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PERSPECTIVE

A perspective on neuromechanical biomarkers for neurorehabilitation: towards reliable assessment in research and clinical practice

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Abstract

Effective neurorehabilitation necessitates a reliable assessment of the patient's sensorimotor status. Such assessment guides clinical decision-making and supports the evaluation of novel interventions. Yet, despite technological progress, it remains limited to clinical scales that are mostly based on subjective scoring systems and measurement protocols with poor reproducibility. Research on neuromechanical biomarkers—metrics of movement derived from kinematic, kinetic and physiological data—has demonstrated significant potential to advance towards more reliable assessment. However, their clinical validation and practical adoption remain limited, impeding the development of more objective, standardized, and clinically relevant measurement of movement. This article consolidates expert perspectives from a multidisciplinary workshop held at the 2024 International Conference on NeuroRehabilitation in La Granja (Spain), focusing on the development of reliable assessment tools useful in clinical practice. The emerging central topic is the urgent need for assessment tools that are grounded in validated measurements. To address this, we structure the discussion around three pillars: *standardization*, to ensure methodological consistency; *transferability*, to support generalization across populations and technologies; and *shareability*, to enable collaboration, validation, and scaling. For each pillar, we outline current challenges and potential steps towards them, proposing a roadmap for developing assessment frameworks that are suitable for real-world use.

1. Introduction

Motor impairments caused by neurological diseases are the third largest contributors to global disability and health burden [1]. As these impairments affect both functional independence and quality of life, there is increasing demand for effective, evidence-based neurorehabilitation strategies [2, 3]. To guide recovery and maximize outcomes, clinical practice depends on accurate evaluation, continuous monitoring of progress, and definition of personalized treatment [4]. That means that clinicians must be able to quantify motor deficits, detect meaningful change, and tailor interventions accordingly. Across all stages of this process, *reliable assessment* of cognitive-motor functions is essential.

We define reliable assessment as one that is based on metrics with demonstrated quality, that is, with validated clinimetric or measurement properties [5, 6]. These include:

(i) **Reliability:** To consistently measure what it is intended to measure, generating repeatable, objective values across sessions, raters and settings so that observed differences reflect true biological change.

(ii) **Validity**: To produce metrics that are interpretable in functional terms so that score changes can be linked to meaningful improvements.

(iii) **Responsiveness:** To detect meaningful change over time. Defined as 'longitudinal validity', it is quantified through minimal detectable change (MDC) or the minimal important difference (MID/MIC), which distinguishes true clinical improvement from measurement noise.

(iv) **Interpretability:** To assign qualitative clinical meaning to a quantitative score and its changes.

These properties have been established by the COnsensus-based Standards for the selection of health Measurement Instruments guidelines through a Delphi study [6].

Yet, despite existing frameworks to build reliable assessment, most current practice remains centered on clinical scales. For example, the European evidence-based recommendations for clinical assessment of upper limb in neurorehabilitation propose three measurement sets: a core set for clinical use, an extended set for both clinical practice and research, and a supplementary set for specific situations [7]. These sets are composed almost entirely of clinical scales, including the Fugl-Meyer Assessment of Upper Extremity (FMA-UE), Action Research Arm Test (ARAT), Box and Block Test (BBT), Chedoke Arm Hand Activity Inventory, Wolf Motor Function Test, Nine Hole Peg Test, ABILHAND, Motricity Index (MI), Chedoke McMaster Stroke Assessment, Stroke Rehabilitation Assessment Movement, Frenchay Arm Test, and Motor Assessment Scale. Kinematic measures and body-worn movement sensors are mentioned only within the extended and supplementary sets, not as core assessment tools.

While these clinical scales are widely used and clinically interpretable, they rely on subjective scoring and offer limited resolution. In addition, they are typically applied at specific timepoints, capturing a singular effort at the moment of evaluation. As a result, they often lack sensitivity to subtle changes in movement quality, compensatory strategies, and short-term recovery dynamics [8, 9].

This was the motivating argument behind an expert group discussion at the 6th International Conference on NeuroRehabilitation (ICNR2024). During this dedicated workshop, clinicians, engineers, and researchers explored existing issues in assessment practices and debated strategies for achieving more reliable assessment in the field of neurorehabilitation [10], which is moving toward data-driven assessment to address current limitations

To enable effective data-driven approaches, it is necessary to collect patient's data using wearable and mobile technologies and to develop more reliable metrics of cognitive-motor functions [11].

This is made possible by advances in technology that allow continuous monitoring of movement, physiological, and biological signals [12]. As a result, high-resolution, multimodal data can be acquired, reflecting how patients perform, adapt, and recover during functional tasks [13]. However, there is still limited evidence regarding the clinical applicability of such data, despite being included in international guidelines '*to quantify movement quality and limb use at both body function and activity levels*' [7].

1.1. Neuromechanical biomarkers for reliable assessment

Patient's data can be transformed into ***biomarkers***, defined as 'indicators of normal or pathogenic biological processes, or responses to […] therapeutic interventions, that are accurately and reproducibly measured from outside the patient' [14].

Biomarkers relevant to cognitive-motor recovery include a wide range, from molecular and genetic indicators to imaging or physiological signals [15, 16]. While a comprehensive assessment would include multiple biomarker types, some are indirectly linked to motor behavior, as they cannot be collected during movement, such as imaging, molecular and genetic biomarkers. For this reason, they are not considered here, and we thus focus on biomarkers that result from the interaction between neural control and biomechanics during movement:

Neuromechanical biomarkers are metrics that characterize the interactions among neural, biomechanical, and environmental dynamics, which result in significant motor behaviors [17]. They are thus derived from biomechanical and physiological signals, such as kinematic measures (e.g. joint angles, movement smoothness), kinetic measures (e.g. ground reaction forces), electromyography (EMG), electroencephalography (EEG), and electrocardiography (ECG).

Why are neuromechanical biomarkers needed for reliable assessment in neurorehabilitation? The demand for rapid and objective assessment tools position them as a promising solution to address current gaps and challenges in motor function assessment, based on the following considerations:

(i) **Physiological and functional relevance:** Neuromechanical signals characterize the mechanisms of motor production, impairment, and recovery [17]. Many measures correlate closely with established clinical scales [18–21], which makes them solid candidates for clinical validation and use.

(ii) **High spatial and temporal resolution**: Neuromechanical data, such as EEG, ECG, EMG, kinematics, provide millisecond timescales, allowing continuous tracking of neural modulation, muscular activation, and movement quality.

(iii) **Practical deployment:** Many sensor technologies to record neuromechanical signals are portable, noninvasive, and relatively low-cost [22–25]. These features support implementation at the bedside, in clinical environments, and home-based programs.

(iv) **Compatibility with rehabilitative technology and readiness for regulatory approval**: Neuromechanical data can be readily integrated with wearable sensors, robotic devices, functional electrical stimulation, and brain–computer interfaces [26]. Although technology-supported assessments are increasingly utilized in research settings, their adoption in clinical practice remains limited. Nevertheless, many metrics, such as digital gait and balance measures, are considered ready for regulatory evaluation and have been identified as candidate digital biomarkers for clinical trials [27, 28]. Significant limitations include the absence of standardized protocols for data application and analysis, as well as insufficient information regarding their psychometric properties across various scenarios [7].

This article provides an expert perspective on how neuromechanical biomarkers can advance novel assessments in neurorehabilitation, structured around three pillars identified from key gaps and challenges in the field. Rather than a comprehensive review, it proposes guiding principles to inform methodological developments and translational efforts. The following section provides a brief overview of representative neuromechanical biomarkers and illustrates how they are derived from multimodal data (figure 1 and table 1). For further details, readers may consult Garro *et al* [26] for comprehensive biomarker catalogs with experimental examples, and Longatelli *et al* [29, 30] for a practical example of implementation frameworks with clinical validation data.

Conceptual framework for neuromechanical biomarkers

Neuromechanical biomarkers are derived from multiple measurement modalities that characterize movement (figure 1, Panel (A): neural activity (EEG), autonomic function (ECG), muscular activation (EMG), kinematics and kinetics such as movement trajectories, joint angles, forces and torques, alongside traditional clinical questionnaires and behavioral observations [26, 29, 30].

Raw physiological signals are transformed into biomarkers through a structured framework (figure 1, Panel (B). During standardized tasks, such as reaching, grasping, or walking, multimodal data are acquired and processed to derive meaningful features into biomarkers. These serve two primary purposes: (1) enabling motor decoding for controlling assistive technologies such as brain-machine interfaces, robotic exoskeletons, or functional electrical stimulation systems (figure 1, Panel (C); and (2) providing objective movement characterization that captures motor impairment severity, compensatory strategies, and recovery dynamics (figure 1, Panel (D). These applications converge toward personalized rehabilitation and enhanced assistive technology [26, 29, 30].

Table 1 summarizes representative biomarker categories by signal modality, illustrating the diversity of available metrics and their assessed motor aspects.

1.2. Gaps, challenges, and pillars for reliable assessment

Neuromechanical biomarkers have the potential to shift neurorehabilitation assessment from isolated time-point evaluations to continuous, quantitative measures of motor function. However, their translation from laboratory proof-of-concept to routine clinical practice remains limited. Based on current evidence and expert discussion, four persistent gaps continue to hinder this process [26].

First, a knowledge gap stems from the limited understanding of recovery mechanisms and the high inter- and intra-patient variability observed in neurorehabilitation. A key challenge is how to model this variability by treating patient diversity as informative signal rather than noise, for example through patient-specific thresholds and adaptive models. At the same time, there is a need to reconcile standardization with personalization, ensuring that shared metrics remain sensitive to individual patient status.

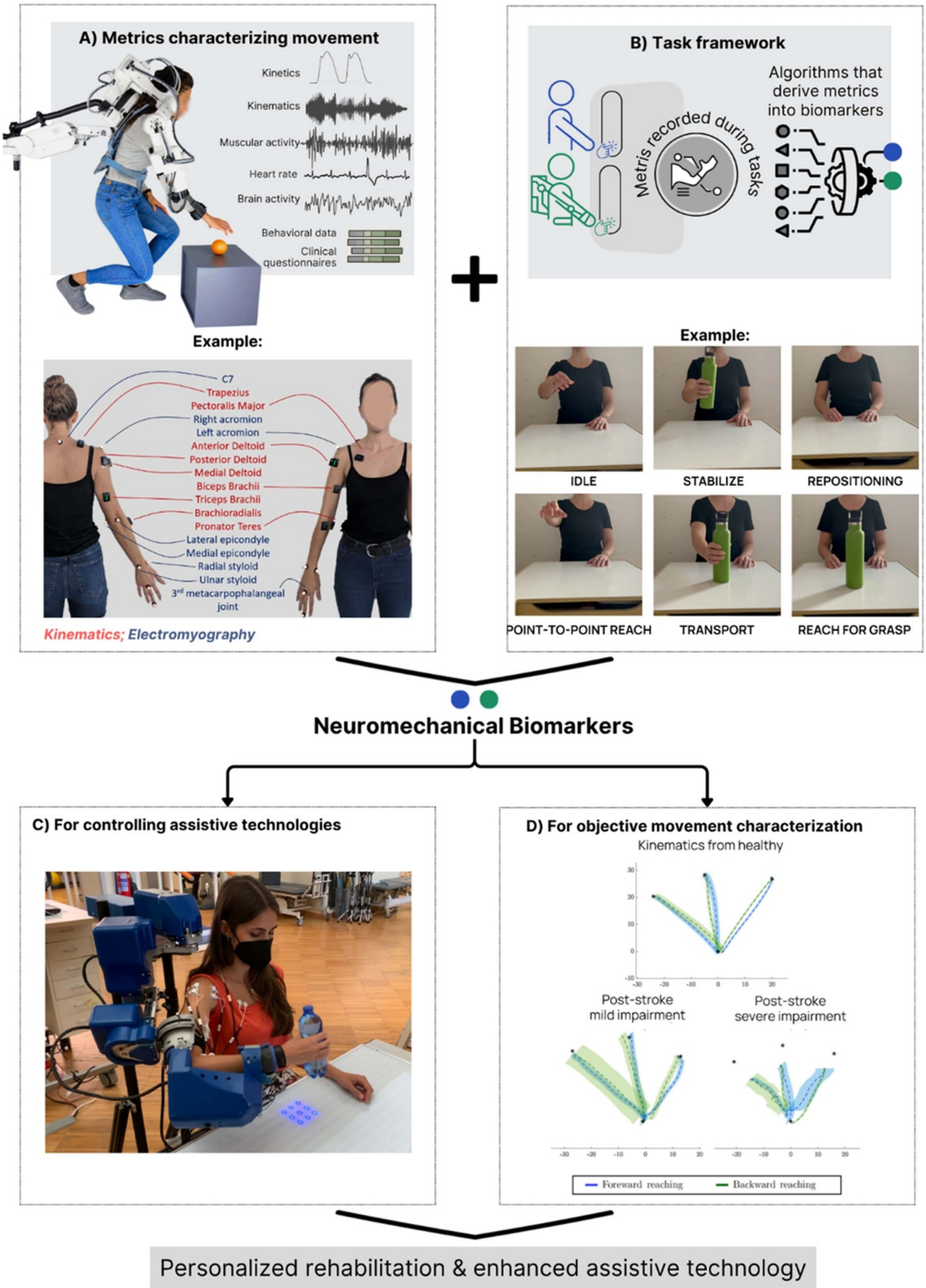

Figure 1. Neuromechanical biomarkers framework: Panel (A) exemplifies multimodal measurements that characterize movement. Panel B shows standardized motor tasks that are performed while multimodal data are acquired; signal processing algorithms extract features and compute performance indicators to generate neuromechanical biomarkers. These biomarkers enable two primary applications: motor decoding for controlling assistive technologies (Panel (C)) and/or objective movement characterization (quantifying impairment, compensatory strategies, and recovery dynamics, Panel (D)); both contributing to personalized rehabilitation and enhanced assistive technology. Example adapted from [29, 30].

Second, clinical gaps arise from insufficient validation of neuromechanical biomarkers against gold-standard practices and their limited integration into existing clinical workflows. For these assessment tools to be usable in routine care, they must be quick to set up, non-invasive, interpretable, and robust to noise and operational variability.

Table 1. Examples of representative neuromechanical biomarkers for neurorehabilitation.

Modality	What is measured	Representative metrics	Parameters assessed	References
Kinematics	Movement quality and efficiency	• Joint angles and range of motion • Movement smoothness (jerk, spectral arc length) • Trajectory accuracy and variability • Velocity and acceleration profiles • Endpoint error	• Movement accuracy • Motor planning • Compensatory strategies • Movement efficiency • Coordination	[26, 29, 30]
Kinetics	Force generation and control	• Ground reaction forces • Joint torques • Grip force modulation • Force-time profiles	• Strength • Force control precision • Balance and stability • Weight-bearing capacity	
Electromyography (EMG)	Muscle activation patterns	• Muscle activation amplitude • Activation timing and duration • Co-contraction indices • Muscle fatigue indices • Onset latency	• Muscle recruitment • Spasticity • Weakness • Abnormal co-activation • Motor unit control	
	Muscle synergies	• Synergy spatial structure (weighting coefficients) • Synergy temporal activation • Number of independent synergies • Synergy similarity indices • Synergy merging patterns	• Motor control organization • Modularity of control • Neuroplasticity • Pathological motor patterns • Recovery trajectories	[21, 31–39]
Electroencephalography (EEG)	Cortical activity and motor planning	• Event-related potentials (ERP) • Sensorimotor rhythm power (mu/beta bands) • Movement-related cortical potentials (MRCP) • Cortical lateralization indices	• Motor intention • Motor planning • Cortical excitability • Brain reorganization • Attention and engagement	[26, 40–46]
Multimodal	Corticomuscular coupling	• EEG-EMG coherence • Corticomuscular coupling strength	• Neural drive to muscles • Sensorimotor integration • Motor control efficiency	[26]
	Integrated task performance	• Gait parameters (spatiotemporal + kinematic + EMG) • Reaching performance indices (combining accuracy, smoothness, efficiency) • Functional task completion metrics	• Functional capacity • Activities of daily living performance • Overall motor competence	[30, 47–74]
Clinical/ Behavioral	Clinical scales and subjective performance metrics	• Fugl-Meyer Assessment (FMA-UE) • Action Research Arm Test (ARAT) • Box and Block Test (BBT) • Modified Ashworth Scale • Task completion time • Error rates and accuracy	While not neuromechanical biomarkers, clinical scales serve as reference standards for validation and bridge quantitative measurements to clinically meaningful outcomes, such as: •Overall functional capacity • Impairment severity • Activity limitations • Treatment response	[7, 26, 29]

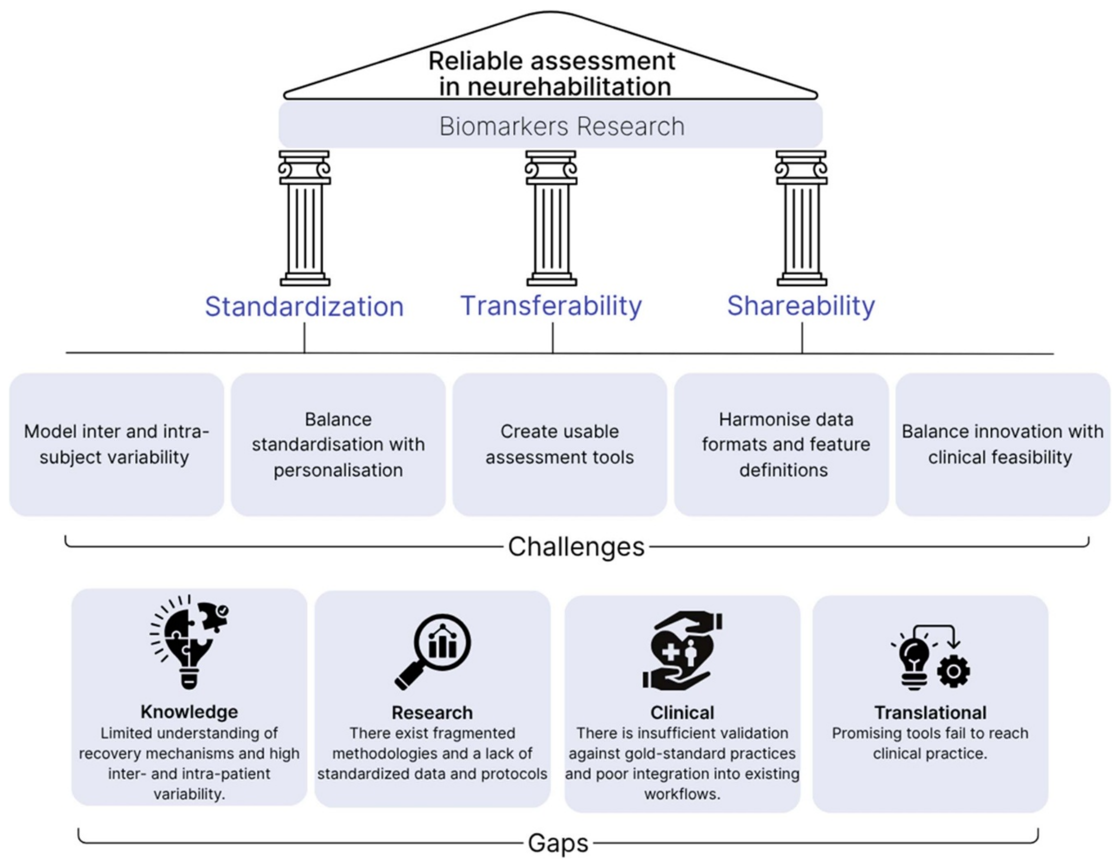

Figure 2. Gaps, challenges and proposed pillars for biomarkers research in reliable assessment in neurorehabilitation.

Third, research gaps reflect fragmented methodologies and the lack of standardized datasets, protocols, and analysis pipelines. A central challenge lies in balancing methodological innovation with clinical feasibility, requiring better alignment among research priorities, clinical needs, and regulatory expectations to ensure the development of truly reliable assessment methods.

Finally, translational gaps persist because promising tools often fail to progress beyond research settings. This is partly due to the lack of harmonized data formats, feature definitions, and reporting standards, which limit comparison, cross-validation, and interoperability across systems and institutions.

These challenges converge into a single insight: reliable assessment is not the outcome of a single technology, protocol, or study. Rather, it emerges from coordinated efforts across disciplines, institutions, and systems to support personalized, data-driven decision-making in the complex context of neurorehabilitation.

Therefore, we argue that addressing these challenges requires a systematic framework that guides how biomarkers are researched and developed. We propose three interconnected pillars: Standardization, Transferability and Shareability, as the foundation for building reliable assessment (figure 2). The remainder of the paper is organized around these pillars, expanding in their definition and current state of the art, and illustrating how each contributes to overcoming the gaps identified above.

2. Standardization: building a common framework for assessment in neurorehabilitation

Currently, there is no formally accepted framework for how biomarkers in neurorehabilitation should be developed, validated, or reported, with wide methodological heterogeneity and poor reproducibility across studies [26]. Although several initiatives are currently underway to bring standardization to clinical assessment [75–77], no specific guidelines have been established for neuromechanical biomarkers. As a result, findings often lack generalizability and cannot support broader clinical adoption.

Standardization refers to the creation of shared procedures, formats, and criteria that ensure precision and consistency across devices, sites, patient groups, and clinical workflows. It enables systematic biomarker validation and regulatory approval, supporting multi-center interoperability.

One of the few areas where standardized approaches have achieved relative consistency in routine clinical practice is instrumented gait analysis, which assesses locomotion by measuring and analyzing movement patterns, using motion capture systems and wearable sensors [78, 79]. International and national societies provide detailed recommendations and accreditation pathways, and a recent European survey of 97 laboratories showed broad agreement in equipment and reporting practice, setting the basis for a Delphi process to define European standards [78, 80–82]. Yet no fully harmonized protocol exists; in fact, significant variation persists in marker sets, biomechanical modeling choices, data-processing pipelines, and validation procedures [11].

These small variations can lead to major discrepancies in outputs, impeding meta-analysis and the creation of normative datasets. For example, the abovementioned European survey found substantial heterogeneity in filter choice, model variants, and software [78]; shifting an IMU placed on the foot to the outer heel can add more than 8 cm error to a single-stride length [83] and moving a knee marker placed in the lateral-epicondyle just 10 mm forward shift hip and ankle angles by about 5° and 4°, respectively [84].

The use of rehabilitation technologies while recording data from the patient to derive biomarkers adds to this complexity. Robotic devices differ in mechanical design and control strategies, from assist-as-needed to challenge-based or impedance-controlled modes [85, 86], leading to the recording of different biomarker profiles even in similar tasks [87].

In addition, differences in preprocessing pipelines add more variability. For instance, surface-EMG features and EEG depend heavily on electrode placement, artifact rejection methods, and bandwidth choices [88–91].

Moreover, many current biomarker systems fail to meet the time, resource, or interpretability constraints of real-world rehabilitation, and lack alignment with emerging regulatory expectations for clinical endpoints. Recent guidance on digital health technologies stresses the need for validated, standardized acquisition and analysis protocols before they can qualify as clinical-trial endpoints [6, 92, 93].

Standardization thus provides the foundational infrastructure that enables biomarkers to be properly developed.

2.1. Benchmarking as a framework for standardization

To convert the abstract goal of standardization into an actionable methodology, it is necessary to implement, validate, and sustain harmonized procedures, protocols, and data structures over time [94, 95]. This can be addressed with *benchmarking*: well-defined, repeatable procedures that enable fair and transparent comparisons across teams, devices, and environments [96].

Recent European initiatives have incorporated the concept of benchmarking in neurorehabilitation robotics and human–robot interaction [97, 98], with the objective of developing methods (benchmarking software) and tools (testing facilities) designed to measure system capabilities in a rigorous, quantitative, and replicable manner.

In addition, recent frameworks define benchmarking as 'a measurable and reproducible evaluation to enable accurate and reliable comparisons' and enumerate seven practical 'ingredients'—performance indicators, sensors, algorithms, experimental protocols, testbeds, datasets and analytics—that must satisfy seven principles (reproducibility, measurability, generalizability, standardizability, shareability, agreement, understandability) to ensure data comparability across laboratories and devices. Experience gained in European projects demonstrates that such a structured approach can deliver interoperable datasets, thereby providing the methodological rigor needed to validate neuromechanical biomarkers and meet emerging regulatory requirements [99].

A multi-center study applied these principles and ingredients of benchmarking to upper limb assessment [29], in which researchers defined a minimal set of motor primitives—reaching, grasping, transporting, and hand-to-mouth—and linked them to quantifiable motor skills such as coordination, smoothness, and effort. The study showed that high-quality benchmarking can generate normative values and validate device performance, paving the way for supporting comparisons of different interventions across sites.

Benchmarking thus serves as both a bridge and a filter, aligning diverse research efforts within a common reference frame and ensuring that only reliable biomarkers progress toward routine use.

Table 2. Challenges for standardization.

Challenge	Description
How can we meaningfully compare neurorehabilitation systems with different sensing modalities, control schemes, and goals?	Technologies used in neurorehabilitation vary widely in their goals, sensing capabilities, and operational principles. Establishing standardized metrics that allow for fair and valid comparisons across such diverse systems remains a key challenge [96]. Without appropriate normalization and contextualization, comparisons may obscure rather than clarify performance differences.
What volume and diversity of data is needed to ensure robust, generalizable benchmarking across centers and populations?	Benchmarking and standardization require large and representative datasets. Yet, collecting high-quality data at scale is resource-intensive and often fragmented across institutions. Defining minimum data requirements and fostering multi-center data sharing is essential to support validation and generalizability of standardized measures.
How can we promote widespread adoption of benchmarking while mitigating reputational and competitive risks?	While benchmarking aims to foster transparency and improvement, it also introduces potential concerns related to competition and reputational risks. Some stakeholders may be reluctant to adopt standardization frameworks that expose performance limitations or invite direct comparison. Creating a supportive benchmarking culture, with clearly defined benefits and protections is vital.
To what extent do lab-based assessments predict functional performance in real-world settings?	Standardized protocols are often developed and validated in controlled laboratory environments. However, translating these results to everyday functional performance remains a significant challenge.
Can we standardize assessments involving active user participation without oversimplifying the inherent variability of human behavior?	Human variability is intrinsic to rehabilitation. Standardizing assessments that involve active user participation must consider cognitive engagement, motivation, fatigue, and adaptation [100, 101]. Rather than eliminating this variability, standardization efforts should seek to incorporate and model it, recognizing the human-in-the-loop as a dynamic component of the system.
What frameworks are needed to evaluate and certify AI-driven neurorehabilitation tools, given their adaptive and opaque nature?	Artificial intelligence is playing an increasing role in biomarker extraction, interpretation, and clinical decision support [102, 103]. The forthcoming EU Artificial Intelligence Act classifies medical AI as a "high-risk" application, requiring documented safety, transparency, and post-market monitoring. Standardization efforts must therefore include auditable development pipelines, performance benchmarks, and continuous-learning safeguards that satisfy these regulatory obligations [104].

2.2. Challenges for standardization

Several challenges reflect the practical, methodological, and conceptual complexities of applying standardization principles in rehabilitation assessment. Table 2 outline six critical challenges that must be addressed to ensure that standardization efforts are both meaningful and sustainable.

These open challenges point to the need for flexibility within standardization frameworks, allowing room for development and validation but providing balancing consistency with adaptability, and comparability with personalization. Addressing them will be critical for advancing toward validated biomarkers for reliable assessment.

2.3. Steps towards effective standardization

Achieving consistency across systems, studies, and clinical environments requires harmonized approaches to development, validation, and reporting. The following recommendations outline key priorities for structuring standardization efforts in neurorehabilitation (figure 3):

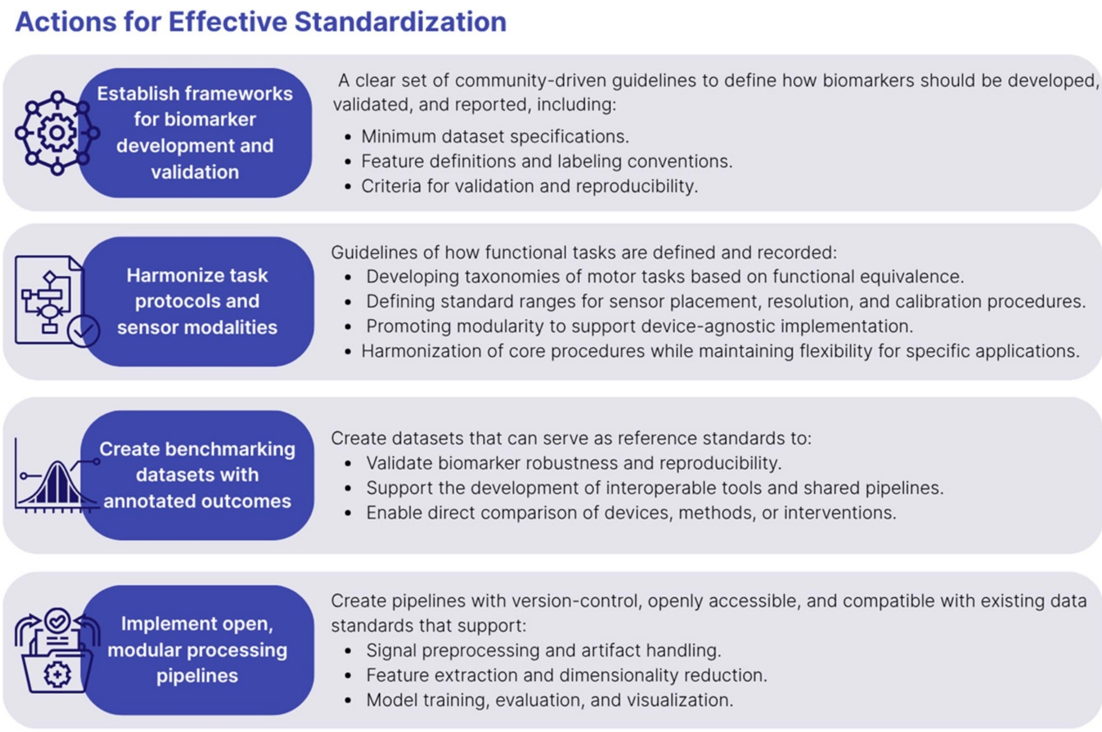

Figure 3. Actions for effective standardization.

3. Transferability: adapting biomarkers across clinical populations and contexts

Standardization creates the methodological foundation for reliable assessment in neurorehabilitation. However, it remains essential that such standardized biomarkers retain their clinimetric properties when applied outside their original development context.

Transferability refers to the capacity of a biomarker to preserve its clinimetric properties and clinical meaning across different patient groups, recording devices, analysis pipelines, and clinical environments, without the need for major re-engineering of algorithms or thresholds.

A transferable biomarker should offer consistent, meaningful insight regardless of who is being assessed, what hardware is used or where the measurement takes place.

However, in practice, many neuromechanical biomarkers are developed in highly controlled conditions using small patient samples and specific devices [105–108]. Such conditions hardly reflect clinical reality, where motor behavior is influenced by physiological, cognitive, environmental and technological factors [101, 109].

Transferability must cope with patient variability, such as diagnosis, impairment severity, compensatory movement strategy, psychological state and recovery trajectory, all of which modulate biomarkers [110]. For instance, patients with stroke and traumatic brain injury show different kinematic profiles and recovery progress even under identical therapy protocols [111, 112]. Moreover, changes in cognitive load or motivation can degrade, or enhance, movement quality during robot-assisted tasks [113].

In addition, another source of variability comes from rehabilitation platforms, which differ in feedback and control modality, generating distinct movement patterns from the same user [97]. For instance, Lokomat walking has been shown to reduce lower-limb EMG amplitudes compared with treadmill gait in stroke survivors and healthy adults [114]; a randomized trial in healthy adults found that a hip–knee exoskeleton altered muscle activation, muscle fatigue, and gait parameters within the first ten minutes of use [115].

In summary, even standardized biomarkers may fail when translated to a new environment, therapy or cohort. Without explicit evidence of transferability, reliable assessment cannot scale across institutions or be tailored to individual patients, which are two essential requisites for real-world impact.

3.1. Transferability and motor control models

Many biomarkers lack transferability because they often reflect specific features (e.g. movement trajectories or muscle activation amplitudes) without accounting for the underlying principles of motor control that drive those features. As a result, biomarkers derived in one context (e.g. a specific task or rehabilitation system) may fail to reflect functional capacity in another.

Thus, to enhance transferability, it is essential to reconsider our approach to modeling motor performance. Biomarkers intended for use across various patient populations should aim to represent fundamental mechanisms of motor control that are consistent among different neuromuscular diseases, accounting for compensatory movements and imbalanced motor modulation [17].

One promising example is the concept of muscle synergies: low-dimensional patterns of coordinated muscle activation that simplify motor control [116, 117]. These synergies can be extracted from surface EMG (sEMG) and analyzed for changes in structure, timing, or merging, offering physiologically meaningful biomarkers that reflect motor organization and adaptation [31].

Because synergy-based biomarkers are grounded in fundamental motor control strategies, rather than device-specific outputs, they offer a robust foundation for transferability, provided that methodological consistency is maintained in data processing (e.g. normalization and dimensionality reduction) [32, 118, 119].

Muscle synergy analysis (typically based on sEMG) has been used to characterize the changes in muscle pattern organization after neurological lesions. For example, studies on stroke populations have revealed changes in timing, structure, or merging of synergies that correspond with motor impairment and recovery trajectories [21, 31–36]. Stroke survivors often exhibit fewer or merged synergies, consistent with a breakdown in modular control [21, 33, 120]. These patterns are not only physiologically interpretable, but also task-relevant, and have been shown to evolve over time with therapy [21, 121–123]. These findings suggest that muscle synergies can effectively capture functional recovery dynamics. Thus, identifying changes in synergistic organization related to lesions may enable the use of muscle synergies as biomarkers for pathological states.

Moreover, recent longitudinal studies in upper-limb stroke rehabilitation have shown how EMG-derived synergies can track individualized recovery across therapy sessions, capturing patient-specific adaptation in both proximal and distal joints [37]. Additionally, muscular synergies have also been used to assess gait in Parkinson disease patients [38], and cerebral palsy [39].

Nonetheless, motor behavior is not only shaped by biomechanics, but it is also influenced by cognitive and psychological factors such as attention, fatigue, and motivation [61, 100]. These variables modulate how a patient engages with tasks, and thus how accurately their measurement of performance reflects their underlying capacity. Without accounting for them, biomarkers risk capturing task compliance or effort, rather than genuine motor ability.

Consequently, recent efforts have emphasized integrating user engagement and cognitive load metrics into biomarker frameworks, especially in human-robot interaction settings [62]. Studies have demonstrated that patient motivation and attentional focus can significantly influence movement quality and task performance [63]. Such factors, if not considered, may confound the interpretation of performance-based biomarkers. Integrating these dimensions is thus proposed as a strategy to improve the robustness and contextual relevance of biomarker models, particularly in long-term interventions involving rehabilitative or assistive robotic systems.

In summary, transferability requires biomarker frameworks that are physiologically grounded and context aware. They must accommodate the diversity of patient behavior and technological implementation while maintaining consistency in their clinical meaning. The following section outlines the core challenges that must be addressed to support this goal.

3.2. Challenges for transferability

Several key challenges continue to constrain transferability in practice, summarized in table 3:

3.3. Steps towards deploying transferability

To ensure that biomarkers can meaningfully support reliable assessment across diverse populations and contexts, we identified the actions listed in figure 4.

4. Shareability: enabling scalable biomarker frameworks

Standardization and transferability establish the basics for reliable assessment in neurorehabilitation. Yet to move to clinical integration at scale, a third pillar is essential: shareability. Shareability closes the loop

Table 3. Challenges for transferability.

Challenge	Description
How can neuromechanical biomarkers remain interpretable across different devices and task protocols, despite variability in mechanics and control strategies?	Biomarkers are often tightly coupled to particular devices or task protocols. Variations in mechanics and control logic introduce differences in signal profiles that undermine generalization [64, 114].
How can we design biomarkers that remain robust across the diverse motor phenotypes seen in stroke, Multiple Sclerosis, and other neurological conditions?	Stroke, spinal cord injury, and other neurological conditions produce highly variable motor phenotypes [65]. Biomarkers developed in homogeneous samples often lack robustness across patients with the same clinical condition.
What level of cross-validation is necessary to ensure that a biomarker reflects true recovery-related changes, rather than artifacts of a specific experimental setup?	Few studies validate biomarkers across different platforms, institutions, or patient subgroups [66]. Without this, it is unclear whether a biomarker reflects recovery mechanisms or experimental design artifacts.
How can cognitive and psychological states, such as attention, fatigue, or motivation, be integrated into biomarker frameworks without overcomplicating data collection?	Psychological and cognitive states (such as mental effort or fatigue) are rarely incorporated into sensor-based models, yet they strongly influence motor output and learning [61, 100].
How much structure is necessary in assessment protocols to ensure standardization, while still allowing adaptability to different clinical settings and patient needs?	Highly structured assessment protocols can limit adaptability to different patients or clinical settings [75]. However, standardization is essential for repeatability and comparability. The challenge lies in defining required fixed elements (such as task templates or calibration steps) that support consistency without sacrificing clinical flexibility.

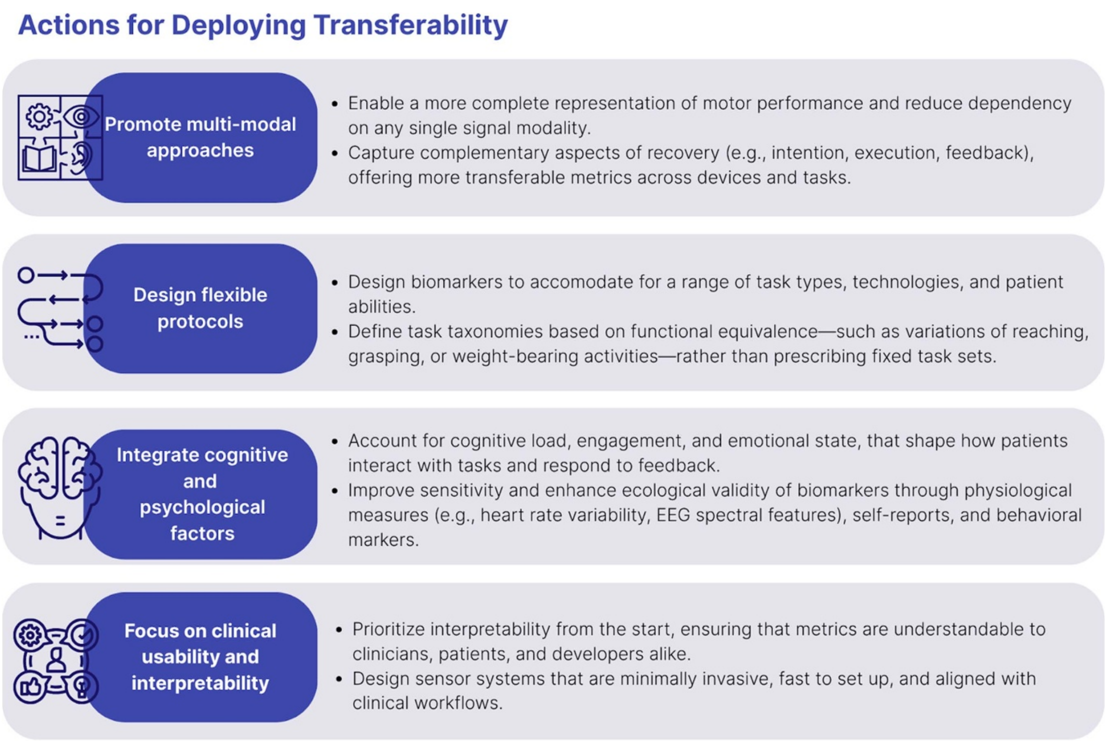

Figure 4. Actions for deploying transferability.

between standardization and transferability by making both the data structures defined under standardization and the external-validation evidence demanded by transferability openly available for inspection, reuse and aggregation. Without shareable datasets, code and metadata, even perfectly standardized and transferable biomarkers remain locked in single laboratories [67, 68].

Shareability means that data, tools, and methods are FAIR: *findable, accessible, interoperable*, and *reusable* across research groups, clinical institutions, and technological ecosystems [69]. It is therefore the pre-condition for reproducibility, multi-center validation, and cumulative scientific progress.

Shareability in neurorehabilitation, however, remains limited: while there exist many efforts to promote data openness [70–72], most raw data and processing scripts are locked in proprietary formats or undocumented in-house pipelines. As previously mentioned, institutions often default to restrictive policies due to regulatory limitations, while academic reward systems still favor novelty over openness. Valuable resources then remain under-used, slowing meta-analysis and consensus building.

In the sections that follow, we examine how increasing the shareability of neurorehabilitation data and tools can directly impact translational success, and why this shift is essential for building reliable, scalable assessment frameworks.

4.1. Shareability as a pathway to real-world implementation

Datasets that are annotated, interoperable, and shareable can be re-used to accelerate clinical validation, train more efficient decoders, validate biomarkers across populations, and streamline future device development. Conversely, datasets confined to isolated formats or lacking contextual metadata remain useful only to their creators, hindering progress. Well-curated datasets optimize resources and cut redundancy: researchers refine methods instead of re-collecting similar data, and clinicians can evaluate commercial tools against public standards.

For example, multimodal systems combining neural interfaces, EMG decoding, and robotic actuators have shown promising outcomes in controlled trials [11, 12]. These approaches generate detailed data on brain activity, muscle coordination, movement dynamics, and behavioral responses over time. In chronic stroke studies, EEG-controlled robotic exoskeleton-based therapy demonstrated sensorimotor rhythm modulation and inter-hemispheric power shifts as potential biomarkers for motor gains and long-term recovery [40–42, 73]. A clinical trial leveraging a hybrid neural interface offered comprehensive insights into patient progress using multimodal assessments [74]. Nonetheless, the clinical scalability of these technologies remains limited by setup complexity, gaps in integrated assessment, and the resources required for clinical validation and long-term data collection [44–46].

Shareability is progressing with an expanding corpus of resources that support neuromechanical biomarkers research: Many multimodal datasets provide publicly accessible resources that integrate neural, physiological, and biomechanical signals during functional motor tasks, suitable for studying longitudinal neuromechanical changes and inter-subject variability.

Although to our knowledge there are no systematic reviews cataloging available datasets for movement characterization, we have listed in table 4 several categories of resources to facilitate dataset discovery and reuse.

Across these resources, common aspects, such as standardized task protocols, detailed metadata, and open licensing, enable reuse for biomarker development and validation. However, significant gaps remain. The limited number of large-scale, fully multimodal datasets highlights the need for continued investment in standardized data collection efforts that combine neural, muscular, and biomechanical domains. What is still missing is a reference workflow endorsed by the community: a harmonized pipeline from raw signal to biomarker with minimum quality requirements.

To illustrate the current landscape of accessible multimodal datasets, we provide concrete examples in table 5. These include datasets for hand-gesture recognition [47–51], object reaching and grasping [52–54], EMG-based weakness mapping after stroke [55], as well as lower-limb datasets integrating EMG, inertial sensors, motion capture, and pressure data during gait and daily locomotor activities [56–60].

In summary, the practical value of shareability includes facilitating benchmark comparisons of biomarkers across various tasks, devices, and centers. It supports the development of generalizable models trained on heterogeneous data. Additionally, it provides traceable evidence required by regulators for clinical endpoints. More broadly, shareability fosters a collaborative culture in which insights and standards evolve through collective experience rather than isolated progress. Thus, engineers and clinicians can iterate together toward usable, scalable solutions.

The next section details the specific obstacles that still limit shareability and proposes concrete steps to overcome them.

Table 4. List of resources for multimodal movement datasets.

Category	Resource	Description	URL/References
Data Repositories	PhysioNet	Repository for physiological signals including EMG, EEG, and clinical waveforms	https://physionet.org
	Zenodo	General-purpose open-access repository maintained by CERN	https://zenodo.org
	Figshare	Open data repository widely used for biomechanical and neurophysiological datasets	https://figshare.com
	Dryad	Curated repository for datasets underlying peer-reviewed publications	https://datadryad.org
	GigaDB	Database supporting large-scale biological and biomedical datasets	http://gigadb.org
Data Journals	Scientific Data (Nature)	Peer-reviewed, open-access journal publishing dataset descriptors with mandatory data availability	www.nature.com/sdata/
Standardized Formats	BIDS (Brain Imaging Data Structure)	Community-driven standard for organizing neuroimaging and electrophysiological data	https://bids.neuroimaging.io
	EUROBENCH	Standardized benchmarking framework for robotic systems and human movement data	[71, 72]
Community Initiatives	ENIGMA	Worldwide consortium for large-scale neuroimaging and genetics studies	http://enigma.ini.usc.edu
	IEEE Standards Association	Developer of technical standards for biomedical signal processing and data exchange	https://standards.ieee.org
Analysis software	EUROBENCH PEPATO toolkit	Reproducible pipeline for performance assessment in biomechanics	[124]
	SynergyAnalyzer	Package for EMG- and kinematic-based muscle synergy extraction	[125]
Resources containing compilations of publicly available movement characterization datasets	Wei *et al*	Ataset of human locomotion during daily activities from 120 healthy participants. The manuscript lists publicly available sEMG datasets for lower limb movement characterization.	[126]
	Dimitrov *et al*	Dataset of high-density sEMG (HD-sEMG), high-resolution IMU signals, motion capture and force data of 10 healthy adults during locomotion modes. Discusses existing available gait datasets and identifies gaps in advanced sensing modalities	[127]
	Abdullah *et al*	Systematic review of 116 studies using multimodal data (motion capture, force plates, EMG) for gait analysis.	[128]
	Kyranou *et al*	Dataset for arm position-invariant myoelectric control. Provides a summary of the existing online datasets that contain recordings from different arm positions, from different sessions in one day or over the period of multiple days	[51]
	Hu *et al*	Presents benchmark datasets for bilateral lower-limb neuromechanical signals from wearable sensors during unassisted locomotion in able-bodied individuals	[129]

Table 5. Examples of publicly available multimodal movement datasets. Links to access the datasets are provided in the corresponding publications.

Study	Dataset Focus	Modalities	Tasks	Participants
Di Domenico *et al* [47]	Reaching and grasping movements	HD-sEMG (64ch), bipolar EMG (16ch), motion capture (Vicon), tactile glove	16 reaching and grasping tasks, including hand opening/closing, wrist movements, grasping (cylindrical, spherical, tridigital)	10 healthy subjects
Martínez-Zarzuela *et al* [48]	Video and IMU daily life activities	Video (webcam, 640 × 480), IMU (5 sensors)	13 daily activities: walking (forward, backward, along line), sit-to-stand, upper limb tasks	54 healthy subjects,16 with IMU
Palermo *et al* [49]	Posture and gait analysis	Inertial and kinematic data (Xsens MTw Awinda)	Gait with a wheeled robotic walker, at 3 different speeds/paths/locations	14 healthy participants
Van Criekinge *et al* [50]	Full-body gait	Full-body Kinematics (Vicon), kinetics (force plates), sEMG (16ch)	Barefoot walking at preferred speed	138 healthy subjects, 50 stroke survivors
Garro *et al* [52]	EEG-EMG reaching task for biomarker research	HD-EEG (128ch), sEMG (11ch)	Anterior reaching to 3 targets, with and without robotic assistance	40 healthy subjects
Boo *et al* [53]	Human locomotion during daily activities	Motion capture system, force plates, and sEMG	Level walking, stair ascent/descent, slope walking (ascent/descent), and sit-to-stand/stand-to-sit movements	120 healthy subjects
Jiang *et al* [54]	Multimodal abnormal movements and postures in rehabilitation training	EMG (16ch), IMU (6 sensors), motion capture, 230 insole pressure sensors per foot	Iiitated normal and abnormal body postures including normal standing still, leaning forward, leaning back, and half-squat	24 healthy subjects and 1 subject with spastic paraplegia
Kueper *et al* [55]	Error detection with active orthosis	EEG (64ch), EMG (8ch)	Tactile feedback to detect errors intentionally introduced during the flexion or extension movements of the active orthosis	8 healthy subjects
Voisard *et al* [56]	Clinical gait	4 IMU sensors	Standing still, walking 10 meters, turning around, walking back 10 meters, and stopping	260 participants: healthy individuals and patients with different neurological disease or orthopedic conditions
Furmanek *et al* [57]	Reach-to-grasp with visual perturbations	Motion capture, sEMG (10ch)	Reach to grasp virtual objects of different sizes, placed at different distances	20 healthy subjects
Mangalam *et al* [58]	Supra postural coordination	Motion capture, force plates, eye-tracker	Trail Making Test on stable/wobble board, standing upright	48 healthy subjects
Mattei *et al* [59]	Hand movements	Dry EEG (32ch), Virtual Glove	3 hand movements: open/close, finger tapping, wrist rotation + rest (motor execution and motor imagery)	11 healthy subjects
Jeong *et al* [60]	Upper extremity movement tasks	EEG (60ch), sEMG (7ch), EOG (4ch)	6 arm-reaching movements, 3 hand-grasping, 2 wrist-twisting (motor execution and motor imagery)	25 healthy subjects

Table 6. Challenges for shareability.

Challenge	Description
How can we establish common data standards and formats so that neuromechanical datasets recorded with different sensors, sampling rates, and task designs remain FAIR?	Collecting data with different hardware and varied task protocols makes integration and comparison complex [130]. Without standardized ways to describe device setups, patient details, and task conditions, bringing datasets together or drawing meaningful comparisons quickly becomes a challenging and error-prone process.
How can we make analysis pipelines transparent, modular, and openly documented so that biomarkers can be independently verified and reused across studies?	Many signal processing and feature extraction methods are developed in-house and remain unpublished or insufficiently documented. Even when similar biomarkers are studied, inconsistencies in preprocessing and analysis prevent meaningful cross-validation [131, 132]. Without transparent, modular pipelines, findings cannot be independently verified or reused.
How can we navigate regulatory and ethical constraints on sensitive physiological data to enable secure, compliant sharing across centers and borders?	Neurorehabilitation data often include sensitive physiological signals, making data sharing subject to strict regulations [133]. GDPR and related frameworks may impose strict conditions [134] and in the absence of clear protocols many institutions default to restrictive practices, especially in multi-center collaborations.
What incentives and resources are needed to encourage researchers to publish FAIR-compliant datasets and tools despite concerns over workload, intellectual property, and competitive advantage?	Preparing shareable datasets demands time, effort and infrastructure yet it is seldom recognized in hiring or funding decisions [135]. The lack of credit, fears of misuse, and perceived loss of competitive advantage are keeping valuable data siloed [136, 137].

4.2. Challenges for shareability

While the scientific value of open, interoperable data is widely acknowledged, several persistent barriers continue to limit the practical realization of shareability in neurorehabilitation, outlined in table 6.

4.3. Steps towards for enabling shareability

Promoting shareability in biomarker research requires both technical infrastructure and cultural change. Figure 5 provide a roadmap for creating collaborative and scalable systems for data and tool dissemination. These recommendations aim to transform shareability from a logistical obstacle into a strategic enabler, allowing to consolidate knowledge and deliver reliable assessment.

5. Future directions

The integration of biomarkers into neurorehabilitation practice represents both a pressing need and a timely opportunity toward reliable assessment. We argue that advancing biomarker use in neurorehabilitation requires focused attention on three key 'pillars': (i) making methods and results consistent, (ii) ensuring that findings can be applied across real-world clinical settings, and (iii) enabling effective data and tools sharing. From this perspective, successful implementation will depend on coordinated efforts that bridge research and clinical practice, establishing systems in which results can be validated, reused, and extended.

Several ongoing large-scale initiatives illustrate how elements of these actions are already being addressed in practice. For example, European research infrastructures such as EBRAINS are actively promoting data sharing, standardization, and interoperability in neuroscience by providing shared platforms and governance models that support collaborative validation and reuse of complex datasets. In parallel, collaborative projects such as AISN (Integrating AI in Stroke Neurorehabilitation) are developing AI-based methods for stroke rehabilitation by integrating multimodal clinical and sensor data into standardized formats, directly addressing challenges related to transferability and shareability.

These initiatives show how coordinated action at the infrastructure and consortium level can support the principles discussed in this paper, without placing the burden solely on individual research groups or clinical centers. They also highlight the importance of shared resources, common data models, and cross-disciplinary collaboration in advancing neuromechanical biomarkers toward clinical relevance.

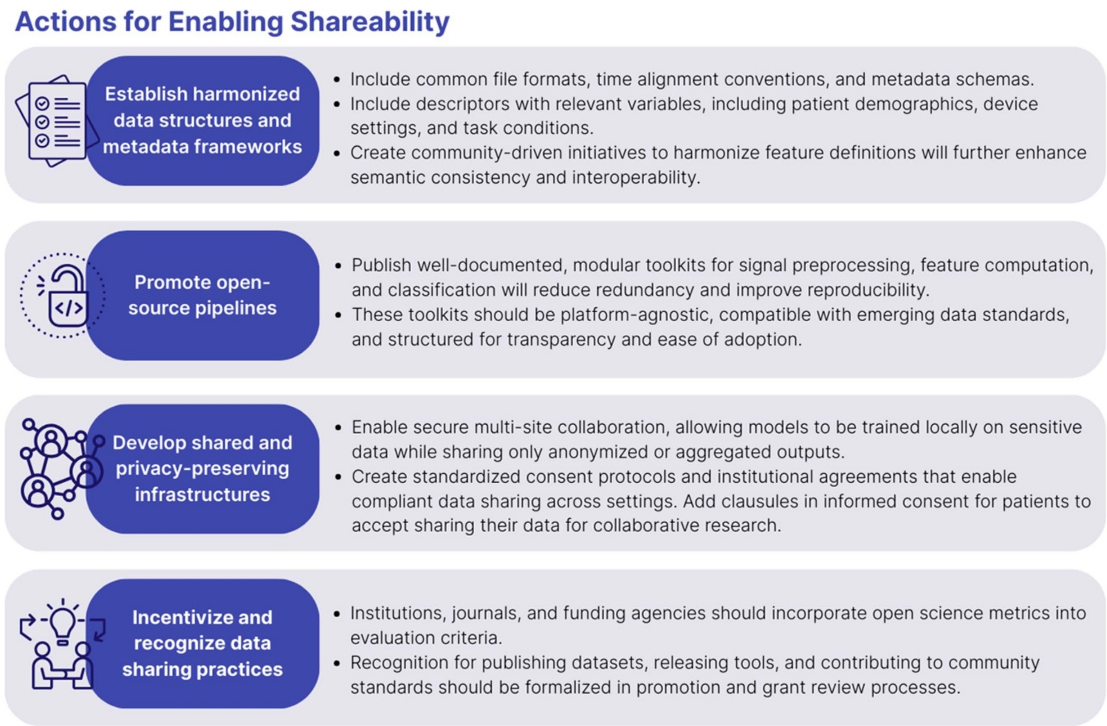

Figure 5. Actions for enabling shareability.

Looking ahead, progress will require collective, multi-stakeholder efforts rather than isolated technical advances-. Aligning methodological development, clinical practice, and data governance is essential to support scalable and reliable assessment in neurorehabilitation. Implementing concrete actions for standardization, transferability, and shareability represents a complex coordination and governance challenge. Crucially, this process must begin with dedicated resources and places that foster dialogue among stakeholders, such as the dedicated workshop that originated this perspective article. Figure 6 summarizes high-level directions identified during this experts' discussion, highlighting potential starting points for action and serving as a call to action for the community.

6. Conclusion

Reliable assessment in neurorehabilitation remains a major challenge. Current practices largely rely on subjective clinical scales, characterized by substantial methodological variability and limited scalability. These limitations hinder personalized treatment planning, longitudinal tracking of recovery, and robust evaluation of intervention effectiveness at both individual and population levels. Neuromechanical biomarkers offer a promising pathway toward more objective, interpretable, and reproducible assessment. However, to achieve broad clinical applicability, they must be developed, validated, and deployed under clearly defined conditions.

Drawing on experts' discussions and representative studies, we have proposed three pillars for achieving this path:

- Standardization: Agreeing on methods and definitions so results are reliable and comparable.
- Transferability: Making sure findings apply to different people, groups, and situations, not just specific research settings and can be adopted in clinical practice with little or no effort.
- Shareability: Creating ways for researchers to share and build on each other's data and tools.

Beyond technical challenges, significant clinical, cultural and institutional barriers continue to impede adoption. Reluctance to share data, misaligned incentives, regulatory uncertainty, and fragmentation between research and clinical workflows limit cumulative progress. Addressing these obstacles will require coordinated efforts that extend beyond technology innovation, including the development of shared frameworks, open infrastructures, and sustained interdisciplinary collaboration. Through such alignment,

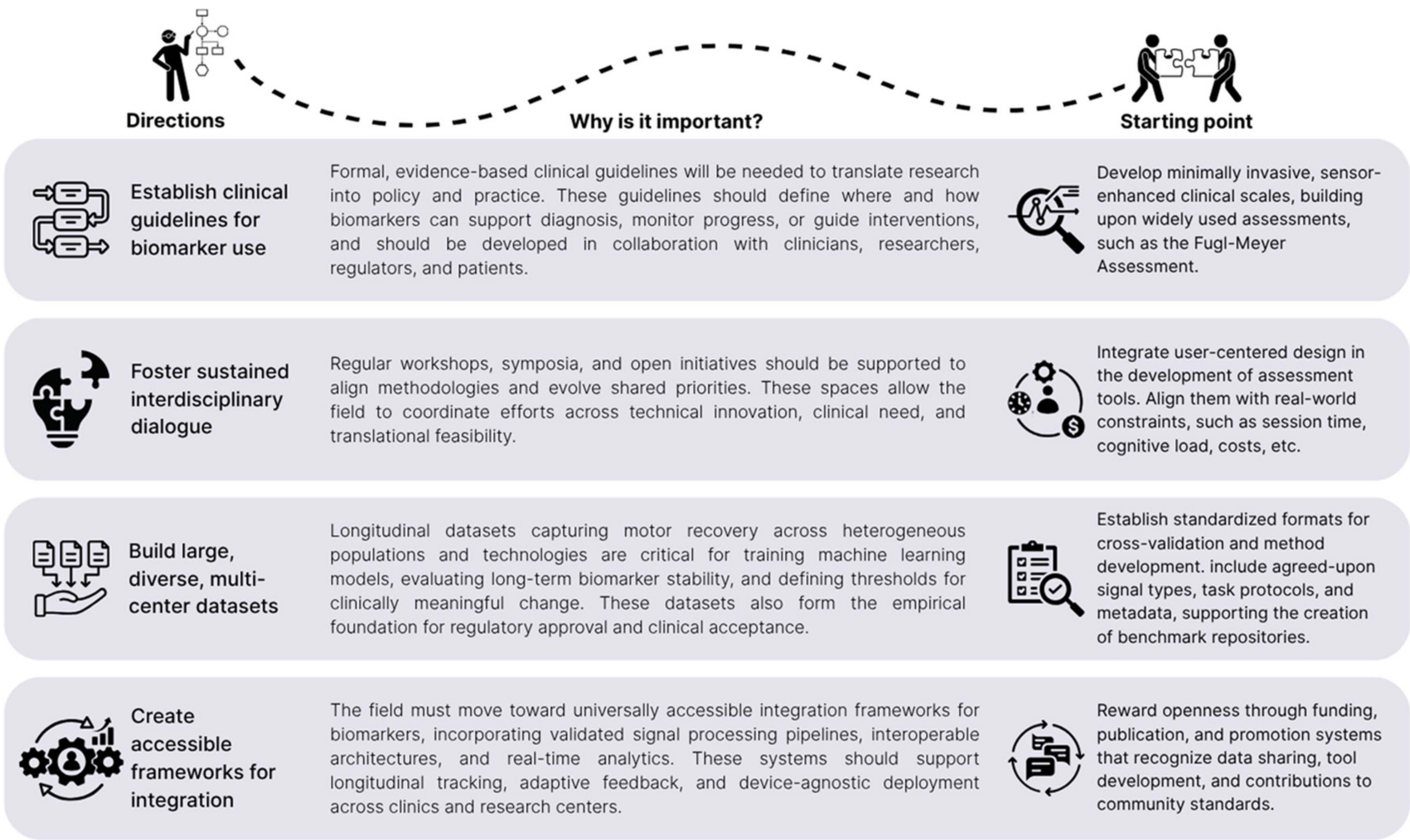

Figure 6. Directions for integrating neuromechanical biomarkers in motor rehabilitation.

biomarker research can evolve from promising prototypes into scalable, clinically meaningful, and readily adoptable tools that effectively address the practical needs of patients, clinicians, and healthcare systems.

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Data availability statement

No new data were created or analysed in this study.

Ethical statement

Authors declare no conflict of interest.

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