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Motion tracking systems in rehabilitation: a comparative analysis of sensor technologies, algorithmic methods, and clinical relevance

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Abstract: Motor impairments are a common consequence of neurological and orthopedic conditions and often require long-term monitoring and rehabilitation. Digital motion-tracking systems — including optical marker-based solutions, optical markerless systems based on red-green-blue cameras and depth sensors, wearable inertial measurement modules, and their hybrid combinations — enable quantitative assessment of body kinematics, detection of compensatory movement patterns, and objective tracking of patient recovery. This review systematises modern sensor technologies for motion tracking in rehabilitation, evaluates their metrological characteristics, algorithmic approaches for data processing and interpretation, and determines their clinical relevance and development pathways. A comparative analysis of four main classes of systems shows that optical marker-based technologies provide the highest spatial accuracy but remain limited by high cost and laboratory dependence; markerless optical systems demonstrate moderate accuracy yet offer promising opportunities for telerehabilitation; inertial measurement modules provide mobility and reproducibility but require drift-compensation algorithms; hybrid multisensor architectures combine the advantages of both optical and inertial approaches and achieve high accuracy even under dynamic conditions. The review also analyses sensor-fusion algorithms such as extended Kalman filters and Madgwick filters, methods for computing kinematic parameters, and machine-learning models for automated motion interpretation, including explainable artificial-intelligence frameworks that improve model transparency and support clinical decision-making. Clinical-validity assessment indicates that commonly used metrics such as range of motion, gait-phase characteristics, and angular parameters show high consistency, whereas more complex indicators may vary and require cautious interpretation. Key challenges include the lack of standardised measurement protocols, environmental influences, limited interpretability of algorithms, and difficulties integrating systems into clinical workflows. Promising future directions include the development of multimodal datasets, adaptive sensor-fusion strategies, transparent artificial-intelligence analytics, and scalable home-based rehabilitation solutions, highlighting the potential of integrated multisensor technologies to support personalised rehabilitation.

Keywords: digital sensor systems, motion tracking, clinical rehabilitation, kinematic analysis, spatiotemporal parameters, machine learning, explainable artificial intelligence, hybrid systems, telemonitoring.

1. Introduction

Motor impairments of the upper and lower limbs are common consequences of neurological, orthopaedic, and musculoskeletal disorders, significantly affecting patients' functional independence and quality of life. According to WHO estimates, more than 1.7 billion people worldwide have musculoskeletal disorders, and up to 80% of individuals after stroke experience upper-limb dysfunction requiring long-term rehabilitation [1]. Successful recovery depends on timely monitoring of motor functions, quantitative assessment of progress, and personalised intervention planning.

Traditional movement-assessment methods based on expert clinical examination or questionnaire-based scales (e.g., Fugl–Meyer Assessment, ARAT) are well established; however, they have significant limitations: subjectivity, low resolution with respect to subtle motor changes, inability to support high-frequency monitoring, and insufficient sensitivity to micro-dynamics of recovery [2]. In addition, many rehabilitation programs occur outside controlled environments, making it difficult to evaluate progress between clinical visits objectively.

The rapid development of digital technologies has enabled non-invasive quantitative monitoring of movement. Modern digital tracking systems — optical marker-based, optical markerless (RGB, RGB-D), wearable inertial modules (IMU), and their hybrid combinations — allow quantitative assessment of movement kinematics, detection of compensatory patterns, objective tracking of rehabilitation progress, and generation of personalised recommendations [3–5]. Marker-based optical systems provide the highest accuracy and are considered the "gold standard," yet their high cost, operational complexity, and dependence on laboratory environments limit their use in clinical and home settings [6]. In contrast, markerless cameras and IMUs are simpler and more accessible, contributing to their active deployment in telerehabilitation and out-of-clinic monitoring [7–9].

The relevance of digital sensors in rehabilitation is driven by the possibility of objective, frequent, and standardised home-based monitoring with minimal dependence on human factors. In this context, growing interest has been directed toward hybrid systems that combine inertial and optical modalities, achieving enhanced accuracy, robustness to occlusion, and broader applicability [10].

Despite significant progress, the optimal technology for routine rehabilitation assessment in real-world conditions remains an open research question. The need for systems that provide accuracy, usability, low cost, and clinically interpretable outputs underscores the importance of comparative evaluation of existing technologies and determining their clinical relevance.

2. Object and subject of research

The object of this study is digital motion-tracking systems used to assess patients' motor function during rehabilitation.

The subject of the study includes operating principles, metrological characteristics (accuracy, reliability), algorithmic processing methods, and the clinical relevance of motion-tracking systems, including: optical marker-based systems; optical markerless (RGB/RGB-D) systems; wearable inertial modules (IMU); and hybrid multisensor solutions.

Optical marker-based systems (Vicon, OptiTrack) employ cameras and reflective markers to reconstruct 3D kinematics with high accuracy (<2°) and are widely used in biomechanics as a reference standard [6]. Their drawbacks include high cost, the need for patient preparation, space requirements, and sensitivity to occlusions.

Markerless optical systems (Kinect, Azure Kinect, OpenPose-like tools) use RGB/RGB-D cameras and computer-vision algorithms to estimate movements without physical markers. Typical errors range from 5–20 mm or 2–4° for joint angles, but depend on acquisition conditions, lighting, and camera positioning [7,11].

Wearable inertial modules (Xsens, DorsaVi, Valor IMU) combine accelerometers, gyroscopes, and magnetometers. They provide mobility, high sampling rates, and suitability for home use. Typical joint-angle errors range from 1.8–4°, but are affected by sensor mounting, magnetic interference, and drift, and require sensor-fusion algorithms (EKF, Madgwick) [8,9].

Hybrid systems integrate IMUs with optical sensors and improve metrological performance through sensor fusion. Several studies have reported ICC >0.9 and RMSE <2° during functional tasks (e.g., "sit-to-stand") [10].

Despite significant progress, key limitations of current systems include:

1) insufficient accuracy in real-world settings;
2) dependence on environmental factors (lighting, occlusions);
3) calibration requirements and sensitivity to sensor placement;
4) limited clinical validity for complex motor patterns;
5) lack of standardised measurement protocols;
6) challenges in data interpretation in clinical practice.

These limitations hinder the widespread adoption of such systems in clinical workflows and home-based monitoring, highlighting the need for detailed analysis, comparison, and optimization of their characteristics.

3. Target of research

The aim of the study is to identify optimal technologies and algorithmic methods for assessing patients' motor function based on a comparative analysis of modern motion-tracking systems, taking into account their technical characteristics, clinical relevance, and practical applicability.

To achieve this aim, the following research objectives are formulated:

1) analyze contemporary motion-tracking technologies (optical marker-based, markerless, IMU systems, hybrid solutions);
2) evaluate their metrological properties (accuracy, reliability, sampling rate, robustness to noise);
3) investigate algorithmic methods for processing and interpreting sensor data (sensor fusion, kinematic models, ML, XAI);
4) assess the clinical validity and relevance of metrics used for motor assessment;
5) determine the limitations of deployment in clinical and home environments.

4. Literature analysis

In rehabilitation practice, digital motion-tracking systems are gaining increasing importance, providing objective quantitative assessment of a patient's motor function and enabling monitoring of therapeutic progress based on kinematic and spatiotemporal parameters [12].

Modern systems can be classified into optical marker-based, optical markerless, non-contact camera-based, wearable inertial measurement units (IMU), and hybrid multisensor solutions, each with specific limitations, advantages, and application domains [5,13,14]. Marker-based optical systems, such as Vicon and Qualisys, are traditionally considered the "gold standard" due to their high accuracy in laboratory environments [13]. In contrast, markerless approaches using depth cameras (e.g., Microsoft Kinect) or computer-vision algorithms provide simpler setup and better scalability in clinical and home environments [14].

Wearable inertial measurement units (IMU), represented by systems such as Xsens, Noraxon, or DorsaVi, are characterized by high sampling rates and mobility, making them suitable for ambulatory monitoring and telerehabilitation [5,8]. Hybrid multisensor systems combining IMUs and optical technologies offer a balance between accuracy and versatility, compensating for the limitations of individual platforms and enabling use in complex scenarios such as home-based tracking or environments with occlusions [14].

4.1 Optical Marker-Based Systems

Optical marker-based systems rely on active or passive reflective markers placed on anatomical landmarks, which are captured by multiple high-speed infrared or visible-light cameras. Marker coordinates are calculated through triangulation, enabling reconstruction of three-dimensional kinematics with high spatial and temporal accuracy [13,16,17].

Due to their very low positioning errors (<1 mm) and high sampling rates (100–500 Hz), marker-based systems such as Vicon, OptiTrack, and Qualisys are considered the "gold standard" for laboratory-based biomechanical research and clinical protocols [13,16]. A review by Ray et al. reported joint-angle measurement errors under controlled conditions below 2°, which represents the highest precision among available motion-capture technologies, as illustrated in Figure 1 [17].

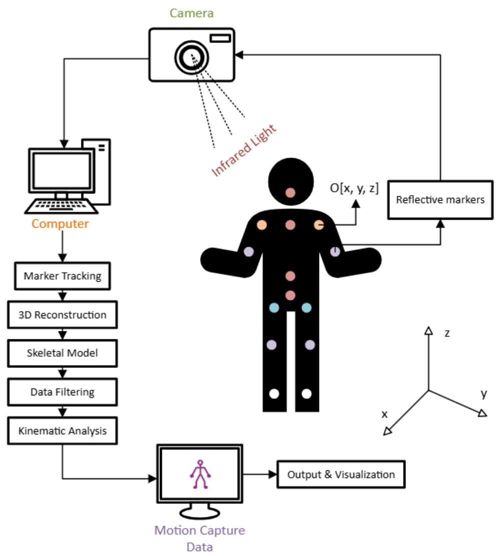

Figure 1. General structure of an optical marker-based motion-tracking system.

Despite their high accuracy, the practical use of marker-based systems in rehabilitation outside laboratory settings is limited. Major disadvantages include the high cost of equipment, complex initial calibration, the need for manual marker placement, strict space requirements, and strong susceptibility to occlusions, which may reduce accuracy or lead to incomplete data [18,19]. These factors make them unsuitable for routine clinical operation or home-based environments, where conditions are less controlled.

Therefore, although marker-based systems offer superior accuracy and repeatability of 3D kinematics, their application remains largely restricted to laboratory studies or specialized clinical centres, while modern rehabilitation practice tends to favour more mobile and accessible instruments.

4.2 Optical Markerless / Non-contact Camera-based Systems

Optical markerless motion-tracking systems operate without the use of physical markers attached to the patient's body. A general schematic of such a system is shown in Figure 2. They employ one or more cameras (RGB, RGB-D, stereo cameras) combined with computer-vision algorithms to detect key points and reconstruct human pose and kinematics in 2D or 3D space [20–22]. These systems offer substantially greater convenience, as they eliminate the need for patient preparation and marker placement, making them promising for telerehabilitation and home-based monitoring [21, 23].

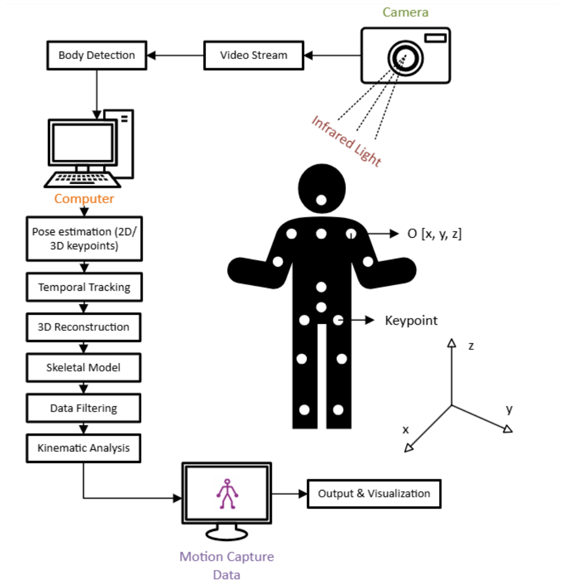

Figure 2. General schematic of a markerless camera-based motion-tracking system.

Depth-camera-based systems (e.g., Microsoft Kinect series) typically demonstrate mean spatial errors of 5–20 mm and joint-angle errors of approximately 2.3° ± 4.0°, with intra-class correlation coefficients (ICC) > 0.80, indicating suitability for many clinical and domestic applications [7, 23, 24]. For example, a review by Webster and Celik (2014) confirmed the reliability of Kinect-based systems for upper-limb tracking during rehabilitation tasks, while Ma et al. (2018) demonstrated high correlation (> 0.90) and low relative error when compared with marker-based systems for several spatial parameters [7, 23].

At the same time, markerless solutions exhibit increased sensitivity to environmental conditions, including illumination, background, clothing, and camera position relative to the body. They also demonstrate higher error in the frontal and transverse planes compared with marker-based systems, due to the limitations of two-dimensional projection and algorithmic challenges in reconstructing complex segmental motion [21, 22, 25].

Therefore, in clinical contexts, their value is determined less by absolute accuracy than by their ability to provide stable and sufficiently informative data for specific scenarios: tracking movement dynamics, telerehabilitation, and assessing functional activity in daily-life conditions. Due to their ease of use and low cost, markerless systems are considered a key direction in the evolution of digital biomechanical monitoring and personalised rehabilitation.

4.3 Wearable Inertial Measurement Units (IMUs)

Wearable inertial measurement units (IMUs) consist of sensing elements — accelerometers, gyroscopes, and sometimes magnetometers — attached to body segments to record linear accelerations, angular velocities, and orientations [26–28]. Data from individual sensors are transmitted to a computer or embedded controller for subsequent filtering, calibration, and sensor fusion, enabling reconstruction of movement in three-dimensional space.

A general operating principle of IMU-based systems is illustrated in Figure 3(a): the measurement module comprises inertial sensors, electronic signal-processing circuitry, a wireless communication module (Bluetooth), a power source, and a housing. During data acquisition, segment orientation parameters (roll, pitch), velocity, and acceleration are represented in the time domain (Figure 3(b)), allowing analysis of kinematics and inter-segmental coordination [29].

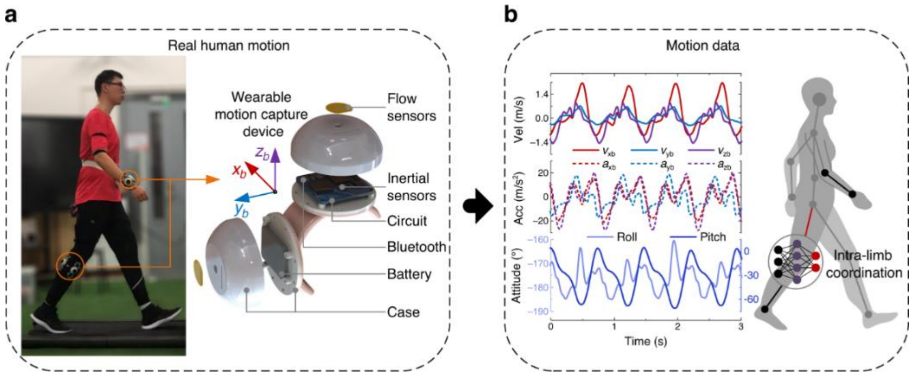

Figure 3. Architecture and operating principle of a wearable IMU system: (a) components of the sensing module (inertial sensors, processing board, battery, wireless communication); (b) example of recorded movement dynamics (velocity, acceleration, angular values) [29].

In standard configurations, IMUs may be positioned on various parts of the body — pelvis, trunk, shoulders, forearms, hands, thighs, shanks, and feet — covering the major degrees of freedom of the musculoskeletal system, as shown in Figure 4 [30]. High-frequency sampling (60–240 Hz) enables assessment of both slow and rapid movements, including gait-phase structure or manipulation characteristics of upper-limb activity.

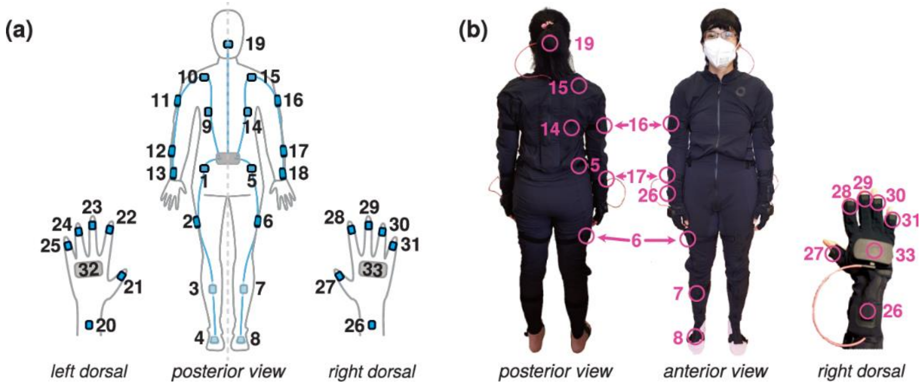

Figure 4. Arrangement of IMU sensors on the human body: (a) standard anatomical segments, (b) example of real sensor placement on an experimental subject [30].

Compared with optical marker-based systems, IMUs demonstrate higher error when estimating spatial joint angles: the root-mean-square error (RMSE) typically ranges from 2° to 8°, and may increase under complex multi-planar kinematic conditions [31, 32]. However, IMU systems show high reliability in repeated measurements, as well as excellent reproducibility of spatiotemporal parameters, making them suitable for clinical monitoring and telerehabilitation [33].

The main methodological challenges include signal drift in the absence of absolute references, sensitivity to sensor displacement on the body, the influence of magnetic fields on magnetometers, and the need for fusion algorithms (e.g., extended Kalman filter) and segment registration [28, 31]. Despite these limitations, IMUs are widely used in sports biomechanics, neurological rehabilitation, and home monitoring due to their portability, low cost, and ease of deployment [29, 33].

4.4 Hybrid and Multisensor Solutions

Hybrid motion-tracking systems combine different sensing technologies — most commonly inertial measurement units (IMUs) with optical devices (RGB, RGB-D, stereo, or marker-based cameras), or IMUs in combination with marker-based motion-capture systems, as illustrated in Figure 5. This approach enables the integration of the advantages of each technology while minimising their individual limitations and providing enhanced accuracy in three-dimensional kinematic reconstruction [27, 28, 30].

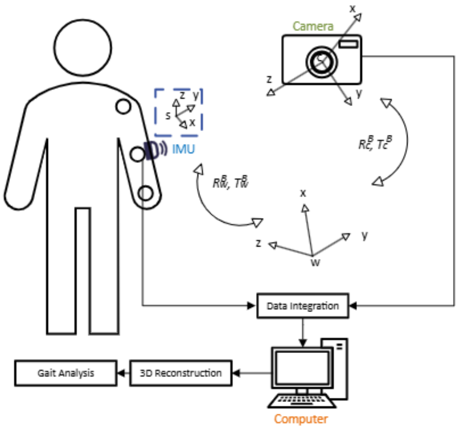

Figure 5. General schematic of a hybrid motion-tracking system combining IMUs and optical cameras.

Combining IMUs with camera-based systems improves robustness against occlusions, since optical data compensates for IMU drift and orientation errors, while inertial data enable movement tracking when the camera partially or fully loses sight of the limbs [2, 4]. Systems of this type are capable of reconstructing segmental joint angles with accuracy approaching that of marker-based systems — RMSE is often < 5°, and the repeatability of movement parameters remains high even in complex scenarios [29, 30, 34].

According to Nagorny et al., hybrid approaches are promising for rehabilitation and clinical monitoring tasks because they provide a balance between accuracy, mobility, and robustness to disturbances, and allow effective application of advanced data-processing methods (ML/XAI) to determine kinematic and functional indicators [35]. Similar results were presented by Spilz et al. (2025), who described a multimodal dataset containing synchronised IMU and MoCap data that enables training of models for gait and exercise analysis with laboratory-level accuracy [30].

Despite these advantages, hybrid systems have significant practical limitations — installation complexity, the need for careful calibration and temporal synchronisation, as well as demanding processing of large data volumes. Furthermore, the cost of such solutions is often higher than for IMU-only or camera-only systems [27, 28, 36].

In the context of rehabilitation, multisensor platforms represent an important development pathway because they provide high laboratory-level accuracy, potential for use outside laboratory environments, and integration with machine-learning algorithms and telemedicine systems.

4.5 Comparative Analysis and Technology Selection

A comparison of modern motion-tracking tools indicates that technology selection cannot be based solely on spatial-accuracy values. Although marker-based optical systems are traditionally regarded as the gold standard due to their high accuracy, repeatability, and capability to perform comprehensive three-dimensional motion reconstruction, their wider use in clinical and rehabilitation settings outside the laboratory is limited. The primary barriers include high cost, installation complexity, requirements for controlled environments, and the need for specially trained personnel [27, 37].

Table 1 (full extended version provided in Appendix) summarises the characteristics of the main classes of motion-tracking systems, including their operating principles, typical measurable parameters, accuracy level, advantages, limitations, and common application scenarios.

Table 1. Comparative characteristics of motion-tracking technologies

Technology class	Operating principle	Typical measured parameters	Spatial accuracy	Advantages	Limitations	Typical scenarios
Marker-based optical	Cameras detect reflective markers	Spatial kinematics, joint angles, trajectories	High	Highest accuracy; validation standard; high sampling rates	High cost; complex setup; laboratory conditions required	Biomechanical research; clinical diagnostics
Markerless optical	Cameras + CV / pose estimation	Keypoints (2D/3D), segmental kinematics	Medium	Easy to use; no markers; rapid setup	Sensitive to lighting changes; lower accuracy than marker-based systems	Clinical use; telerehabilitation; home use
Wearable IMUs	Accelerometer + gyroscope (+ magnetometer)	Segment orientation; velocity; acceleration	Medium	Mobility; low environmental dependence; long-term monitoring	Drift; sensitivity to placement; require filtering	Home monitoring; long-term observation
Hybrid systems	Combination of IMU + optical	Combined parameters; extended kinematics	High–very high	Compensate for individual system drawbacks; higher accuracy in real-world environments	Higher cost; complex calibration; synchronisation required	Clinical use; high-precision assessment; telerehabilitation

The aggregated data show that methodology selection should rely not only on hardware characteristics but also on the specific clinical or research scenario. Marker-based optical systems remain the preferred choice for high-precision laboratory studies and complex biomechanical modelling [27, 37]; however, their use in telerehabilitation and everyday monitoring is limited.

Markerless optical systems offer substantially greater practicality due to easy deployment and no requirement for marker attachment, while providing sufficient accuracy for clinical assessment and remote monitoring [30, 37].

Wearable IMU systems provide the highest mobility and minimal dependence on environmental conditions, while modern sensor-fusion algorithms help reduce orientation error. This makes them a promising solution for home monitoring, long-term data acquisition, and telerehabilitation.

Hybrid platforms combine the strengths of optical and inertial methods, offering enhanced reconstruction accuracy and better measurement stability during occlusions or complex kinematics. Their disadvantages include more complex setup and higher operational cost; however, they are gaining popularity in clinical studies and predictive modelling due to the improved quality of data [36, 38].

5. Methodology of Comparison

The review was conducted as a comparative, systematised analysis with the possibility of quantitative synthesis (meta-analysis) where methodological and sampling homogeneity of data was sufficient [39]. The research question was formulated using the PICO framework, where:

1. P (Population) — patients with neurological or orthopaedic impairments undergoing rehabilitation;
2. I (Intervention) — application of motion-tracking technologies (e.g., Kinect/Azure Kinect, IMU systems, Vicon, Leap Motion, LiDAR);
3. C (Comparator) — standard therapy or other sensor networks;

4. O (Outcomes) — measurement accuracy, clinical effectiveness, usability, and economic indicators [40].

Studies were included if they involved patients or healthy participants and used technologies for rehabilitation assessment or support with measurable outcomes. Exclusion criteria comprised: absence of primary clinical data, review papers, animal studies, and articles without full text available [41, 42].

A search was performed in PubMed, IEEE Xplore, Scopus, and Google Scholar from 2011 to the present, in English, Ukrainian, and Polish [43]. Primary screening was carried out independently by two reviewers, and inter-rater agreement was calculated using Cohen's κ, with values ≥ 0.70 considered acceptable [44].

To standardise indicators, measurement harmonisation was performed: angular values were converted to degrees, distances to millimetres, temporal parameters to milliseconds, and economic indicators normalised to US dollars according to current-year inflation indices [45].

Risk of bias was assessed using:

1. RoB 2 — for randomised studies,
2. ROBINS-I — for non-randomised studies [46].

Where data were sufficiently homogeneous, a meta-analysis with a random-effects model was performed, with heterogeneity assessed using I^2. In cases of high heterogeneity, narrative synthesis was applied with grouping by technology type and clinical profile [47].

Visualisation of results included construction of forest plots, "error–cost" diagrams, and radar charts, as well as a PRISMA flow diagram of study selection [48]. As the review was based on published data, no additional ethical approval was required. The review protocol was registered in an open repository (specific registry stated according to journal requirements).

6. Comparative Analysis of Motion-Tracking Technologies

To systematically compare the characteristics of motion-tracking technologies and their applicability in clinical and home environments, 20 studies were analysed, covering markerless optical systems, wearable IMU platforms, and hybrid solutions.

A concise description of authors, publication year, system type, study context, sample size, and primary aim is presented in the Appendix (full version of Table 1 is provided in the Appendix). These data informed the comparative analysis and subsequent stratification of technologies according to their clinical application, summarised in Table 2 (full extended version available in Appendix). Notably, the studies demonstrate a clear advantage of IMU-based and markerless systems for telerehabilitation and home monitoring, whereas marker-based optical systems remain the gold standard for precise laboratory-based biomechanical measurements.

Table 2. Structured review of studies on contemporary motion-tracking systems

№	Authors, year	System type	Domain	Sample size	Aim
1	Faity, G.; Mottet, D.; Froger, J., 2022	Kinect v2 vs Vicon	Upper limb post-stroke	26 healthy	Validity & reliability
2	Mengxuan Ma, Rachel Proffitt, Marjorie Skubic, 2018	Kinect V2 + game	Post-stroke rehabilitation	30	Accuracy, validity
3	S. Almasi et al., 2022	Kinect systems	Post-stroke rehabilitation	various	Review of validity
4	David Webster & Ozkan Celik, 2014	Kinect-based	Elderly care and stroke	various	Review
5	A. Mobini, S. Behzadipour, M. Saadat, 2015	Kinect	Upper-body rehabilitation	30	Reliability
6	Young-Shin Cho et al., 2018	IMU	Gait	3	Validity, reliability
7	Young-Shin Cho et al., 2018	IMU	Gait	3	Validity

Continuation of Table 9

8	Giuseppe Prisco et al., 2025	IMU (review)	Gait	32 studies	Systematic review
9	Yiou Sun et al., 2025	IMU	Post-stroke gait	16	Optimal placement
10	Myeounggon Lee et al., 2018	IMU (shoe)	Parkinson's disease	17	Validity
11	Smith J. et al., 2024	IMU	Upper/lower limbs	n/a	Validity
12	Ye Zhu et al., 2024	IMU + Vicon	STS force & angles	28	Validity
13	Bojan Milosevic et al., 2020	IMU + Kinect	Home rehabilitation	n/a	Comparison with marker-based
14	Pfister A. et al., 2014	Kinect vs Vicon	Gait	20	Correspondence
15	Andreas Spilz et al., 2025	IMU + MoCap	Rehab exercises & gait	19	Multimodal dataset
16	Gabrielle E. Deane et al., 2024	IMU + Vicon	Gait	10	Kinematic prediction
17	Gök et al., 2017	Kinect + rehab	Upper limb	20	Effectiveness
18	Liquan Guo et al., 2023	IMU + glove	Remote rehabilitation	120	Effectiveness
19	Rajat Kumar Das et al., 2016	Kinect + OpenSim	Single-Limb Stance	n/a	Feasibility
20	A. Kaku et al., 2020	IMU	Neurorehabilitation	48	Primitive classification

The complete dataset underpinning the analysis of accuracy, reliability, and clinical effectiveness of the various sensing technologies is presented in the Appendix (full text of Table 2 is provided there).

Angular measurement error was evaluated using root-mean-square error (RMSE). Figure 6 presents summarised RMSE ranges for different sensor systems, derived from the aggregated dataset (Table RMSE_Ranges). Inertial sensors demonstrated the best accuracy: mean RMSE values for the estimation of kinematic parameters during gait ranged from approximately 1.39–4.37°, corresponding to high-quality reconstruction of joint angles across multiple planes. When predictive IMU-based models were used during tasks involving varying speeds, accuracy remained stable (1.9–6.9°).

Comparisons between IMUs and Kinect for ROM analysis revealed error values of approximately 3–8°, somewhat higher but still acceptable for numerous rehabilitation scenarios, including home-based monitoring. This aligns with the physical properties of the respective technologies: Kinect relies on optical reconstruction and virtual estimation of joint centres, whereas IMUs directly register segment accelerations.

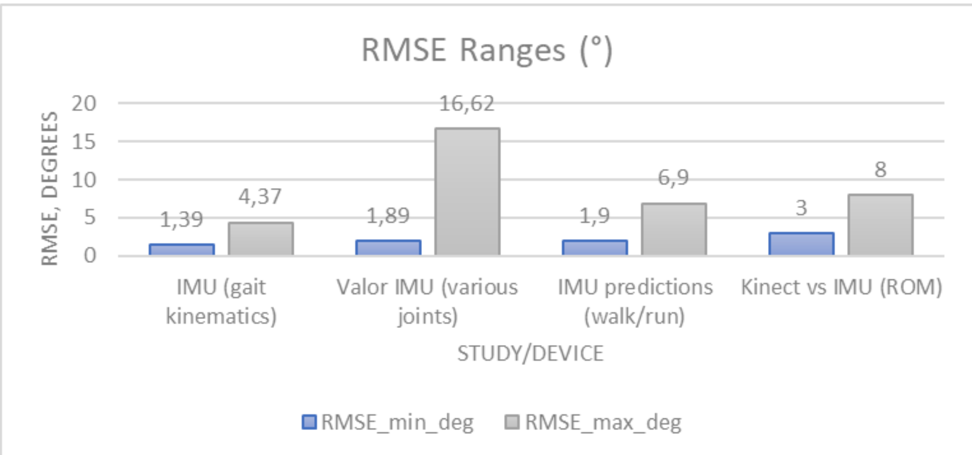

Figure 6. Comparison of RMSE for different sensor systems.

Measurement repeatability was assessed using the intra-class correlation coefficient (ICC), presented in Figure 7 and summarised in Table ICC_Ranges. Inertial systems demonstrated the highest reliability across repeated measurements and different operators (ICC ≈ 0.864–0.999), confirming their suitability for long-term clinical observation. Camera-based systems showed notably lower stability during complex movements, particularly for internal and external hip rotations (ICC ≈ 0.368). Kinect demonstrated moderate reliability (ICC ≈ 0.70–0.90), sufficient for non-invasive monitoring but less accurate than IMUs. Thus, IMU-based systems exhibit the greatest robustness to variations in movement execution and external influences, whereas Kinect may serve as a compromise tool with moderate setup requirements and spatial constraints.

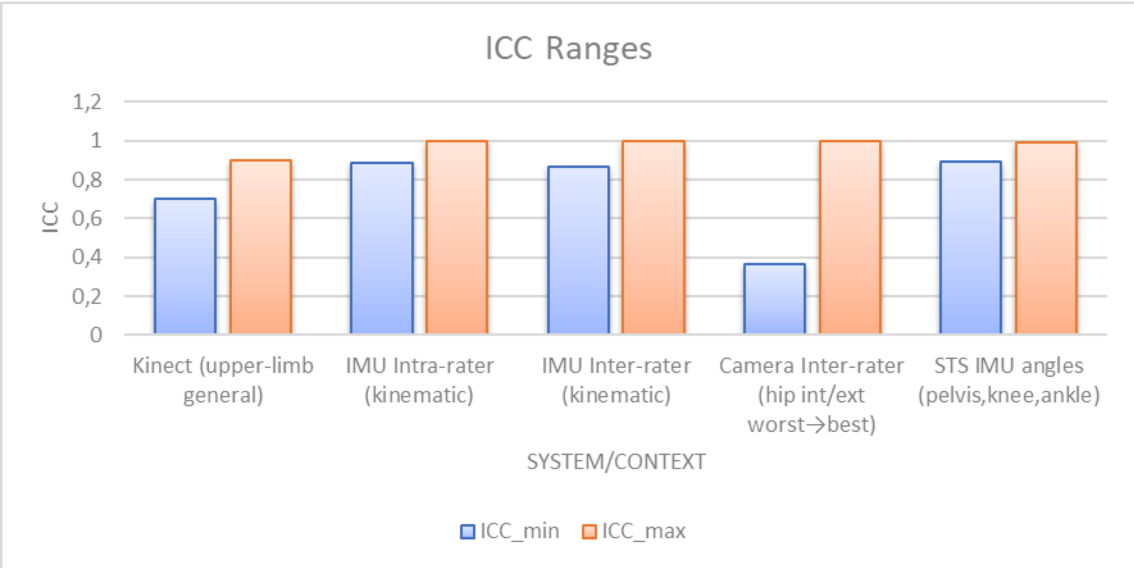

Figure 7. Comparison of ICC between sensor systems.

Clinical impact on patients undergoing rehabilitation programmes was assessed using changes in the Fugl–Meyer scale, shown in Figure 8. Across the examined patient groups, inclusion of Kinect in the rehabilitation protocol resulted in greater recovery progress: total improvement averaged approximately +11.98 points in control groups and +17.56 points in experimental groups. When analysing upper-limb function separately, results were again superior in the Kinect-assisted group (+7.45 vs +11.28 points). These findings suggest that interactive environments promote greater patient engagement in active movement and stimulate functional recovery.

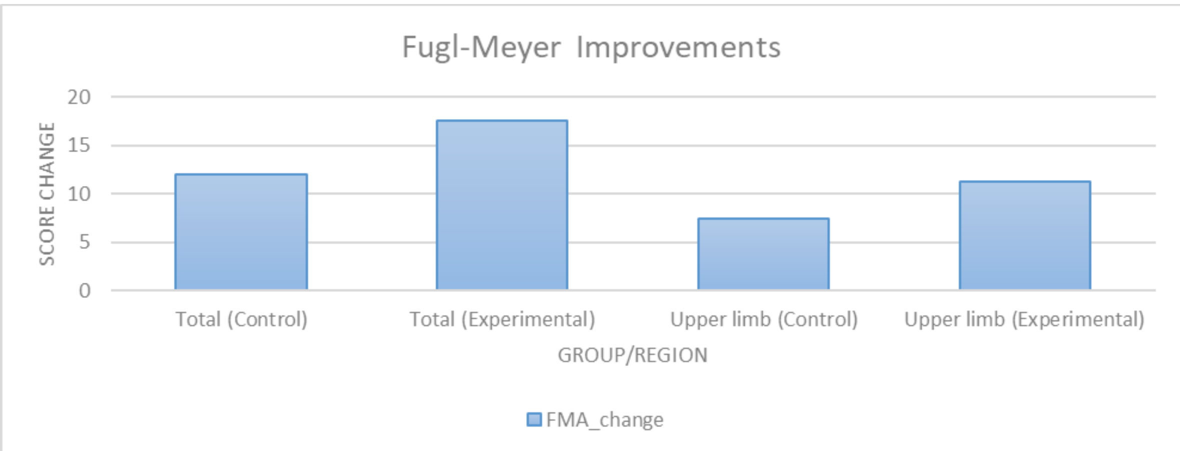

Figure 8. Improvement in Fugl–Meyer scores in control and experimental groups.

To provide an integrated assessment of the practical utility of different sensing technologies in rehabilitation, accuracy, usability, cost, and overall feasibility were jointly evaluated. The radar chart in Figure 9 demonstrates that the configuration using three inertial sensors provides the best balance across all assessed criteria, delivering high-precision motion analysis with minimal hardware. Kinect occupies a mid-range position: although its accuracy is somewhat lower, its ease of use and low cost significantly enhance its practical value in rehabilitation programmes, particularly in home-based settings. Hybrid IMU systems utilising machine-learning algorithms combine high accuracy with reasonable implementation complexity.

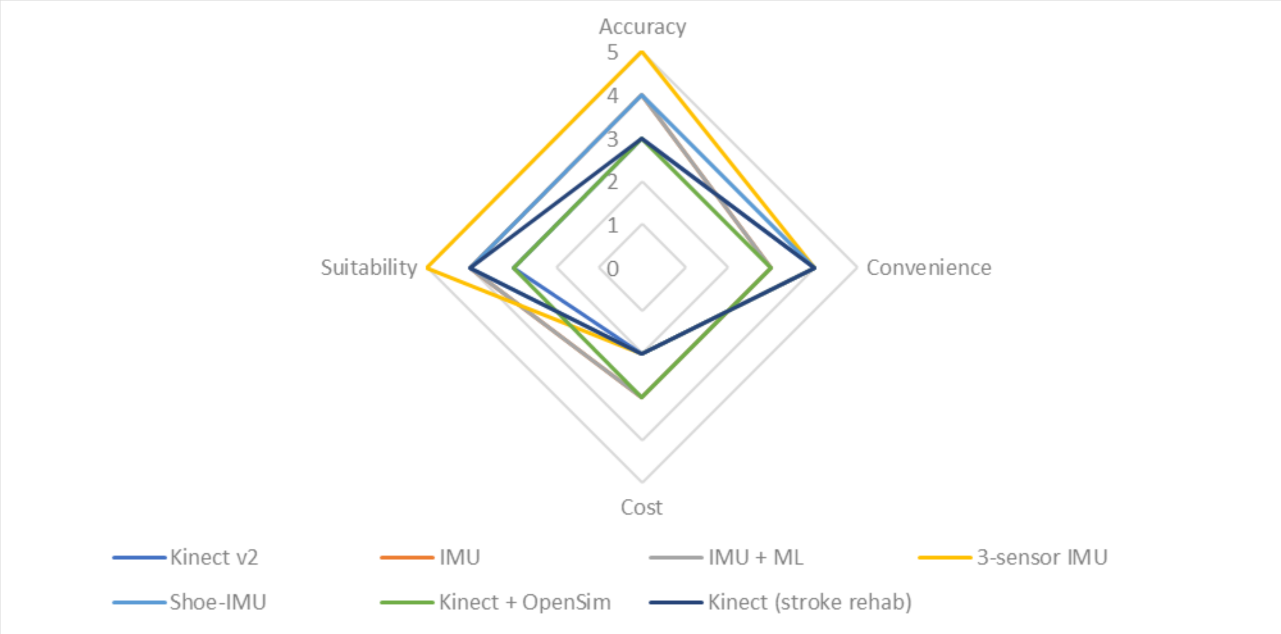

Figure 9. Integrated assessment of technologies by accuracy, practicality, and cost.

Overall, the presented charts indicate that IMU-based systems provide the highest measurement accuracy and stability; however, Kinect remains an acceptable and cost-effective alternative for non-invasive home rehabilitation, delivering clinically meaningful improvements in functional outcomes. Hybrid approaches combining IMUs with intelligent algorithms may substantially improve accuracy without greatly increasing implementation complexity, and therefore have strong potential for broader adoption in clinical practice.

6.1 Algorithmic Approaches to Motor Assessment

Algorithmic methods for motor analysis aim to transform sensor-derived measurements into quantitative kinematic, spatiotemporal, and functional indicators that enable assessment of patient condition, rehabilitation effectiveness, functional progress, and response to therapy [7]. Contemporary approaches rely on signal-processing methods, sensor-fusion algorithms, kinematic models for estimating body-segment motion, and machine-learning models used for interpreting and predicting motor behaviour [9, 32, 49].

Typical stages of data processing in modern motion-monitoring systems include acquisition from optical or inertial sensors, noise filtering, calibration, and reconstruction of spatiotemporal movement parameters, such as velocity, trajectory, or range of motion (ROM). Higher-level metrics are then computed, including spectral features, logarithmic jerk, trajectory curvature, and the number of velocity peaks [32, 33]. For IMU-based systems, the fusion of accelerometer, gyroscope, and magnetometer signals using Kalman filtering and its extended variants (EKF, InEKF) is essential to compensate for drift and provide stable estimates of orientation and joint angles [9, 36]. Studies have demonstrated that invariant forms of EKF significantly improve orientation-estimation accuracy under conditions of sensor misalignment, which is critical in ambulatory monitoring [36].

Algorithmic methods are effectively employed in both markerless camera-based systems and inertial systems. A summary of results from the Appendix (full version of Table 1) shows that, for Kinect v2, mean ROM estimation accuracy is approximately 1–10°, while mean linear error is 10–15 mm, with increases up to 80 mm in extreme limb positions [2, 3]. Temporal movement characteristics (mean velocity, duration) exhibit moderate to high reliability, whereas the number and magnitude of velocity peaks are less stable; these parameters should therefore be interpreted with caution, particularly when evaluating complex tasks in patient populations [32, 49]. Comparison with Vicon marker-based systems demonstrated that upper-limb movement parameters tracked using Kinect may exceed a correlation of 0.9, and maximum amplitude error < 5 %, indicating the potential of such systems for semi-automated clinical use [49].

Inertial systems provide high sampling rates (typically ~100 Hz), making them suitable for analysing intensive and rapid movements, including gait. In studies using IMUs, the RMSE of lower-limb joint-angle estimation ranged from 1.83° to 3.98°, and intra- and inter-operator reliability (ICC) reached 0.88–0.99, confirming high reproducibility and validity of the methods [9, 33]. When location and personnel changed, the accuracy of IMU algorithms sometimes exceeded that of marker-based systems, which demonstrated greater variability, particularly when assessing internal and external rotation of the hip [9].

Key analytical parameters used in algorithmic systems include ROM, normalised velocities, number of velocity peaks, log jerk (LJ), trajectory curvature (C), spectral length, and shoulder and elbow functional parameters. The reliability of these metrics varies: MV, LJ, C, SA, and EA demonstrated ICC > 0.9, whereas normalised speed peaks (NSP) and spectral arc length (SAL) showed low agreement, limiting their utility in routine clinical practice [33].

Machine-learning algorithms are increasingly applied for automated movement interpretation, including classification of motor primitives and functional patterns. For example, in studies involving post-stroke patients, use of CNN models with IMU signals enabled motor-primitive classification with ~70 % accuracy in participants with mild or moderate impairment, while accuracy decreased to ~44 % in more severely impaired groups [30]. Such models enable real-time identification of movement mechanisms (e.g., reach/transport, stabilise), potentially supporting automated estimation of rehabilitation "dose".

A promising direction involves hybrid algorithmic approaches combining IMU and camera signals. These systems achieve joint-angle and moment-measurement accuracy of ICC ~0.99 for the hip and knee during sit-to-stand functional tests [49]. Hybrid solutions can provide high accuracy with a minimal number of sensors, are suitable for use outside laboratory environments, and form the basis for constructing large multimodal datasets for algorithm development and validation.

6.2 Explainable Artificial Intelligence in Motion Tracking (XAI)

With the widespread adoption of machine-learning and deep-learning algorithms in movement analysis — particularly in gait assessment, post-stroke rehabilitation, and upper- and lower-limb kinematics — there is increasing need to ensure transparency and interpretability of model outputs. This is critically important in clinical practice, where automated solutions must not only demonstrate high predictive accuracy, but must also remain interpretable to clinicians who make therapeutic decisions. Consequently, explainable artificial intelligence (XAI) is becoming a key development direction for sensor-based motor-assessment systems [50, 51].

In the field of skeleton-based human-activity recognition, studies show that modern deep-learning models (e.g., graph convolutional networks, GCNs) provide high-quality classification of movement patterns; however, they remain "black boxes", meaning that the specific features driving the model's decisions are not transparent [50]. Research by Pellano et al. (2024) demonstrated the importance of selecting appropriate explanation-evaluation metrics: for instance, faithfulness (i.e., correspondence of an explanation to the true decision logic of the model) is not sufficiently stable, whereas stability (robustness of explanations to minor perturbations of the input) appears better suited to skeletal-movement analysis [50, 51].

At a practical level, XAI in movement analytics encompasses several key directions:
1) evaluation of the contribution of individual joints or body segments to classification or prediction;
2) generation of counterfactual scenarios to assess causal effects (e.g., "what would change if the patient did not engage the right arm?");
3) integration of explanations into clinical interfaces, allowing specialists to analyse the features influencing a model's output [52].

A systematic review of XAI in gait analysis found that out of 31 studies, 16 employed model-agnostic methods, 12 used model-specific methods, and 3 adopted hybrid approaches [3]. The most widely used techniques were SHAP, LIME, and Grad-CAM. These enable identification of key movement parameters — for example stride length, stance phase, and knee-flexion amplitude; in upper-limb movements, indices such as lifting speed or the number of velocity peaks. Together with Appendix data (Appendix Table 1), this indicates that algorithms can not only produce numerical outputs (RMSE, ICC) but also explain their origin, thus bridging the gap between quantitative analytics and clinical decision-making [51].

The use of XAI within motion-tracking systems offers several essential advantages:
1) increased trust among clinicians towards automated assessments;
2) improved reproducibility and transparency of procedures;
3) facilitation of regulatory or clinical certification;
4) use of explanations for training patients and rehabilitation specialists, for example, to illustrate compensatory movement strategies [53].

Despite its benefits, XAI integration presents several challenges. Key issues include the absence of standardised interpretability metrics (e.g., stability, faithfulness, contrastivity), the risk of "masking" true model logic behind superficial explanations, the potential for generating a false sense of confidence (the so-called trust paradox), and the considerable computational resources required to provide explanations in real time [53, 54].

For full integration of XAI into clinical motion-monitoring systems, the following are required:
1) development of large multisensor datasets with annotated explanations (attribution maps);
2) standardisation of interpretability metrics;
3) integration with biomechanical models and clinical indicators;
4) implementation of real-time interfaces that allow specialists to interpret explanations while making clinical decisions [52].

6.3 Clinical Relevance and Validation

One of the key aspects of integrating motion-tracking systems into clinical practice is their clinical relevance — that is, the ability not only to record motor parameters, but also to provide information meaningful for diagnosis, prognostication, planning, and monitoring of rehabilitation interventions. To serve these purposes, a system must be valid (i.e., comparable with the "gold standard" or with clinically meaningful indicators) and reliable (i.e., capable of producing stable results across measurements, operators, and conditions) [55–58]. Without these characteristics, the clinical deployment of such technologies remains limited.

Systematic reviews indicate that markerless and wearable technologies are still in the process of accumulating evidence supporting their clinical utility. According to a review by Pardell et al. (2024), only 16 studies have directly compared markerless systems (MLS) with marker-based systems (MBS), and nearly two-thirds of them reported statistically significant differences between the two technologies, particularly for lower-limb assessment [55]. These findings are consistent with reports that, although markerless systems reduce technical complexity, their accuracy in estimating peak joint angles and complex movement patterns remains below laboratory standards.

Results from the comparative analysis (see expanded Table 1 in the Appendix) support these conclusions. For example, in Study №1, mean linear accuracy was 10–15 mm and joint-angle accuracy 1–10°, whereas parameters associated with peak velocity and the number of peaks showed only low to moderate reliability. This suggests that, although such systems are suitable for evaluating basic kinematic characteristics, their applicability to more complex metrics remains limited. In contrast, inertial systems (Studies №6–7) demonstrated joint-angle RMSE values of approximately 1.8–4°, and ICC values of 0.88–0.99, meeting clinically acceptable thresholds of accuracy and stability [56].

From a clinical perspective, three key criteria determine the suitability of a sensing technology.

First, the system must be optimised for patients with actual motor impairments (e.g., post-stroke, Parkinson's disease). However, most studies have been conducted on healthy volunteers, and therefore, extrapolation to patient populations is constrained [58].

Second, the technology must provide adequate technical performance: appropriate sampling frequency, minimal subject preparation, and low invasiveness. A frequency of 30 Hz (Kinect-class devices) is typically sufficient for basic movement assessment; however, analysis of rapid movements, manipulation tasks, or gait events requires ≥ 100 Hz, as offered by IMU systems [56].

Third, the system must be integrated into clinical workflows — its output must support therapeutic decision-making, intervention adjustment, and prognostication of functional recovery.

Clinical validity also requires reproducibility under varied conditions. Bae et al. (2024) evaluated the markerless MoCap system Ergo and reported $R^2 = 0.88–0.99$ for joint-angle time series and ICC = 0.92–0.99 on test–retest, consistent with "excellent agreement" with the gold standard [57]. Although this demonstrates progress towards clinical accuracy, the authors emphasised the need for broader studies involving pathological cohorts, as most available data have been collected from healthy participants.

In summary, the essential criteria defining the clinical relevance of a motion-tracking technology are:

1) validity with respect to the gold standard;
2) high reproducibility of results (test–retest, inter-operator);
3) demonstrated suitability for the target patient population;
4) integration of system outputs into clinical workflows (assessment, prognosis, monitoring, intervention);
5) technical and procedural compatibility with clinical and home environments (sampling frequency, ease of use, calibration requirements).

6.4 Multisensor Integration and Hybrid Systems

Multisensor integration and the use of hybrid technologies represent a key development direction in motion-tracking systems, as combining different sensing modalities allows mitigation of the limitations inherent to each and increases the suitability of such systems for real clinical and home environments. Traditional optical motion-capture (OMC) systems provide high spatial accuracy, but require markers, controlled environments, and are highly sensitive to occlusion. In contrast, wearable inertial sensors (IMUs) are portable, easy to deploy, and suitable for long-term use, but suffer from drift and reduced accuracy during prolonged measurement. Combining these approaches within hybrid systems yields more versatile solutions with improved stability and reproducibility.

The relevance of hybrid approaches is supported by systematic reviews. For instance, Callejas-Cuervo et al. (2023) report that approximately 21% of lower-limb studies use mixed optical–inertial systems, indicating growing interest in multisensor solutions for clinical movement monitoring [59]. This trend stems not only from technical advantages but also from the need to ensure continuous data capture in cases of marker loss or complex scene geometry.

Practical examples confirm the effectiveness of sensor fusion. Hicks, Chen and Harper (2025) demonstrated that algorithmic integration of OMC and IMU can compensate for fragmented optical data caused by occlusions, providing motion reconstruction with RMSE < 1.8° over five-minute upper-limb tracking cycles [10]. Such an approach helps avoid critical data loss and improves the overall quality of long-duration, continuous motor assessment.

Hybrid systems require synchronisation of data from multiple sensors, calibration, alignment of coordinate systems, drift filtering and error compensation. In practice, such systems operate adaptively: if optical tracking is lost (due to occlusion or shadow), IMUs maintain measurement continuity, while under magnetic interference, optical data provide corrective input. This is particularly important in clinical or home monitoring, where environmental conditions are variable and less controlled.

In clinical contexts, hybrid systems offer substantial advantages: the ability to refine kinematic assessment (angles, moments, phases), broaden coverage of movement patterns and reduce the influence of artefacts. For example, results from IMU+Vicon studies during sit-to-stand tests in older adults demonstrated ICC values of 0.99 and 0.92 for hip and knee angles, respectively (see Table 1, Appendix), corresponding to clinically valid measurement quality.

Despite these advantages, hybrid systems have several limitations: more complex installation, higher cost, and requirements for calibration, synchronisation and processing of large data volumes. Nonetheless, they provide the foundation for developing multimodal datasets, combined sensing platforms and algorithms capable of operating across a wide range of use cases — from laboratory studies to home monitoring and telerehabilitation. The integration of optical and inertial systems brings us closer to universal, high-precision, scalable solutions for automated motor assessment in real-world clinical scenarios.

7. Challenges, Limitations, and Future Directions

The development of motion-tracking systems — from marker-based optical platforms to markerless cameras, inertial sensors, and hybrid solutions — has enabled significant advances in clinical rehabilitation and monitoring of motor recovery. However, these technologies face several critical challenges that limit their widespread integration into routine clinical practice, particularly in ambulatory and home environments.

One of the key technical limitations is the need to ensure stable accuracy and reproducibility of measurements under real-world conditions. For wearable inertial measurement units (IMUs), persistent issues include sensor drift, sensor-placement variability, dependence on the magnetic environment, variability in data quality, and the need for regular calibration [60]. For markerless camera-based systems, notable concerns include occlusion, sensitivity to variations in lighting and background texture, and limited accuracy in frontal and transverse planes, which may distort joint-angle reconstruction. Factors related to sampling frequency, signal latency, and synchronisation quality between modalities also significantly affect the validity of these technologies outside laboratory settings.

Practical use in clinical and home environments is further complicated by organisational and ergonomic constraints: correct placement of sensors, patient-specific setup, dependence on motor profile (e.g., post-stroke), wearability comfort, network connectivity, and limited battery autonomy [61, 62]. Additional barriers include medical-data privacy concerns and regulatory requirements, which affect the adoption of such systems in home-based monitoring [61].

Clinical relevance also remains limited for many systems. As shown in the comparative analysis (Table 1, Appendix), even when joint-angle error reaches 1–4° for IMUs or <5% for markerless systems, several parameters — including number of velocity peaks, complex kinematic patterns, and classification of motor primitives — demonstrate only moderate agreement. This indicates a substantial gap between technical validity and the representation of clinically meaningful motor function, especially in patients with neurological disorders, where compensatory mechanisms may reduce interpretability.

The lack of standardised calibration procedures, data-collection protocols, and cross-platform validation is a major constraint in adopting these systems within rehabilitation centres. Most clinical institutions lack the material or personnel resources required to deploy multimodal systems, integrate them with clinical information systems, and support long-term monitoring. Moreover, the absence of large-scale studies involving substantial patient cohorts and long-term monitoring of movement in real-world conditions further limits the strength of the evidence base.

Despite these barriers, future development pathways are relatively well-defined.

First, the creation of large multimodal datasets combining IMUs, RGB-D cameras, OMC, and force platforms is crucial for training machine-learning models, improving algorithmic reconstruction fidelity, and building universal validation frameworks (Study №15, Table 1).

Second, the development of adaptive sensor-fusion and self-calibration algorithms — including drift compensation, coordinate alignment, and outlier detection — will improve measurement stability in portable scenarios.

Third, integration of explainable AI (XAI) models into clinical interfaces will enhance transparency and trust in algorithmic recommendations, which is essential in medical decision-making.

Finally, standardisation of protocols, cybersecurity and privacy requirements, and regulatory frameworks is necessary for large-scale adoption of these systems in clinical practice and home monitoring.

In conclusion, although modern motion-tracking systems demonstrate high potential and can provide quantitative assessment of kinematics and functional motor activity, their implementation remains constrained by technical, organisational, and ethical challenges. The future of the field depends on advancing multimodality, adaptive sensor-fusion algorithms, explainable AI, and standardised clinical validation — developments that will support the creation of patient-centred, transparent, and scalable systems for rehabilitation monitoring.

Appendix:

Table 1. Structured review of studies on sensor technologies in rehabilitation

№	Authors, year	System type	Domain/object of study	Participants (n)	Primary aim
1	Faity, G.; Mottet, D.; Froger, J., 2022	Kinect v2 (markerless) vs Vicon (marker-based)	Upper-limb kinematics during seated reach — post-stroke modelling	26 healthy participants	Validate and assess the reliability of Kinect v2 versus Vicon for upper-limb movement measurement in a post-stroke rehabilitation context
2	Mengxuan Ma, Rachel Proffitt, Marjorie Skubic, 2018	Kinect V2 + Mystic Isle game (NUI rehab game)	Post-stroke rehabilitation movement tracking	30 adults	Assess spatial accuracy and measurement validity of Kinect V2 in Mystic Isle, compared with the gold-standard motion-capture system (Vicon)

Continuation of Table 1

3	S. Almasi et al., 2022	Kinect-based rehabilitation systems (various studies)	Movement tracking / post-stroke rehabilitation and other kinematic assessments	Summary across multiple studies (dozens of patients)	Summarise and evaluate the validity, accuracy, and effectiveness of Kinect systems in rehabilitation applications; review the broader literature on Kinect in rehabilitation, including accuracy and reliability
4	David Webster & Ozkan Celik, 2014	Kinect-based systems (review)	Elderly care and post-stroke rehabilitation	Various (not specified): narrative literature review	Provide an overview of the status, limitations, and directions of Kinect applications in elder care and post-stroke rehabilitation
5	A. Mobini, S. Behzadipour, M. Saadat, 2015	Microsoft Kinect (Xbox 360, skeleton tracking)	Upper-body assessment — post-stroke motor recovery testing	30 (18 post-stroke patients, 12 healthy)	Assess test–retest reliability of Kinect-derived composite motor activity indices in post-stroke patients and healthy adults
6	Young-Shin Cho et al., 2018	IMU-based gait analysis system (wearable IMUs)	Gait analysis (kinematics and spatiotemporal parameters)	3 healthy; each walked 10 trials across three hospitals	Evaluate validity (vs camera systems) and reliability (multi-site, multi-operator) of an IMU gait system
7	Young-Shin Cho et al., 2018	Wearable IMU-based gait analysis (AHRS modules: abdomen, thighs, shanks, feet)	Gait: spatiotemporal and kinematic parameters	3 healthy; each walked 10 m ten times in three hospitals	Assess validity (vs camera system) and reliability (intra- and inter-rater) of an IMU system for clinical gait analysis
8	Giuseppe Prisco et al., 2025	Systematic review of IMU-based studies	Validation of wearable IMUs for gait analysis versus optical motion capture (OMC)	32 studies (2014–2023), per-study n up to 51	Systematically compare wearable IMUs with the OMC “gold standard”; quantify accuracy and limitations for kinematic and spatiotemporal gait parameters

Continuation of Table 1

9	Yiou Sun et al., 2025	Wearable IMUs	Quantitative gait assessment in post-stroke patients	16 post-stroke	Determine optimal IMU placement for gait assessment from gait data and clinical scores (Fugl–Meyer subscale)
10	Myeounggon Lee et al., 2018	Shoe-type IMU sensors	Validation in Parkinson's disease during treadmill walking	17 with PD	Compare shoe-type IMU data with 3D motion capture during 1-minute treadmill walking
11	Smith J., Parikh D., Tate V., Siddicky S. F., Hsiao H.-Y.; 2024	Valor wearable IMU sensors	Validation of Valor IMU for upper- and lower-limb joint angles	Not specified	Compare Valor IMU accuracy with the Vicon gold standard for joint-angle estimation
12	Ye Zhu et al., 2024	Wearable IMUs (Xsens MTw) + Vicon + force platform	Lower-limb forces and angles during sit-to-stand (STS) in older adults	28 healthy older adults (13 M, 15 F; 60–70 yrs)	Verify IMU accuracy for lower-limb forces (joint angles and moments H–K–A during STS) vs MoCap
13	Bojan Milosevic, Alberto Leardini, Elisabetta Farella, 2020	Wearable IMU + Kinect video-based system	Effectiveness of home motor rehabilitation technologies	Not specified	Compare IMU and Kinect accuracy with marker-based gold standard for simple home exercises
14	Pfister A., West A. M., Bronner S., Noah J. A., 2014	Microsoft Kinect (Xbox 360, Brekel Kinect) vs Vicon Nexus	Sagittal-plane gait analysis (flexion/extension, stride timing)	20 healthy adults (9 M, 11 F)	Assess correspondence of Kinect with Vicon for gait kinematics
15	Andreas Spilz et al., 2025	Wearable IMUs (9 sensors) + optical MoCap (35 markers)	Motion capture — rehab exercises and normal vs impaired gait patterns	19	Create a multimodal dataset with synchronised IMU and MoCap for training ML models in gait/exercise analytics
16	Gabrielle E. Deane, Michael H. Schwartz, Andrew R. Cutler, 2024	IMU (DorsaVi ViMove2) + marker-based optical (Vicon)	Predicting lower-limb kinematics across walking types (normal, fast, running)	10 healthy adults	Evaluate effects of speed/task specificity on IMU-based kinematic prediction accuracy

Continuation of Table 1

17	Gök et al., 2017	Xbox Kinect™ + conventional rehabilitation	Post-stroke rehab (upper-limb training)	20 (analysed: 19)	Assess safety, feasibility, and effectiveness of Kinect as adjunct rehabilitation
18	Liquan Guo et al., 2023	Wearable IMUs + rehab gloves + human–computer interaction	Remote rehab for post-stroke motor dysfunction	120 (60 experimental, 60 control)	Evaluate efficacy and safety of an ICT-guided remote-rehabilitation system
19	Rajat Kumar Das et al., 2016	Microsoft Kinect (markerless depth) + OpenSim model	Telerehab: stability and functional metrics during Single-Limb Stance across body-mass groups	Not specified (healthy)	Assess feasibility of estimating musculoskeletal forces/moments from Kinect via OpenSim
20	A. Kaku et al., 2020	IMUs (Noraxon MyoMotion)	Neurorehabilitation post-stroke; identification of upper-limb "functional primitives"	48 chronic stroke	Develop and evaluate automatic primitive classification from IMUs; compare ML (RF, FCNN, LSTM, CNN) with a proposed model

Table 2. Comparative metric characteristics of contemporary motion-tracking systems

№	**Metrics**	**Accuracy / error**	**Sampling rate (Hz/FPS)**	**Key results**	**Authors' conclusions**
1	Upper-limb/torso ROM, movement time, mean/peak velocity, number of velocity peaks, path-length ratio, compensations (trunk, shoulder, elbow)	Distances: mean accuracy 10–15 mm (up to 80 mm at extremes); angles (ROM): error 1–10°	Kinect v2 – 30 Hz; Vicon – 100 Hz	Mean velocity, movement time, ROM — moderate to high reliability. Shoulder/elbow ROM, time to peak velocity, trajectory length — low to moderate reliability. Instantaneous peaks and peak count — unreliable due to limb-tracking issues.	Kinect v2 can be used clinically for semi-automated quantitative assessment, but accuracy limitations (especially for peak-related metrics) must be considered; further studies in patient cohorts are needed.

Continuation of Table 2

2	Pearson's r; SNR; 3D joint-distance error; mean/RMSE for max hand extent, velocities; % errors; ICC	Per-joint hand correlations: > 0.90; SNR: > 5; mean 3D joint-distance error: < 10 cm; max hand-extent error: < 5%; mean-velocity error ≈ 10%; max-velocity error < 5%	Kinect V2: 15 or 30 FPS; Vicon: 100 Hz	Kinect V2 showed high arm-movement correlation (r > 0.9), good SNR, error distance < 10 cm; amplitude error < 5%; mean velocity ≈ 10%, max < 5%.	Mystic Isle with Kinect V2 provides movement measurements comparable to Vicon; accuracy varies by joint; most reliable for upper limbs; Kinect V2 is a valid tool for game-based rehab assessment.
3	Validity of kinematic measures; reliability statistics	Statistical/clinical findings vary; Kinect shows "sufficient accuracy for rehabilitation"	Often 30 FPS (typical Kinect)	Kinect used across tasks from limb to whole-body tracking; in many cases measurements align well with reference systems.	Kinect is accessible and practical for rehabilitation, but quality depends on configuration, task, and environment.
4	Spatial accuracy; evaluation methods in Kinect literature	Accuracy varies by study; recurring Kinect-specific constraints	—	Kinect used for spatial accuracy and in rehab methods (games, movement control).	Potential in elder care and post-stroke rehab, with limitations in accuracy, tracking volume, and user interaction; further work needed.
5	MV; NMS; NSP; LJ; C; SAL; SA; EA	Intra-/inter-session reliability: MV, LJ, C, SA, EA — ICC > 0.9; poorest: NSP, SAL (low ICC); EA CV > 15% (lowest agreement)	~30 Hz (range ≈ 25.6–34.7; mean 29.9; SD 2.67)	MV, LJ, C highly reliable; only MV, LJ, C changed beyond MDD after one month, hence suitable for progress monitoring; NSP, NMS, SAL, SA, EA less sensitive to change.	Kinect metrics (esp. MV, LJ, C) are reliable and suitable for monitoring stroke recovery; supports low-cost home-rehab systems using Kinect.

Continuation of Table 2

6	Spatiotemporal: speed, stride length, stance/swing; Kinematics: hip/knee/ankle angles in three planes	RMSE (IMU vs camera): 1.83–3.98° (~1% tolerance)	—	Spatiotemporal IMU measures closely match camera: IMU speed ~1.18–1.22 m/s vs camera ~1.23–1.30; similar stance/swing. Angle RMSE: ankle frontal 1.39° to transverse hip up to 4.37°. Reliability (ICC): intra-rater 0.884–0.998 (kinematic), 0.830–0.894 (spatiotemporal); inter-rater 0.864–0.999 (kinematic), 0.800–0.883 (spatiotemporal). Camera inter-rater more variable: kinematic ICC 0.368–0.996; spatiotemporal 0.733–0.802.	IMU gait systems show high validity (low RMSE) and stable reliability intra- and inter-rater; often more reliable than camera systems across operators/locations; compact, economical, practical for clinical gait assessment.
7	Spatiotemporal (speed, stride length, stance/swing); kinematic hip/knee/ankle angles in sagittal/frontal/transverse	RMSE 1.83–3.98° (~±1%); IMU intra-rater ICC: kinematic 0.884–0.998; spatiotemporal 0.830–0.894; inter-rater: kinematic 0.864–0.999; spatiotemporal 0.800–0.883; camera ICC: kinematic 0.368–0.996; spatiotemporal 0.733–0.802	—	IMU spatiotemporal metrics align well with camera (e.g., speed IMU ~1.18–1.22 m/s vs camera ~1.23–1.30 m/s). Angle RMSE from 1.39° (ankle, frontal) to 4.37° (ankle, transverse) across hospitals. IMU shows high reliability; camera more variable, especially hip internal/external (ICC < 0.4).	IMU systems show high validity and reliability, often surpassing camera systems under operator changes; promising, accessible alternative to bulky, costly MoCap for clinical gait analysis.

Continuation of Table 2

8	PCC, ICC, CMC, LCC, R^2; RMSE, MAE; Bland–Altman; Passing–Bablok; ES; ΔROM; absolute/relative error	Kinematics: good–moderate agreement with OMC; spatiotemporal: moderate–weak depending on task and placement	Mostly 100–200 Hz (device-dependent)	Best accuracy with waist placement and multi-sensor configs; some parameters (stride length, frontal/transverse angles) less reliable.	Wearable IMUs have strong potential for clinical/field gait analysis; sufficiently accurate in many cases, but not always interchangeable with OMC; accuracy depends on placement, signal choice, and task.
9	Adjusted R^2, MAE, RMSE; predicted FMA-LL	adj. $R^2 = 0.999$; MAE = 0.07; RMSE = 0.08; rounded prediction error = 0	—	Fewer sensors did not reduce accuracy; key features from pelvis and bilateral thigh sensors; propose a three-sensor scheme (pelvis + both thighs) with very high accuracy.	Three sensors (pelvis + both thighs) deliver exceptional accuracy with minimal hardware; suitable for clinical and home use in post-stroke gait quantification.
10	ICC (95% CI)	Excellent agreement for cadence, step length/time, linear acceleration	—	High agreement between shoe-type IMU and MoCap.	Shoe-type IMUs are reliable for objective gait analysis in PD clinical settings.
11	MAD, RMSE, ICC	MAD 1.81°–17.46°; RMSE 1.89°–16.62°; ICC 0.57–0.99	—	Valor IMU accuracy varies by joint/movement; some excellent, others moderate.	Valor IMU is a promising portable alternative to lab MoCap; needs improvement in mounting/calibration and transverse-plane measurements.
12	ICC, correlations, Bland–Altman	Angles: hip 0.99, knee 0.99, ankle 0.89; Moments: hip 0.94, knee 0.92, ankle 0.89	IMU 100 Hz; MoCap 200 Hz; force plate 1000 Hz	High agreement of IMU with MoCap for STS in older adults.	IMUs are accurate, portable alternatives to MoCap.
13	RMSE (joint-angle error)	3–8°	—	IMU and Kinect similar for large movements; IMU with fusion slightly better.	Both suitable for home rehab; IMU fusion improves accuracy.

Continuation of Table 2

14	Peak hip/knee flexion–extension; stride timing; correlations/errors	Hip correlation very low, large error; knee better but still insufficient; stride timing high correlation, small error; minimal variability at lowest speed	—	Kinect underestimated flexion, overestimated extension; hip correlation very low; knee modest; stride timing strong.	Kinect may suit stride-timing assessment, but requires major accuracy improvements for clinical kinematics.
15	Raw + processed IMU/MoCap; OpenSim models; IK results; movement labels	—	—	Large dataset provided: IMU (raw + aligned orientations), MoCap, IK, segmentation, annotations.	Dataset accelerates ML development/validation for automatic movement assessment, gait analysis, and activity segmentation.
16	RMSE, Pearson r	RMSE 1.9°–6.9°; r 0.79–0.99	IMU 100 Hz; Vicon 120 Hz	Prediction accuracy drops from normal walking to running; best when train/test speeds & tasks match.	High accuracy requires task-/speed-matched training for predictive models.
17	Attendance ratios; patient surveys; adverse events; Borg CR10; BBT, WMFT, BMRS, FIM	Attendance: 87% overall; 90% per session; 96% sessions completed. All found training enjoyable; ≥70% felt safe; no serious events; fatigue common (Borg ≈ 7.8). Greater gains in BBT, WMFT, BMRS for Kinect vs control.	—	Kinect training is safe, acceptable, and improves upper-limb motor/functional outcomes post-stroke.	—

Continuation of Table 2

18	Fugl–Meyer scores (total; upper/lower limb)	Control: +11.98 (SD 8.46); Exp.: +17.56 (SD 11.65), p=.005; upper limb: control +7.45 / exp. +11.28 (p=.01); lower limb: non-significant (p=.06)	—	Experimental group showed substantially better upper-limb recovery.	System is a safe, effective alternative to routine OT.
19	Joint forces/torques (hip, lumbar, pelvis) during SLS; pelvic list & tilt biomarkers	—	—	Kinect + OpenSim can estimate key stability biomarkers (pelvic list/tilt); potentially useful for personalised telerehab.	—
20	Classification of 5 primitives (reach, transport, reposition, stabilise, idle); balanced accuracy	Mean ≈ 70% (mild/moderate; Test set 1; ensemble 70.11%); severe group 44.39%	IMU 100 Hz (9 sensors at C7, T12, pelvis, shoulders, forearms, hands); video labelling 60 FPS (2 cameras)	Proposed CNN with instance normalisation & embeddings outperformed RF, FCNN, LSTM; main confusions: reach/transport and idle/stabilise.	IMU + deep learning enables automatic primitive detection and towards objective “dose” quantification; needs improvement for severe cases and possibly fusion with computer vision for grasp tracking.

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