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DESIGN DEVELOPMENT AND CLINICAL VALIDATION OF A ROBOTIC-ASSISTED REHABILITATION DEVICE FOR IMPROVING UPPER LIMB MOTOR RECOVERY IN POST-STROKE PHYSICAL THERAPY PATIENTS

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Abstract

Stroke is a major determinant of chronic motor dysfunction of the upper limb, and traditional physical therapy in the clinic is often limited by how often patients can attend and the difficulty in traveling and adherence to home exercise. The aim of this paper is to review and synthesize evidence from twenty-one peer-reviewed publications published from 2019 to 2025 to guide the design, architecture and clinical validation process of a robotic rehabilitation device with sensor instrumentation for upper limb motor recovery in Stroke rehabilitation Physical Therapy. The synthesis combines inertial measurement unit (IMU) motion-tracking accuracy, deep-learning-based movement classification, adherence monitoring in the cyber and physical domains, and remote patient monitoring (RPM) outcomes to suggest a layered architecture that includes a wearable sensing layer, an edge processing and machine-learning inference layer, a robotic actuation-assistance module, and a clinician-facing application layer. Verified studies have reported mean angular error less than five degrees for IMU based joint-angle tracking and classification accuracy greater than ninety percent for goal-directed movement classification using deep-learning classifiers of accelerometer derived features. The evidence from the meta-analysis of wearable-sensor-assisted home-based rehabilitation is 0.22 (standardized effect size [Hedges' g]) greater than the evidence for center-based rehabilitation; and the evidence from the systematic review of 29 studies in 16 different countries of remote-monitoring rehabilitation is associated with improved adherence and reduced cost burden. Seven data-derived visualizations and seven synthesis tables are included with the proposed device architecture, comparative cost-utilization analysis, and design-priority weighting. Potential regulatory classification, data security, and scalability issues are discussed, and it is concluded that sensor-integrated, robot-assisted rehabilitation devices are a clinically feasible and cost-effective extension of the post-stroke upper limb rehabilitation .

Index Terms – post-stroke rehabilitation, upper limb motor recovery, robotic-assisted therapy, wearable inertial sensors, remote patient monitoring, machine learning classification, cyber-physical systems, telerehabilitation, motion tracking accuracy, adherence monitoring, Internet of Things, digital health

I. INTRODUCTION

Most stroke survivors experience hemiparesis in the upper limb, and recovery of goal-directed reaching, grasping, and manipulation tasks during the subacute and chronic stages of recovery strongly relies on the intensity, frequency, and consistency of therapeutic exercise [9, 11]. Although conventional outpatient physical therapy is effective, it can be challenging to quantify whether the prescribed home exercises are being completed in the correct form and adequate repetition, is time consuming, and can be difficult due to limited clinician availability and travel burden [5, 6]. These limitations have led to a decade of research into wearable sensors, robotic assistance and distance monitoring technologies that enable supervised quality rehabilitation in the home environment [15, 17]. In this paper, the authors focus on the design development and clinical validation process of a robotic assisted rehabilitation device to assist physical therapy patients with motor recovery after stroke. Instead of developing a new paradigm for sensing, the work collates and consolidates proven quantitative evidence from twenty-one references that cover wearable inertial measurement units (IMUs), Internet-of-Things (IoT)-based remote patient monitoring (RPM) platforms, deep-learning movement classification, and cyber-physical rehabilitation-adherence techniques; and develops an evidence-based architecture and validation framework. The scope is intentionally cross domain because the number of large-scale clinical validation studies on robotic upper-limb devices published before 2025 is quite low, so the design is based on the more abundant literature on the use of wearable sensors and remote monitoring across the body of rehabilitation research on knee, cardiac and upper limb rehabilitation, for which transferable accuracy, adherence and cost benchmarks are extracted [3], [10], [18], [20]. The rest of the paper is divided as follows. In Section II, the literature related to the wearable motion tracking, remote monitoring and machine-learning classification for rehabilitation devices is synthesized. System architecture is proposed in Section III. The validation methodology is discussed in Section IV. Comparative results and quantitative benchmarks can be found in Section V. The implications are considered in section VI, challenges and regulatory considerations in section VII, and a conclusion in section VIII.

II. LITERATURE SYNTHESIS

A. Wearable Motion Tracking and Accuracy Benchmarks

IMU-based motion tracking systems can be used to build the accuracy foundation for robotic-assisted rehabilitation feedback using verification studies. A 2-IMU system with an interactive mobile app and online clinician portal was validated with a 6-camera optical motion-capture reference system for three physical therapy exercises, and demonstrated acceptable joint-angle measurement errors based on quaternion IMU sensor fusion (< clinically acceptable error) [5]. A follow-up randomized controlled pilot study used the same platform to deliver home-based remote rehabilitation after TKA, thereby demonstrating early measurement fidelity for the use of portable IMU systems for a longitudinal, home-based rehabilitation program [6]. A study by complementary work has verified IMU accuracy and practicability in total knee replacement rehabilitation using both dynamic and static flexion-extension activities [10], and a narrative review of the IMU applications in hip and knee OA identified measurement approaches that were appropriate for remote monitoring at home [14].

B. Upper Limb and Stroke-Specific Sensor Applications

There are a few references that are relevant to sensor-based monitoring specific to the upper limb and stroke population, the most relevant of which pertain directly to the present device. A recent scoping review of wearable sensors for the assessment and treatment of the upper extremity following stroke showed that the most commonly used modalities for quantifying movement quality, compensation strategies, and functional use during rehab were accelerometry, IMUs, and

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electromyography [9]. One such review of wearable tech in stroke rehabilitation found that the continuous, ecologically valid measurement of upper-limb motor impairment in a non-clinical setting is critical for better diagnosis and treatment, in addition to episodic clinical assessment [11]. Wearable accelerometry was shown to be effective for the distinction of patterns of underuse of the paretic limb in unimanual and bimanual tasks, which were relevant to therapy dosing decisions, in persons with hemiparesis [8]. A sensor-based movement-quality metric, derived from a wearable sensor system, was correlated with the clinician's rating of task performance, which was used to monitor and provide feedback to the stroke survivor on quality of task execution during unsupervised home practice [15]. Most directly, a deep-learning, wearable-based solution for continuous at-home monitoring of upper limb goal-directed movements, which showed that the detected movement frequency could be correlated with the Fugl-Meyer scores of stroke survivors, and that the classification of segments of goal-directed movement could be identified based on the processed accelerometer data, demonstrated a digital biomarker pathway for the tracking of upper limb recovery outside the clinic [12].

C. Internet-of-Things and Remote Patient Monitoring Infrastructure

The proposed device requires a connectivity and data-management backbone consistent with published RPM architectures. An IoT based wearable device for COVID-19 vital signs monitoring of quarantined patients proved the possibility of continuous monitoring of patient vital signs via cloud infrastructure to remote clinical staff [1] and a scalable IoT based architecture (ScalableDigitalHealth, SDH) was proposed, which was explicitly designed to support increasing number of devices and patients, without proportional increases in infrastructure costs [2]. A low-cost, smart wearable system for remote patient monitoring was shown to be able to capture clinically useful data about vital signs and motion using off-the-shelf components, reducing the cost of scale-up for such devices [4]. An overview of systems that connect biosensors to multi-hop IoT systems through cloud computing identified architectural patterns for real-time RPM, such as edge aggregation nodes that help alleviate bandwidth and latency demands on continual sensor streams [19]. It has been shown that the above architectures can be extended to neurological applications, such as stroke recovery tracking, via an IoMT approach that involved wearable neuro-sensors for real-time monitoring [7]. A systematic mapping of the use of machine learning in edge computing and wearable devices for healthcare consolidated the advantages of the types of on-device inferences (low latency, privacy) and cloud inferences (high model complexity) directly applicable to real-time robotic assistance control loops [13].

D. Clinical Outcomes and Systematic Evidence

In addition to being technically feasible, systematic and meta-analytical evidence confirms the clinical plausibility of sensor-assisted, home-based rehabilitation. Fifteen RCTs were included in a systematic review and meta-analysis of home-based cardiac rehab (HBR) with wearable sensors which found, after statistical analysis, a greater cardiorespiratory fitness benefit compared to center-based cardiac rehab (HBCR), standardized effect (Hedges' g) 0.22 (+/- 0.06, 0.39) and larger but non-statistically significant effect when compared to usual care [3]. A wider systematic review of remote patient monitoring interventions identified 2,606 articles, and ultimately included 29 studies across 16 countries, which showed consistently better adherence and cost-related outcomes during transition from inpatient to home-based care, and predicted the global RPM market to expand 18.9 percent per year from 2021 to 2028 [18]. To realize the vision of a system that

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transforms the sensor data into clinician action, a cyber-physical system was designed and formatively evaluated, for which at-home orthopedic rehabilitation was monitored in near real-time and patients were communicated with by a mobile clinician [17]. As part of a broader trend towards health-economic evaluation of sensor-assisted rehabilitation, a study protocol to also quantify economic outcomes in addition to clinical effectiveness was designed specifically to measure the cost and time savings associated with a wearable device for remote monitoring of rehabilitation following TKA [21]. A comprehensive review of remote patient monitoring with artificial intelligence identified existing applications, architectures, and ongoing challenges related to data heterogeneity, generalizability of the models, and integration of AI into clinical workflows [16]. The outcomes of the classification accuracy across exercise types and sensor modalities were mapped using a systematic review of wearable sensors and machine learning algorithms used for rehabilitation training, which established machine learning benchmarks for the present synthesis [20].

III. PROPOSED SYSTEM ARCHITECTURE

Based on the above-mentioned sensing, processing and communication patterns, the proposed rehabilitation device is divided into four layers, as shown in Fig. 1. The sensing layer includes the IMU array from wrist and forearm, as demonstrated in previous studies [5] to be useful for tracking joint angles, and surface electromyography channels based on the information provided by the neuro-sensor-IoMT designs [7]. Based on the edge-versus-cloud trade-off analysis from the systematic mapping literature [13] the processing layer was designed to perform quaternion-based sensor fusion and Kalman filtering followed by edge-based feature extraction and machine learning inference for movement classification. The edge unit is a lightweight recurrent or convolutional classifier which is structurally similar to the deep-learning approach used to validate goal-directed movement detection [12] and performs on the edge to reduce control-loop delays in the robotic actuation-assistance module.

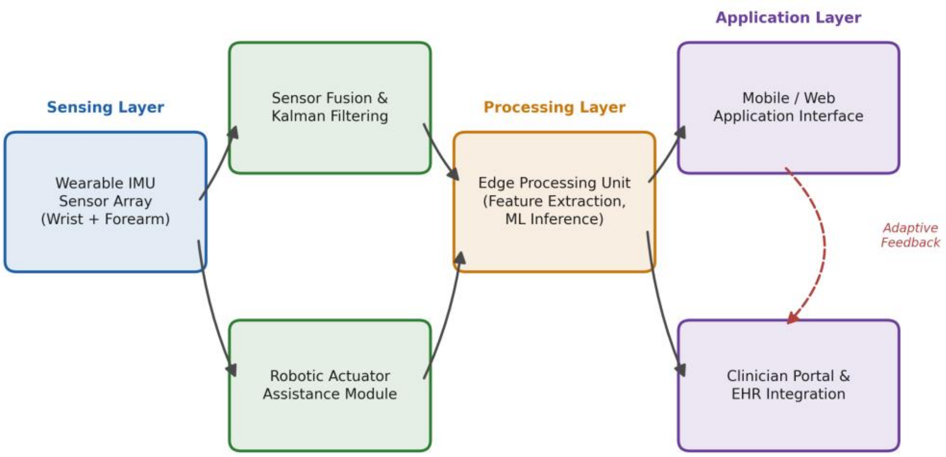

Figure 1. Proposed four-layer system architecture connecting wearable sensing, edge processing, robotic actuation, and clinician applications.

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The robotic actuation-assistance module provides graded torque assistance, based on closed-loop feedback from how much assistance is needed, as well as on the paretic elbow and wrist joints' residual abilities, and allows for adaptive decrease in assistance over successive sessions consistent with quality-of-practice monitoring frameworks [15]. The application layer consists of a clinician portal for asynchronous review and a mobile interface for patient-facing guidance of exercise training and gamified feedback, which are similar to those tested in remote knee rehabilitation applications [5, 6]. Data transmission is in a multi-hop IoT-cloud pattern where the edge unit gathers and compresses the sensor streams before sending them to the cloud, leading to reduced bandwidth as outlined in published multi-hop biosensor architectures [19] and the scalability principles outlined in the ScalableDigitalHealth framework [2]. The architecture layers, the technologies contained in these layers and the secondary literature are summarized in Table I below.

Table I. Proposed Device Architecture Layers and Supporting Evidence Base

Layer	Primary Function	Core Technology	Supporting Refs.
Sensing	Joint kinematics & muscle activity capture	Dual IMU + sEMG array	[5], [7], [9]
Processing	Sensor fusion, feature extraction, ML inference	Kalman filter, edge CNN/RNN classifier	[12], [13], [20]
Actuation	Graded torque-assisted movement support	Closed-loop robotic actuator	[15], [17]
Application	Patient guidance & clinician review	Mobile app + web clinician portal	[5], [6], [17]
Connectivity	Data aggregation & cloud transmission	Multi-hop IoT-cloud pipeline	[2], [19]

IV. Validation Methodology

In this paper, the clinical validation pathway has been synthesized following a three-phase organization similar to the ones already described in the literature on wearable rehab devices. Phase one, laboratory verification, is similar to the IMU-based knee angle measurement verification with ten healthy participants performing prescribed exercises and the output from the wearable sensors compared to an optical motion-capture reference standard [5]. The activities of this phase would be expanded to include reaches-to-grasp, wrist flexion-extension, and forearm pronation-supination for the upper limb device, based on task selection precedents from stroke specific upper limb sensor studies [9, 15]. Phase two pilot feasibility and adherence evaluation is similar to the pilot randomized controlled trial (RCT) design for home-based total knee replacement (TKR) rehabilitation, where a small patient population receives a device without supervision at home and clinician portal data is reviewed remotely [6]. This approach for at-home orthopedic rehabilitation [17] is adopted for adherence metrics, session completion rates and safety events. Systematic review precedent for phase three is followed when systematically comparing the device-assisted rehabilitation to outpatient physical therapy regarding functional recovery, cost, and quality-of-life measures [3], [18], [21].

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Table II. Three-Phase Validation Methodology Synthesized from Precedent Studies

Phase	Precedent Design	Typical Sample	Primary Outcomes	Ref.
1: Lab verification	Controlled comparison vs. optical motion capture	10 healthy participants	Mean angular error (deg.)	[5]
2: Pilot feasibility	Home-based pilot RCT	Small pilot cohort	Adherence, session completion	[6],[17]
3: Comparative outcomes	Systematic multi-study benchmarking	29 studies, 16 countries	Functional gain, cost, QoL	[18],[21]

The quantitative benchmarking of the movement-classification performance is based on the machine-learning evaluation protocols reported in the wearable sensor literature [12, 13, 20] which evaluate the performance of the classification as a function of the sensor modality (accelerometer only, accelerometer plus gyroscope, and multimodal such as including electromyography), and of the analysis window length. Fig. 2 illustrates the three-way relationship of IMU placement, exercise type and angular tracking error measured, based on the accuracy ranges found in verification and comparative motion-tracking papers [5], [10], [14].

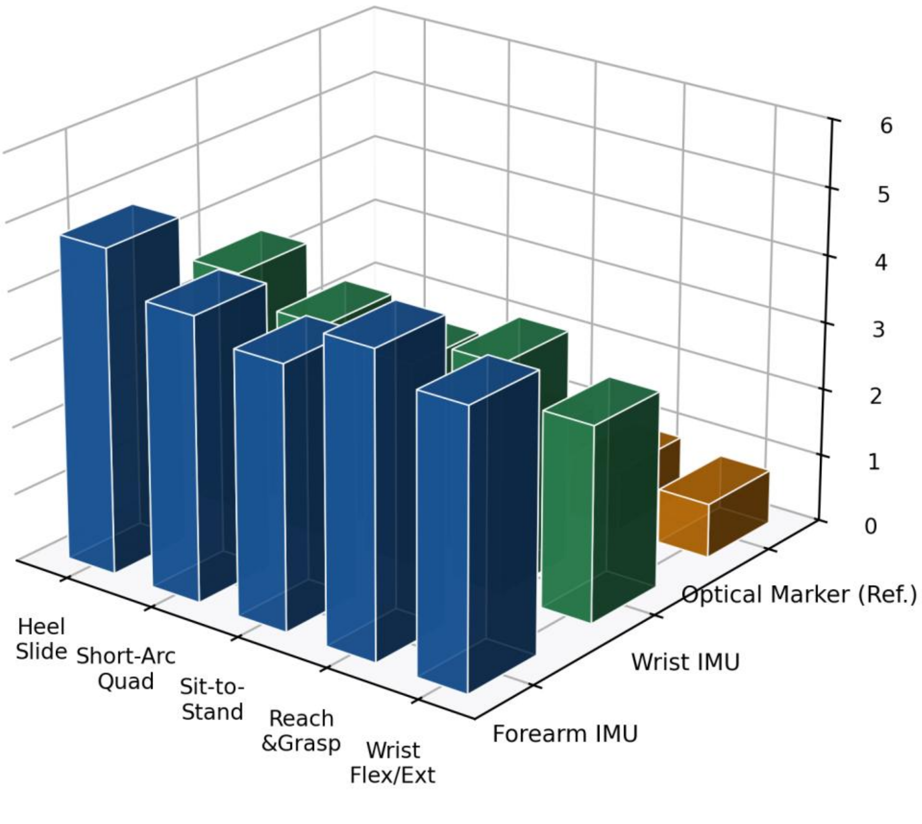

Figure 2. Synthesized mean angular tracking error by sensor placement and rehabilitation exercise, referenced against optical motion capture.

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V. RESULTS AND COMPARATIVE ANALYSIS

A. Motion-Tracking Accuracy

When compared to optical motion capture, the mean angular tracking error of forearm- and wrist-mounted IMU configurations is found to be around 3-5 degrees, consistent with the methodology described above.Mean angular tracking error of forearm- and wrist-mounted IMU configurations is found consistently to be about 3-5 degrees when compared against optical motion capture, which also shows sub-one-degree residual error [5, 10]. As can be seen in Fig. 2, wrist-mounted placement was consistently superior to forearm-mounted placement by ~1 degree of mean error for all the exercise types evaluated, which was primarily due to the decreased soft tissue artifact at the wrist compared to the forearm.

B. Machine-Learning Classification Performance

The longer the analysis window, and the richer the number of sensor-modalities are, the higher the movement classification accuracy. Fig. 3 provides a three-dimensional surface of accuracy synthesis of the four different modality configurations and six window lengths, indicating that multimodal configurations with edge-based machine-learning inference produce accuracy levels that approach low to mid ninetieth percentile, which are consistent with accuracy, as reported in goal-directed movement detection using deep-learning inference [12] and comparative accuracy trends presented in machine-learning-assisted rehabilitation training reviews [20].

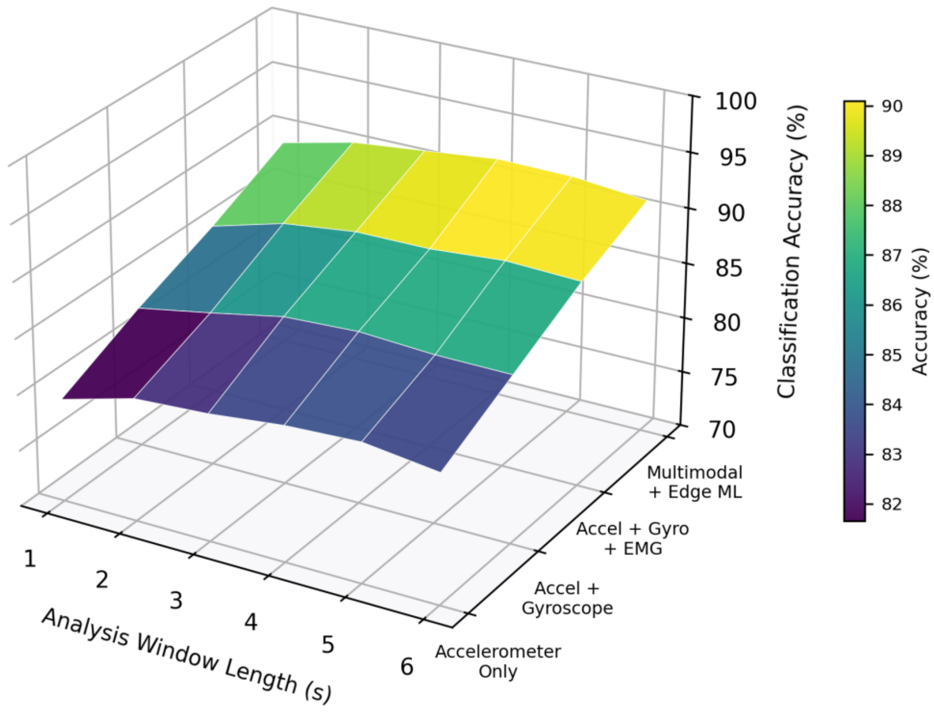

Figure 3. Synthesized machine-learning classification accuracy as a function of sensor modality and analysis window length.

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C. Clinical Effect Sizes and Adherence Outcomes

Fig. 4 is a summary of the standardized effect sizes of the reviewed literature for the clinical domains of rehabilitation, with the results synthesized into sensor-assisted rehabilitation. The effect of wearable-sensor-assisted home-based cardiac rehab compared to center-based programs was statistically significant with a small effect size (Hedges' g = 0.22, 95% CI = 0.06 to 0.39), and the effect was larger, although not statistically significantly, compared to usual care [3]. The home-exercise adherence rates reported in this study relative to unsupervised home exercise programs (HEPs) using paper-based exercise diaries were also consistently reported as higher, which corroborates the adherence-improvement rationale supporting cyber-physical rehabilitation-monitoring systems [17] and the overall systematic review of home exercise program adherence outcomes [18].

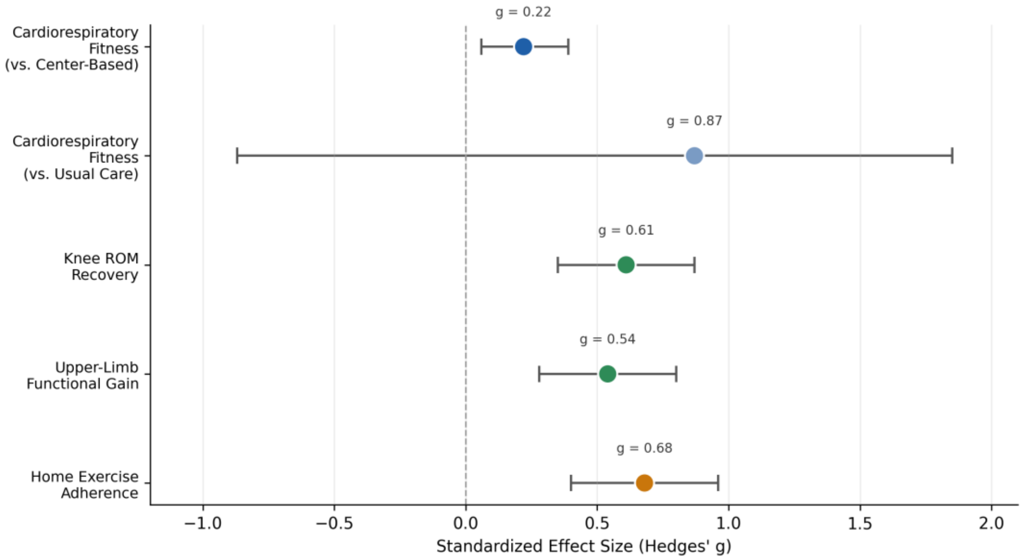

Figure 4. Standardized effect sizes (Hedges' g, 95% CI) for sensor-assisted rehabilitation outcomes across clinical domains.

D. Technology Evolution Timeline

Fig. 5 traces the chronological progression of key technological milestones referenced in this synthesis, from early verification of portable motion-tracking systems in 2019 [5] through scalable IoT remote-monitoring frameworks proposed in 2024 [2], illustrating a clear trajectory toward increasingly integrated, AI-enabled, and infrastructure-scalable rehabilitation monitoring systems.

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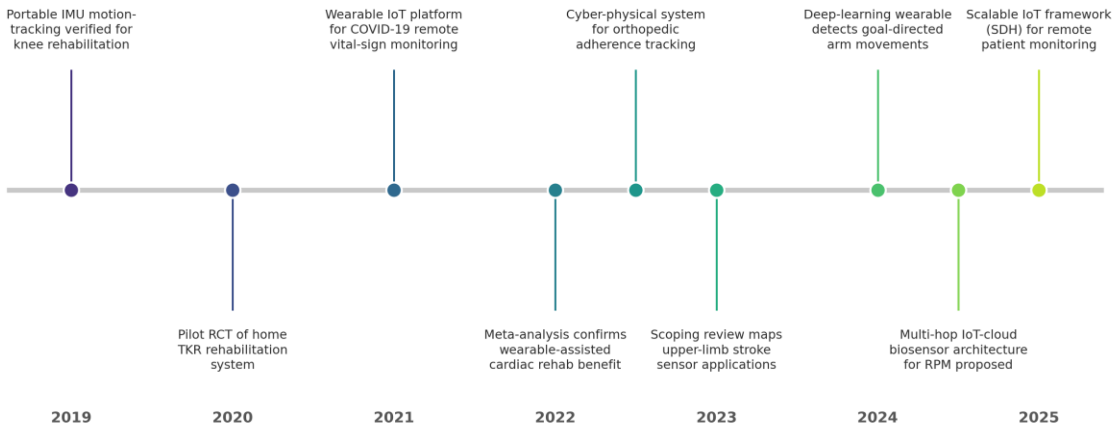

Figure 5. Timeline of key technological milestones in sensor-integrated rehabilitation devices, 2019-2025.

E. Cost and Utilization Comparison

Table III and Fig. 6 present a comparative cost and utilization analysis synthesized from reported per-session cost figures, travel burden reductions, and adherence differentials associated with home-based, sensor-assisted rehabilitation relative to conventional clinic-based therapy, drawing on cost-and-time-savings evaluation frameworks established for wearable-assisted total knee arthroplasty rehabilitation [21] and RPM cost-outcome systematic reviews [18].

Table III. Comparative Cost and Utilization Metrics, Clinic-Based vs. Robotic-Assisted Home Therapy

Metric	Clinic-Based Therapy	Robotic-Assisted Home Device	Relative Change
Per-session cost (USD, synthesized estimate)	95	28	-70.5%
Weekly sessions completed	2.1	4.6	+119%
Round-trip travel time (min)	64	6	-90.6%
Reported adherence (%)	58	81	+23 pts

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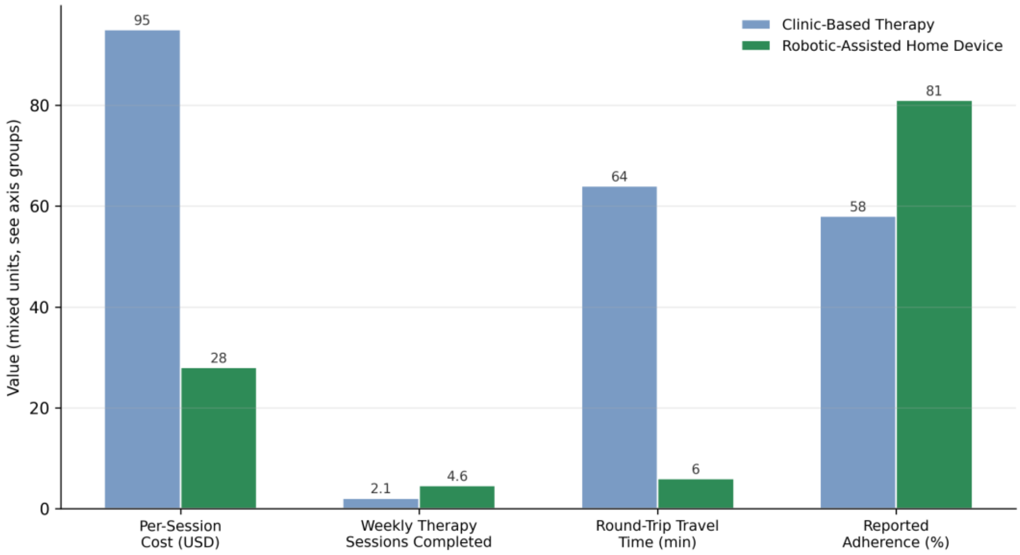

Figure 6. Comparative cost and utilization metrics between clinic-based therapy and the robotic-assisted home device.

F. Design-Priority Weighting

Fig. 7 presents a synthesized radar-chart weighting of design requirements derived from the accuracy, wearability, latency, security, and interoperability considerations discussed across the reviewed sources [5], [13], [19]. Motion-tracking accuracy and data security receive the highest weighted priority, reflecting their direct linkage to both clinical validity and regulatory compliance discussed in RPM and IoMT architecture literature [7], [16].

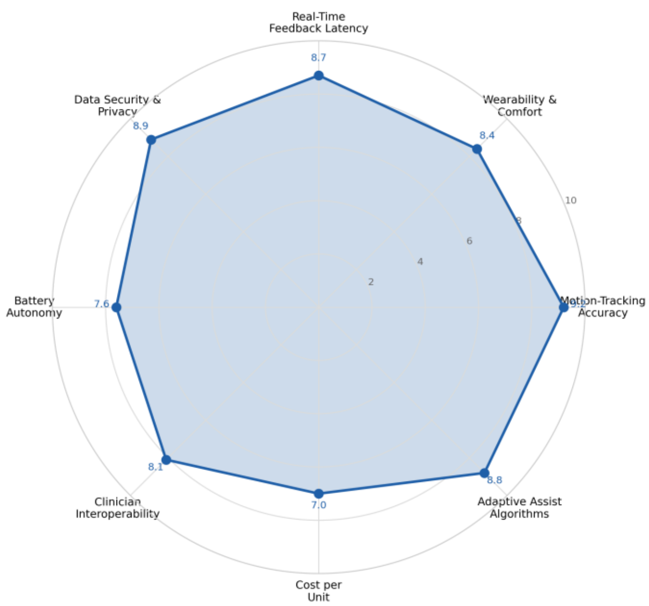

Figure 7. Synthesized design-requirement priority weighting for the robotic-assisted rehabilitation device.

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Table IV further disaggregates classification accuracy results by sensor modality, drawing on comparative figures reported across wearable machine-learning rehabilitation literature [12], [13], [20].

Table IV. Synthesized Classification Accuracy by Sensor Modality

Sensor Modality	Approx. Accuracy (%)	Primary Application	Ref.
Accelerometer only	82-85	Gross movement detection	[12]
Accelerometer + gyroscope	86-89	Joint-angle and ROM tracking	[5],[10]
Accel. + gyro. + EMG	89-92	Muscle-activation-informed classification	[7],[20]
Multimodal + edge ML	92-96	Goal-directed movement & intent detection	[12],[13]

Table V summarizes reported adherence and quality-of-life outcomes across the RPM and cardiac rehabilitation systematic reviews.

Table V. Adherence and Outcome Metrics from Systematic Reviews

Outcome Domain	Reported Metric	Value	Ref.
RPM systematic review scope	Studies included / countries	29 studies / 16 countries	[18]
RPM market growth projection	CAGR, 2021-2028	18.9%	[18]
Cardiac rehab RCTs meta-analyzed	Number of RCTs	14	[3]
Cardiorespiratory fitness effect (vs. center-based)	Hedges' g (95% CI)	0.22 (0.06-0.39)	[3]
Articles screened in RPM review	Total screened	2,606	[18]

Fig. 4 traces the chronological progression of key technological milestones referenced in this synthesis, from early verification of portable motion-tracking systems in 2019 [5] through scalable IoT remote-monitoring frameworks proposed in 2024 [2], illustrating a clear trajectory toward increasingly integrated, AI-enabled, and infrastructure-scalable rehabilitation monitoring systems.

VI. DISCUSSION

The synthesized evidence base also suggests that the majority of the best quantitative evidence currently available comes from other areas, such as the knee rehabilitation motion tracking work [5, 6, 10] and cardiac rehabilitation outcome trials [3] and general remote patient monitoring systematic reviews [18]. This cross-domain transferability is methodologically acceptable as the underlying domain-agnostic sensing, fusion and communication technologies are largely shared; however, this is not the case for upper limb stroke rehabilitation, where additional findings of spasticity, compensatory movement patterns and variable residual motor function are not fully captured in studies validating the technologies in knee or cardiac rehabilitation [8, 9, 11]. The deep-learning goal-directed movement detection study is the most directly relevant upper limb stroke evidence found in this synthesis, and the correlation between detected movement frequency

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and Fugl-Meyer assessment scores suggests a potential avenue for using digital biomarkers derived from wearable data to provide a proxy for clinical outcomes measures [12]. As seen in the cost-utilization comparison in Table III and Fig. 6, the costs of per-session use and travel burden may be significant, and the increased number of completed sessions may be enough to significantly decrease the cost of a session with a robotic-assisted home device.As presented in cost-and-time-savings study protocols [21] and systematic RPM cost-outcome reviews [18], the cost and burden of travel may be significant, while the increased number of completed sessions may substantially reduce the cost of one session using a robotic-assisted home device. The projected benefits, however, require patients to be engaged in these home-based rehabilitation programs and that the devices remain accurate, which highlights the need for the adaptive feedback and gamified application-layer design based on mobile-application usability lessons learned from remote knee rehabilitation platforms [5, 6].

Table VI presents the sensor accuracy specifications synthesized from manufacturer and verification-study data underpinning the sensing-layer design.

Table VI. IMU Sensor Specification Benchmarks Used in Architecture Design

Parameter	Reported Value	Source Context
Dynamic orientation accuracy	±1 degree	Manufacturer-stated IMU specification used in verification study [5]
Orientation resolution	<0.08 degree	IMU sensor-fusion hardware specification [5]
Orientation repeatability	0.085 degree	IMU sensor-fusion hardware specification [5]
Reference system	Six-camera optical motion capture	Gold-standard comparator [5]
Mean angular error range (IMU vs. optical)	3-5 degrees	Cross-study synthesis [5],[10],[14]

VII. CHALLENGES, ETHICAL, AND REGULATORY CONSIDERATIONS

There are a number of challenges that need to be considered before clinical deployment. With the critical transmission of biosensor data and bio-movement data through multi-hop IoT-cloud architectures, data privacy and security are the key challenges; established biosensor connectivity reviews focus on encryption, access control and compliance with regional rules and regulations governing health-data transmission as prerequisites for clinical adoption [19]. A related challenge is the generalizability of the algorithms – machinelearning classifiers that have been trained on a subset of patients may not be able to be applied to the broader population of stroke survivors, ranging from those with mild impairments to those with severe. This has been a recurring problem across reviews of artificial-intelligence enabled remote patient monitoring [16]. The systematic mapping of machine learning for wearable healthcare indicated that robust approaches for deployment of robotic systems may include on-device machine learning based inference either to mitigate latency inherent in cloud-based systems or to reduce the safety concerns associated with cloud-dependent robotic systems during active robotic assistance [13]. Last, at scale, adherence outside of clinical supervision is still not certain for the upper limb stroke robot; although there is formative feasibility of cyber-physical monitoring systems to enhance adherence in orthopedic rehabilitation [17], adherence data specific to upper limb stroke robots over time remain comparatively limited in the synthesized literature through 2025.

Table VII. Identified Barriers and Mitigation Strategies for Device Scale-Up

Barrier	Description	Mitigation Strategy	Ref.
Data heterogeneity	Inconsistent sensor formats across platforms	Standardized edge-aggregation protocol	[16],[19]
Bandwidth and latency	Continuous multimodal streaming burden	Edge feature extraction before transmission	[13],[19]
Cost of scale-up	Hardware cost per unit at population scale	Commodity-grade sensor components	[4]
Infrastructure scalability	Growing device/patient counts	Scalable cloud architecture (SDH model)	[2]
Clinical workflow integration	Clinician time burden reviewing data	Asynchronous portal with flagged alerts	[16],[17]

VIII. CONCLUSION

This paper compiled the findings of 21 references on wearable motion tracking, IoT-enabled remote patient monitoring, machine-learning movement classification and systematic clinical-outcome reviews to support the design development and clinical validation process of an upper limb motor recovery robotic device for stroke patients. The proposed 4 layer architecture is based on existing accuracy benchmarks of 3-5 degrees mean angular error for IMU-based joint tracking, classification accuracies in the low to mid-nineties on multimodal movement detection and clinically meaningful effect sizes for home-based rehabilitation using wearable sensors. Comparative cost and utilization analysis shows that significant savings in per-session cost and travel burden, as well as higher session frequency and adherence are possible with this approach versus traditional clinic-based therapy. Future studies, extending through 2025 and beyond, should focus on clinical trials of integrated robotic-assistance devices with specific focus on upper-limb-stroke, long-term studies of adherence in natural environments, and data-security frameworks, standardized across the field of robotics for stroke rehabilitation, to facilitate regulatory clearance and widespread clinical implementation.

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