao et al., 2024). A separate meta-review reported benefits of VR for upper-limb and lower-limb recovery, gait, and balance, particularly when VR was used as an adjunct to conventional rehabilitation (Khan et al., 2024). These findings suggest that technology-assisted environments are most clinically meaningful when embedded within an established rehabilitation program rather than treated as isolated technological interventions.

An important next stage is adaptive VR. Machine-learning algorithms can use movement accuracy, completion time, range of motion, fatigue, and previous performance to alter task difficulty or feedback automatically. Recent systematic evidence specifically examining ML-based adaptive personalization in stroke VR rehabilitation demonstrates growing interest in this closed-loop approach, while also identifying the need for stronger clinical validation and patient-based evidence (Al Tawil et al., 2026). Thus, VR may evolve from a standardized digital exercise environment into an individualized therapeutic platform that responds dynamically to recovery.

Neuromodulation and brain-computer interfaces

Neuromodulation and brain-computer interfaces (BCIs) extend precision rehabilitation from observable movement toward direct interaction with neural activity. BCIs typically acquire neural signals, commonly through electroencephalography, identify activity associated with motor intention or imagery, and translate this information into feedback or control of an external device. The resulting output may activate functional electrical stimulation (FES), robotic devices, exoskeletons, or visual feedback shown in Figure 3. This creates a closed sensorimotor loop in which intended movement can produce meaningful sensory consequences even when voluntary motor output is severely impaired. Evidence is particularly developed for post-stroke upper-limb rehabilitation. A systematic review and meta-analysis found that BCI-based interventions have potential to improve upper-extremity motor function after stroke, supporting their emerging role as adjunctive neurorehabilitation technologies (Zhang et al., 2024). Combining BCI with FES may be particularly valuable because detected motor intention can trigger peripheral muscle stimulation, thereby temporally coupling cortical activation with movement and sensory feedback. Meta-analytic evidence indicates beneficial effects of BCI-controlled FES training on post-stroke upper-limb rehabilitation (Ren et al., 2024).

More recently, integrated approaches combining BCI with different neuromodulatory or rehabilitation technologies have attracted increasing attention. A 2026 systematic review and network meta-analysis examined BCI combined with neuromodulation for upper-limb stroke rehabilitation, including approaches involving robotic rehabilitation and FES (Zhu et al., 2026). Nevertheless, clinical translation requires reliable signal acquisition, appropriate patient selection, standardized protocols, simplified calibration, demonstration of durable functional benefits, and evidence that neurophysiological changes translate into meaningful improvements in everyday activity.

Adaptive and patient-specific rehabilitation

Adaptive rehabilitation represents the convergence of therapeutic exercise, sensing, predictive analytics, robotics, VR, and neurotechnology into a continuously responsive rehabilitation system. Conventional rehabilitation commonly involves periodic assessment followed by modification of a treatment plan. A patient-specific system instead has the potential to collect longitudinal information throughout therapy and modify intervention parameters as functional capacity changes. This approach can be conceptualized as a closed loop: patient assessment → data acquisition → performance interpretation → individualized intervention → response monitoring → treatment adaptation → reassessment. For example, wearable sensors may identify improving gait symmetry; a robotic device may consequently reduce assistance; a VR platform may increase task complexity; and exercise dosage may be adjusted according to performance and fatigue. ML-based adaptive personalization in VR provides an emerging example of this architecture, in which algorithms use patient performance to modify rehabilitation rather than delivering identical digital protocols to all participants (Al Tawil et al., 2026).

Patient specificity, however, should extend beyond algorithmic optimization. Rehabilitation goals are influenced by occupation, home environment, social roles, preferences, cognitive status, motivation, comorbidities, and access to technology. Adaptive rehabilitation should consequently combine objective data with patient-reported outcomes and therapist judgement. The optimal model is therefore not autonomous rehabilitation but human–technology collaboration, where technology increases measurement precision and responsiveness while clinicians retain responsibility for interpretation, safety, goal setting, and patient-centered decision-making.

Clinical translation, challenges, and future directions

Despite rapid technological progress, the central challenge is translating experimental rehabilitation technologies into interventions that produce reproducible and meaningful patient benefits. Many systems demonstrate technical feasibility or promising performance under controlled conditions but have substantially less evidence supporting effectiveness in routine physiotherapy practice. A systematic review of rehabilitation technologies potentially suitable for physiotherapists identified numerous opportunities for technology-supported rehabilitation while emphasizing the importance of their practical incorporation into clinical care (e Siqueira et al., 2024).

Translation is constrained by heterogeneous protocols, small samples, short follow-up periods, inconsistent outcome measures, limited external validation, equipment cost, training requirements, interoperability, usability, and unequal access. Robotic rehabilitation additionally faces challenges involving device complexity, safety, physical space, maintenance, and selection of patients most likely to benefit (Banyai & Brişan, 2024). VR systems must address cybersickness, accessibility, engagement, hardware variability, and the uncertain transfer of improvements in virtual tasks to real-world participation. BCI and neuromodulation introduce further issues involving signal reliability, calibration, neurophysiological heterogeneity, specialized expertise, and long-term efficacy.

Future research should consequently move beyond asking whether a technology *can* improve rehabilitation and determine which intervention works, for which patient, at what stage of recovery, at what dose, and under which clinical conditions. Multicenter trials, standardized reporting, externally validated algorithms, longer follow-up, cost-effectiveness analyses, patient-centered outcomes, and real-world implementation studies are priorities. Technology should ultimately support not displace the therapeutic relationship. Precision rehabilitation is most likely to emerge from the integration of therapist expertise, individual patient goals, objective functional measurement, and adaptive technologies capable of responding to recovery over time.

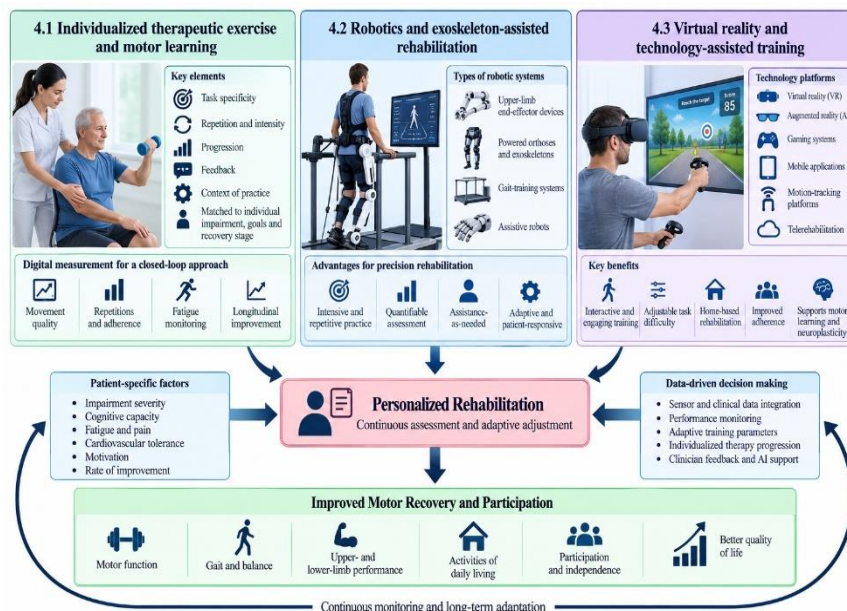


Figure 3. Personalized technology-assisted neurorehabilitation integrating therapeutic exercise, robotics, and virtual reality to optimize motor recovery and functional participation

Clinical translation challenges and future directions in precision neurorehabilitation

Clinical Translation Barriers and Implementation Challenges

The transition from experimental neurorehabilitation technologies to routine clinical practice remains a major challenge despite rapid advances in artificial intelligence (AI), wearable sensing, virtual reality (VR), robotics, brain-computer interfaces (BCIs), and telerehabilitation. Clinical translation requires more than demonstrating technical accuracy or short-term improvements under controlled laboratory conditions. Technologies must be effective, safe, usable, affordable, interoperable, and compatible with existing rehabilitation workflows. An integrative systematic review of digital health technologies in neurological rehabilitation identified five broad implementation domains: individual factors, user experience, intervention content, technology access, and support for technology use (Jarvis et al., 2024). These findings demonstrate that implementation failure may occur even when the underlying technology performs adequately. Evidence quality presents another important translational barrier. Neurorehabilitation technology studies frequently involve small samples, single-center designs, heterogeneous populations, different intervention doses, and inconsistent functional outcomes. For example, an umbrella review of VR after stroke identified generally encouraging functional findings, but methodological quality varied considerably across systematic reviews, with most rated as low or critically low quality (Hao et al., 2024). Similarly, wearable sensor and machine-learning applications show potential for rehabilitation assessment and optimization, yet differences in sensors, algorithms, rehabilitation protocols, and clinical populations restrict direct comparison and generalizability (Wei & Wu, 2023). Consequently, technically successful algorithms cannot automatically be assumed to produce meaningful improvements in disability, independence, participation, or quality of life.

Implementation is also influenced by organizational readiness. Rehabilitation professionals require appropriate training, technical support, adequate time, and confidence in interpreting technology-generated information. Digital tools that create additional workload or operate independently of electronic clinical systems may be difficult to sustain. WHO guidance similarly emphasizes that digital interventions must be integrated into functioning health systems and evaluated in terms of feasibility, acceptability, resource requirements, and equity rather than being treated as replacements for health-system capacity has been shown in [Figure 4](#). Therefore, future translational research should incorporate implementation outcomes alongside clinical efficacy, including adoption, fidelity, sustainability, cost-effectiveness, accessibility, clinician acceptance, and integration into real-world care pathways.

Personalization, Safety, and Patient-Centered Neurorehabilitation

Precision neurorehabilitation requires treatment to be adapted to the individual rather than determined exclusively by diagnostic category. Patients with the same neurological disorder may differ substantially in impairment severity, cognition, fatigue, comorbidities, recovery potential, motivation, social support, treatment preferences, and environmental circumstances. Personalized

rehabilitation should therefore integrate clinical characteristics with longitudinal functional data and patient-defined goals. Wearable sensors combined with machine-learning approaches provide an important foundation for this model because continuously generated movement and physiological information can potentially identify changes in performance that are not captured during periodic clinical assessment (Wei & Wu, 2023).

Patient-centered personalization should nevertheless extend beyond algorithmic selection of exercises or prediction of recovery. Treatment goals must remain meaningful to the individual and reflect activities and participation that patients consider important. Digital systems should support shared decision-making rather than impose recommendations solely on the basis of model outputs. Experiences with technology are particularly relevant because comfort, perceived usefulness, motivation, digital literacy, accessibility, and availability of support can influence whether patients engage with an intervention (Jarvis et al., 2024). Telerehabilitation illustrates this balance: it can expand access and continuity of post-stroke rehabilitation, but its effectiveness and implementation depend on the characteristics of the intervention, patient population, technological infrastructure, and service model (Alwadai et al., 2024).

Safety is equally fundamental when technologies influence therapeutic decisions or directly interact with patients. Adaptive robotics must avoid excessive or inappropriate assistance; VR systems should account for fatigue, dizziness, falls, and cybersickness; and BCIs require attention to adverse events, signal reliability, and suitability for individual patients. Recent evidence indicates that noninvasive BCI-assisted rehabilitation can enhance post-stroke motor recovery and that reported adverse events are generally uncommon, but safety surveillance remains necessary as systems become more autonomous and clinically complex (Zhang et al., 2026). AI-based decision support introduces additional concerns involving privacy, algorithmic bias, transparency, accountability, and explainability. A systematic review of healthcare AI decision-support systems demonstrated that explainability is closely connected to ethical considerations such as autonomy, trust, responsibility, and informed clinical decision-making (Vassilakopoulou et al., 2024). Precision neurorehabilitation should consequently follow a human-in-the-loop model, in which algorithms assist with measurement, prediction, and treatment adaptation while rehabilitation professionals retain responsibility for contextual interpretation, safety, and shared therapeutic decisions.

Emerging Technologies and Future Directions in Precision Neurorehabilitation

Future precision neurorehabilitation is likely to emerge from the convergence of multiple technologies rather than from a single device or algorithm. Wearable sensors, computer vision, AI, robotics, immersive environments, BCIs, neuromodulation, and remote rehabilitation platforms can potentially form interconnected systems capable of continuously measuring patient function and adapting treatment. Robotics and VR already provide mechanisms for increasing the intensity, repetition, feedback, and engagement of post-stroke training, while their integration may enable increasingly responsive therapeutic environments (Rajashekar et al., 2024).

BCIs represent a particularly important frontier because they create a direct pathway between neural activity and therapeutic feedback. By identifying motor intention and linking it to robotic movement, functional electrical stimulation, or visual feedback, BCIs may strengthen sensorimotor coupling and provide training opportunities for individuals with severe motor impairment. Current meta-analytic evidence supports improvements in upper-extremity motor recovery following BCI-based stroke rehabilitation, although further standardization and clinical validation remain necessary (Zhang et al., 2024). Future BCI platforms may increasingly integrate neural signals with biomechanical and physiological information to provide multidimensional representations of recovery. VR is also progressing from standardized gaming environments toward adaptive therapeutic ecosystems. Current evidence supports potential benefits for upper-limb function, gait, balance, mobility, and functional independence after stroke, particularly when VR complements conventional rehabilitation (Hao et al., 2024; Khan et al., 2024). Future platforms could automatically modify task complexity, repetition, environmental demands, and feedback according to real-time performance. Combined with wearable sensors and computer vision, these environments could support rehabilitation across hospitals, community settings, and patients' homes.

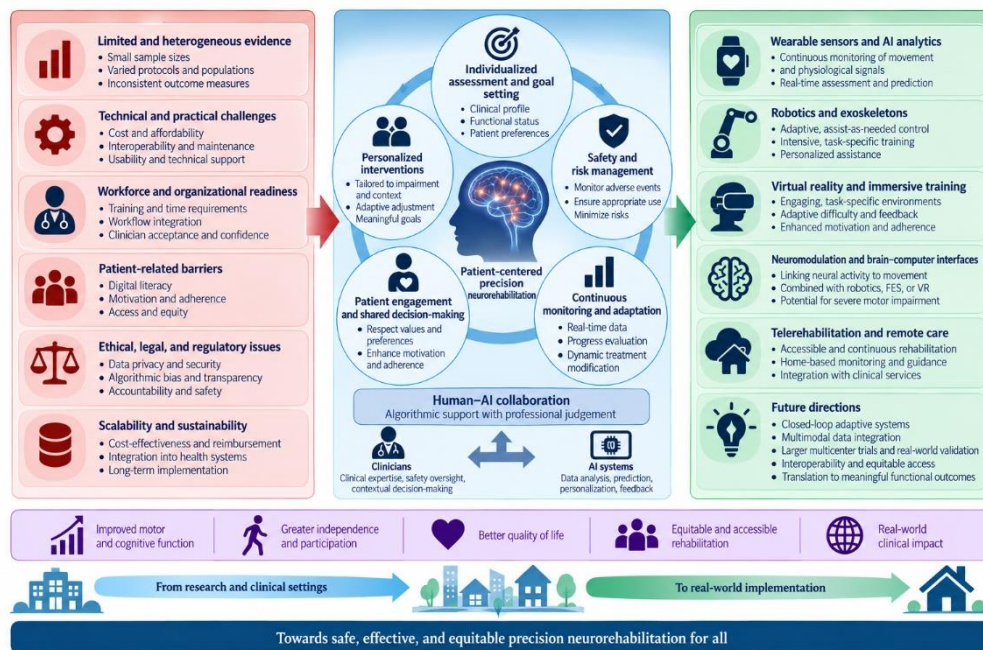


Figure 4. Framework linking clinical translation barriers, patient-centered personalization, and emerging technologies for precision neurorehabilitation

A major future direction is the development of closed-loop precision neurorehabilitation, in which multimodal data are continuously acquired, analyzed, and translated into therapeutic adaptations. Rather than making a single prognosis at baseline, predictive models could be updated throughout recovery as movement patterns, physiological responses, treatment adherence, and functional

outcomes change. Wearable sensing and machine learning already demonstrate the technical foundations for such longitudinal rehabilitation monitoring (Wei & Wu, 2023). Ultimately, progress should be judged not by technological sophistication alone but by whether these systems generate durable improvements in function, independence, participation, accessibility, and quality of life. Future research should prioritize multicenter trials, external algorithm validation, standardized outcomes, longer follow-up, cost-effectiveness, interoperability, equitable access, and co-design with patients and rehabilitation professionals.

Conclusion

Precision neurorehabilitation represents an important evolution in neurological physical therapy, shifting rehabilitation from predominantly standardized, diagnosis-driven protocols toward individualized, data-informed, and dynamically adaptive care. This review demonstrates that the integration of digital functional assessment, wearable sensors, movement biomarkers, artificial intelligence, robotics, virtual reality, brain-computer interfaces, neuromodulation, and remote rehabilitation provide new opportunities to characterize motor impairment and recovery with greater precision. These approaches can complement conventional clinical assessment by capturing longitudinal changes in gait, balance, movement quality, activity, treatment response, and real-world functioning, thereby supporting more individualized therapeutic decisions.

The emerging model is increasingly closed-loop: patient function is assessed, multidimensional data are acquired and interpreted, interventions are individualized, treatment responses are monitored, and rehabilitation parameters are progressively adjusted. Such an approach may enable exercise dosage, robotic assistance, virtual task complexity, feedback, and other therapeutic components to evolve according to individual performance, fatigue, goals, and recovery stage. Nevertheless, personalization should not be reduced to algorithmic optimization. Patient preferences, meaningful functional goals, cognition, motivation, comorbidities, environmental circumstances, and therapist judgement remain essential components of rehabilitation.

Despite considerable technological promise, translation into routine practice remains limited by methodological heterogeneity, small samples, inconsistent outcomes, inadequate external validation, short follow-up, cost, usability, interoperability, professional training requirements, and unequal access. Future research should therefore emphasize multicenter clinical trials, standardized outcome frameworks, externally validated and explainable algorithms, long-term effectiveness, cost-effectiveness, implementation science, accessibility, and co-design with patients and rehabilitation professionals. Ultimately, the value of precision neurorehabilitation should be determined not by technological sophistication alone, but by its ability to produce durable improvements in motor function, independence, participation, and quality of life. The most clinically sustainable model is therefore a human-technology partnership in which advanced technologies strengthen, rather than replace, therapist expertise and patient-centered decision-making.

Author contribution statement:

Neelam Devi: Conceptualization, Methodology, Formal analysis, Writing-original draft preparation, Software, Visualization, Data curation.

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