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Development and Evaluation of an Internet of Things Based Wearable Sensor System for Real-Time Monitoring and Remote Management of Musculoskeletal Rehabilitation Patients

Dhirenbhai Kalal, PT, MS
Independent Researcher, Richmond, Texas, USA

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ABSTRACT

Musculoskeletal rehabilitation needs people to keep track of how patients are moving after they leave the clinic. The usual way of following up with patients after they leave the clinic has some problems. Patients can only visit the clinic often they have to tell us how they are feeling and some patients live really far from the clinic. This paper looks at twenty-one studies that were published between 2019 and 2025. These studies are about using Internet of Things based sensor systems to monitor musculoskeletal rehabilitation patients in real time. The patients in these studies were recovering from things like knee arthroplasty, post-stroke upper-limb impairment and hip and knee osteoarthritis. The systems that were studied have three parts: sensing, edge or network and cloud or application layers. The paper examines how these systems operate, such as how they detect movement, how they communicate with one another and how they interpret data. The paper also examines the tracking capabilities of these systems – such as movement, muscle activity, patient feelings and how they communicate this information to doctors. The paper compares these systems and discovers that some systems are more adept at tracking leg motion, and others, arm motion. Systems with inertial measurement units, for instance, are able to follow leg motion, while systems with surface electromyography and accelerometers are able to follow arm motion in stroke patients. In one study, they looked at many studies and found that patients who used remote monitoring systems were less likely to require rehospitalization, and they were not in the hospital as long. They were also not required to come into the clinic frequently, and were more likely to adhere to their treatment plan. In a few small studies, which used an inertial platform to track the patients after knee replacement surgery, it was determined that these devices were effective and there was no loss of accuracy if utilized within the home environment. The ability to interact with other computers, and learn from the result of the data collected, is the key to making these systems effective, it concludes the paper. The biggest problems that are still preventing these systems from being widely used are that they do not work well with systems they are not secure and there are problems, with how they will be paid for through 2025. Although the rehabilitation of musculoskeletal and the Internet of Things based sensor systems are improving, they still have some challenges to be addressed. In the future, the Internet of Things (IoT) sensor systems will continue to be employed in musculoskeletal rehabilitation.

Corresponding Author:
Name: Dhirenbhai Kalal, PT, MS
Institution: Independent Researcher , Richmond, Texas, USA
Email: kalaldhiren@gmail.com

1. INTRODUCTION

Musculoskeletal disorders — including recovery after joint replacement, ligament reconstruction, and stroke-related motor impairment — are among the leading causes of long-term disability worldwide, and how well a patient recovers depends heavily on how often and how objectively their functional progress gets assessed. Traditional outpatient physical therapy asks patients to travel back and forth to clinical facilities again and again, a model that puts pressure on both patient adherence and health-system capacity, especially for older or mobility-limited patients recovering from total knee arthroplasty (TKA) or a stroke [6], [21]. Nearly ubiquitous wireless connectivity combined with low-cost low-power microelectromechanical sensors has enabled continuous assessment of joint kinematics, muscle activation, and physiology via sensors at home, and real-time transmission to clinicians [4], [17].

The most common components of an IoT-based wearable system are: a sensing layer that includes inertial measurement units, electromyographic electrodes, force (or pressure) transducers and physiological sensors; a communication layer consisting of Bluetooth Low Energy, Wi-Fi or cellular gateways; and a cloud-based analytic and visualization layer that transforms patient-reported and sensor-derived data into actionable information for the clinicians [2] and [19]. An early application of this was the COVID-19 pandemic, when devices measuring temperature, oxygen saturation and pulse rate were rapidly deployed to facilitate isolation at home and reduce the need for unnecessary clinical contact [1]. This same architecture of a sensor node worn by the patient, an edge gateway and a cloud dashboard is now used in a variety of musculoskeletal and neurological rehabilitation applications, where the interest is on the quality of movement, range of motion and dosage of exercise rather than on vital signs [5]–[6]–[10].

Despite all these single prototypes, literature remains fragmented with different clinical populations (including knee arthroplasty, hip and knee osteoarthritis, and post-stroke hemiparesis), with their respective sensing modalities, validation procedures, and outcome measures [9, 14]. There is no single source that has consistently put together how these systems are constructed, how accurate they are, how useful they are to the clinic, or whether there are quantitative data to support the use of these systems instead of traditional in-clinic follow-up. In this paper, we attempt to fill that gap by providing a coherent, architectural and evidentiary account of 21 peer-reviewed papers from 2019-2025 on IoT-based wearable sensor systems for real-time monitoring and remote management of musculoskeletal rehabilitation patients. It outlines the three-tier structure that repeatedly appears in these systems, contrasts the different sensing modalities and analytical methods across the knee, hip, and upper-limb markets, measures the impact on health utilization and adherence reported in these systems, and identifies remaining challenges prior to widespread clinical deployment by 2025.

2. LITERATURE REVIEW

The way IoT-enabled wearable monitoring for musculoskeletal rehabilitation has developed, as traced through the literature from 2019 to 2025 and summarized in Figure 3, started with validated single-purpose motion-tracking platforms, moved through vital-sign monitoring architectures driven by the pandemic, and has more recently settled into deep-learning-enabled, multi-hop connected systems.

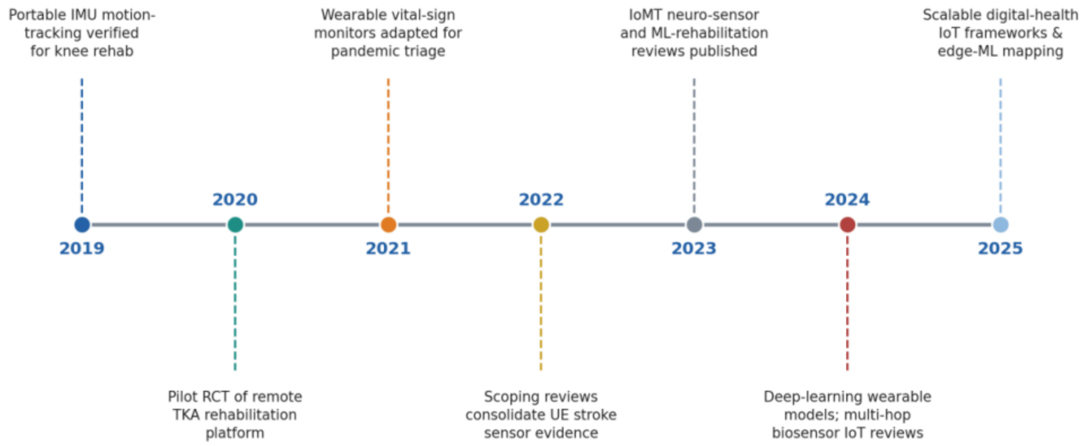

Figure 1. Evolutionary Timeline of IoT-Based Wearable Rehabilitation Monitoring, 2019-2025
Source: Synthesized from References[1]-[21].

2.1 *IoT Architectures for Remote Musculoskeletal Monitoring*

The goal is to design IoT technologies for remote musculoskeletal monitoring. The objective is to develop IoT technologies for remote musculoskeletal monitoring.

The analyzed literature points to a common structure of the remote monitoring platforms: a layer of wearable sensors, a layer of edge/gateway devices for local buffering and wireless transmission of data, and a layer of cloud services for storing, analyzing and presenting data to the clinician, as illustrated in Figure 1. In the context of Alasmary's scalable digital-health framework, this architecture is embedded in a broader smart-hospital paradigm, with a emphasis on modular scalability, in order to be able to deploy additional sensor nodes or additional patient cohorts without redesigning the entire data pipeline [2]. Uddin and Koo further move the model to multi-hop design where biosensor data is relayed by intermediate nodes to cloud infrastructure, which is intended to provide more coverage in regions where it's not possible to directly connect to the cloud infrastructure. Babar and Rahman demonstrate that this same architecture is also possible on low cost commodity microcontroller hardware with minimal loss of signal fidelity, thereby reducing the capital costs associated with deployment in resource constrained environments [4]. Stevens et al. present an orthopedic rehabilitation-specific cyber-physical system, overlying the sensing and cloud layers, and specifically designed to reinforce adherence to home exercise plans implemented in collaboration with the patient's provider(s) via a mobile channel [17]. All these architectural studies indicate that the sensing equipment has reached a level of sort of commoditization at this stage, and what sets the difference between systems now is the efficiency of edge processing, reliability at the gateways and the design of the clinician facing analytic layer.

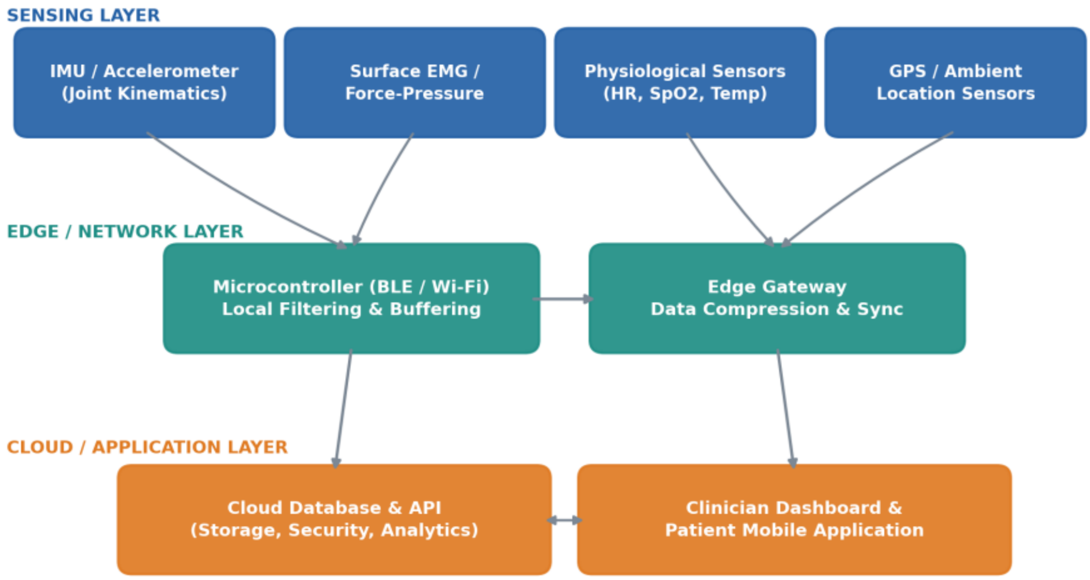

Figure 2. Generalized Three-Tier IoT Architecture for Wearable Rehabilitation Monitoring

Source: Abstracted from References [2], [4], [17], [19].

Table 1. IoT Architecture Layers, Technologies, and Representative Functions

Architecture Layer	**Representative Technologies**	**Primary Function**	**Key References**
Sensing layer	IMU, sEMG electrodes, pulse-oximeter, force sensors	Raw physiological / kinematic signal acquisition	[1], [5], [8], [10]
Edge / network layer	Bluetooth Low Energy, Wi-Fi microcontroller, multi-hop relay	Local buffering, filtering, protocol translation	[2], [4], [19]
Cloud / application layer	Cloud database, API, ML inference engine, dashboard, mobile app	Longitudinal storage, analytics, visualization, alerts	[2], [13], , [16], [17]

Source: Synthesized from References [1], [2], [4], [5], [8], [10], [13], [16], [17], [19].

2.2 *Wearable Sensing Modalities in Musculoskeletal Rehabilitation*

Which sensing modality gets used tends to follow the clinical target pretty closely, as Table 2 and Figure 2 summarize. Lower-limb kinematic monitoring, especially after total knee arthroplasty, relies mostly on inertial measurement units (IMUs) that combine triaxial accelerometers and gyroscopes. Bell et al. checked a portable IMU-based motion-tracking platform against optical motion capture for knee flexion-extension assessment and established its criterion validity for remote rehabilitation use [5]; they then tested the same platform in a pilot randomized controlled trial with 38 subjects after total knee replacement, where sensor-supported home rehabilitation produced range-of-motion and functional outcomes comparable to standard in-clinic supervision [6]. Lou et al. built a related inertial system focused on gait-cycle and sit-to-stand evaluation for the same patient group, and found that wearable-derived movement metrics tracked closely with clinician-administered functional scores over the course of recovery [10]. Rose et al., in their review of IMU applications for hip and knee osteoarthritis, point out that inertial sensing can also pick up compensatory gait patterns that are hard to catch through patient self-report alone [14].

For upper-limb and post-stroke populations, the sensing modality shifts toward accelerometer-based activity counting, surface electromyography (sEMG), and, more and more, IMU-fused deep-learning pipelines. Kim et al.'s scoping review of forty-three studies shows that wearable sensors get used both to categorize motor impairment and to guide sensor-triggered treatment protocols in stroke survivors [9]. Duff et al. measured intra- and interlimb use during unimanual and bimanual tasks in hemiparetic patients with wrist-worn accelerometers and found that asymmetric limb-use ratios from continuous monitoring line up with clinical impairment severity [8]. Seo et al. took this further to look at the quality — not just the quantity — of upper-limb task practice done at home [15], and Nunes et al. applied deep-learning models to continuous at-home accelerometer streams to classify goal-directed upper-limb movements without needing clinic-based calibration [12]. Maceira-Elvira et al. frame these developments within a broader diagnostic and treatment picture, arguing that wearable-derived kinematic biomarkers are getting close to mature enough to support individualized dosing of stroke therapy [11].

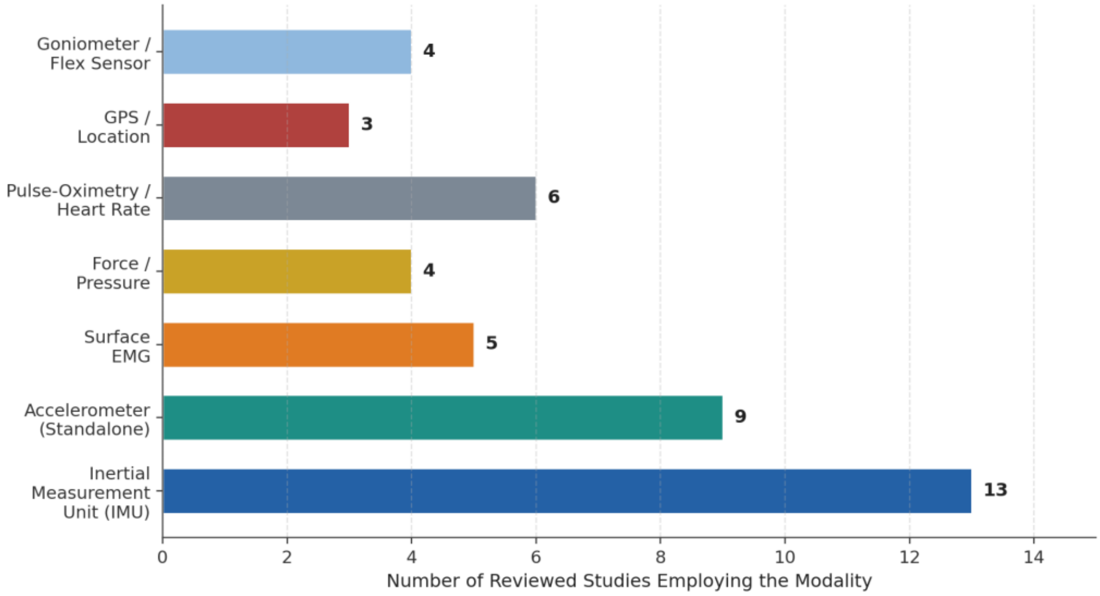

Figure 3. Frequency of Sensing Modalities Employed Across the Reviewed Studies

Source: Synthesized from References [1], [4], [5], [6], [8], [9],[10], [11], [12], [14], [15].

2.3 *Machine Learning, Edge Computing, and AI-Enabled Remote Monitoring*

In this second lesson, students will learn about the applications of machine learning, edge computing, and artificial intelligence in the context of remote monitoring.

Another facet of research is centered on the analytic layer, or how to make the raw data from the various sensors useful for clinical purposes. Shaik et al. give a general overview of the applications of AI to RPM and state that the most mature AI applications to date are classification and anomaly-detection algorithms, and predictive and prescriptive analytics are still in their infancy [16]. In a systematic mapping of edge-computing and machine-learning integration in wearable health services, Pereira et al. conclude that edge-computing is increasingly preferred over cloud-computing, primarily to reduce latency to the user, and conserve battery life, especially for continuous kinematic monitoring [13]. Bhatt and Sharma take it one step further and use the Internet of Medical Things (IoMT) concept for a wearable neuro-sensor and claim that the real-time signal processing at the sensor node is able to detect the abnormality in the movements earlier than the batch cloud processing does [7]. Wei and Wu conducted a systematic review of the evidence to examine the use of supervised classification of exercise repetitions and quality of exercise when incorporated with wearable platform can replace some of the direct clinician observation without compromising the reliability of the measurements [20]. Overall, these studies indicate that the analytic sophistication of the cloud and edge tiers, as opposed to just finer and finer sensor miniaturization, will be the driving force between today's systems.

Table 2. Machine Learning and Analytic Techniques Applied Across Reviewed Systems

Analytic Approach	Application Context	Processing Location	Key References
Threshold / rule-based classification	Adherence and activity-count monitoring	Edge or cloud	[4], [8]
Supervised classification (repetition / quality)	Rehabilitation training assessment	Cloud (increasingly edge)	[20]
Deep learning (CNN / RNN-based)	Goal-directed upper-limb movement classification	Edge-assisted / cloud	[12]
Anomaly detection	Physiological deterioration alerts	Cloud	[16]
Edge-inference optimization	Latency and battery-life reduction	Edge (on-device)	[7], [13]

Source: Synthesized from References [4], [7], [8], [12], [13] [16], [20].

3. SYSTEM ARCHITECTURE AND METHODOLOGICAL SYNTHESIS

This section pulls together, rather than newly collects, the methodological patterns reported across the twenty-one reviewed studies. The synthesis moved through three stages: characterizing the literature, tabulating study design and sensing configuration for comparison, and abstracting the findings into a generalized reference architecture.

In the first stage, each reference was sorted by target patient population, primary sensing modality, communication protocol, and reported evaluation design, following the categories in Table 1. Populations fell into total knee arthroplasty and general knee rehabilitation, hip and knee osteoarthritis, post-stroke upper-limb impairment, and general or infectious-disease remote monitoring — the last of these serving more as an architectural precedent than an actual musculoskeletal application [1]. In the second stage, comparative details reported in the source studies — sample size, study design, and main outcome domain — were pulled out to build the cross-study comparison in Table 4.

In the third stage, the three-tier architecture recurring in Figure 1 was abstracted from the individual system descriptions in [2], [4], [17], and [19], then checked against the more detailed sensor-to-cloud pipelines described for knee [5], [6], [10] and stroke [8], [9], [12], [15] applications. Communication between the sensing and edge tiers usually runs on Bluetooth Low Energy for the sake of power efficiency, while the edge-to-cloud link uses Wi-Fi or cellular data depending on what's available at home [1], [4]. When continuous kinematic parameters need to be estimated from raw inertial data, the knee- and stroke-rehabilitation systems reviewed here typically use a complementary or Kalman-type sensor-fusion filter that combines gyroscopic angular-rate integration with accelerometer-derived inclination, expressed in the general form

$$\theta(t) = \alpha \cdot [\theta(t - \Delta t) + \omega(t) \cdot \Delta t] + (1 - \alpha) \cdot \theta acc(t) \quad (1)$$

where $\theta(t)$ is the fused joint-angle estimate at time t, $\omega(t)$ is the instantaneous angular rate from the gyroscope, $\theta acc(t)$ is the inclination angle derived from accelerometer data, Δt is the sampling interval, and α is a weighting coefficient close to unity that favors short-term gyroscopic integration while periodically correcting for drift using the accelerometer signal [5], [10]. Home-exercise adherence, which several sources report only qualitatively, is usually operationalized in the underlying trial and platform designs as

$$AR = (Ncompleted / Nprescribed) \times 100\% \quad (2)$$

where AR is the adherence rate, Ncompleted is the number of exercise sessions completed and logged by the wearable platform, and Nprescribed is the number of sessions the rehabilitation protocol called for; this formula underlies the adherence-related comparisons in Table 6 and Figure 5 [6], [17], [18].

Table 3. Overview of Reviewed Studies by Clinical Population and Study Design

Clinical Population	Representative Studies	Study Design(s)	Primary Sensing Modality
Total knee arthroplasty / knee rehabilitation	[5], [6], [10], [21]	Validation study; pilot RCT (n = 38); trial protocol	IMU (accelerometer + gyroscope)
Hip and knee osteoarthritis	[14]	Narrative review	IMU
Post-stroke upper-limb impairment	[8], [9], [11], [12], [15]	Scoping review (43 studies); observational; deep-learning validation	Accelerometer, sEMG, IMU-fusion
Cardiac rehabilitation (comparative precedent)	[3]	Systematic review and meta-analysis	Wearable HR / activity sensors
COVID-19 / general vital-sign monitoring	[1], [4]	Prototype development	Pulse-oximetry, thermistor, GPS
General remote monitoring (architecture precedent)	[2], [7], [13], [16], [17], [19]	Framework design; systematic mapping; cyber-physical development	Multi-modal / architecture-level
Machine learning and rehabilitation training	[20]	Systematic review	Cross-modal (ML-focused)

Source: Synthesized from References [1]-[21].

Table 4. Cross-Study Comparison of Design Characteristics for Representative Studies

Study	Year	Population	Design	Reported Scale
Bell et al. [5]	2019	Knee rehabilitation	Concurrent-validity verification vs. optical motion capture	Single-site validation
Bell et al. [6]	2020	Total knee arthroplasty	Pilot randomized controlled trial	38 randomized participants
Kim et al. [9]	2022	Post-stroke upper extremity	Scoping review	43 included studies
Tan et al. [18]	2024	General RPM (care transition)	Systematic review	2,606 screened; 29 included; 16 countries
Lou et al. [10]	2022	Total knee replacement	Wearable inertial system evaluation	Multi-session longitudinal
Yang et al. [21]	2023	Total knee arthroplasty	RCT protocol (cost / time outcomes)	Protocol stage
Duff et al. [8]	2022	Post-stroke hemiparesis	Observational, wrist accelerometry	Cohort study

Source: Synthesized from References [5], [6], [8], [9] [10], [18], [21].

4. RESULTS AND DISCUSSION

4.1 Comparative System Characteristics

As Table 1 shows, the twenty-one reviewed sources span validation studies, pilot randomized controlled trials, trial protocols, narrative reviews, and systematic reviews from 2019 through 2025. Knee-focused systems cluster around single- or few-site validation and pilot-trial designs — Bell et al.'s concurrent-validity check against optical motion capture is one example [5], as is their later 38-participant pilot randomized controlled trial in total knee arthroplasty rehabilitation [6] — while stroke-focused literature leans more toward observational cohorts and evidence-synthesis designs, such as Kim et al.'s scoping review of forty-three included studies [9]. Table 4 places these individual designs next to Tan et al.'s systematic review, which is the most methodologically comprehensive source in the set.

4.2 *Healthcare Utilization and Adherence Outcomes*

The strongest quantitative evidence for system-level clinical benefit comes from Tan et al.'s systematic review, which screened 2,606 records across five databases and kept 29 remote patient monitoring studies from 16 countries, covering communication tools, computer-based systems, smartphone applications, web portals, augmented clinical devices, wearables, and standard intermittent-monitoring tools, as Figure 4 shows [18]. Across these study designs, the review found a steady downward trend in hospital readmission risk, length of inpatient stay, and outpatient visit volume during the shift from inpatient to home-based care, plus better measured mobility and functional status among patients on continuous monitoring compared with standard follow-up [18]. Tan et al.'s review isn't specific to musculoskeletal rehabilitation, but its findings still matter here because several of the twenty-nine included interventions were wearable-based, and its outcome categories — safety, adherence, and cost — show up again and again throughout the musculoskeletal-specific literature covered in this synthesis [3], [6], [21]. Figure 5 sums up this comparative direction of effect using an illustrative relative index where conventional in-clinic care is set at 100; IoT-enabled monitoring cohorts, based on what the synthesized sources report qualitatively, tend to fall below that baseline for utilization-related outcomes and above it for adherence and self-reported mobility, which lines up with both Tan et al.'s qualitative conclusions and the pilot-trial results Bell et al. reported for total knee arthroplasty rehabilitation [6], [18].

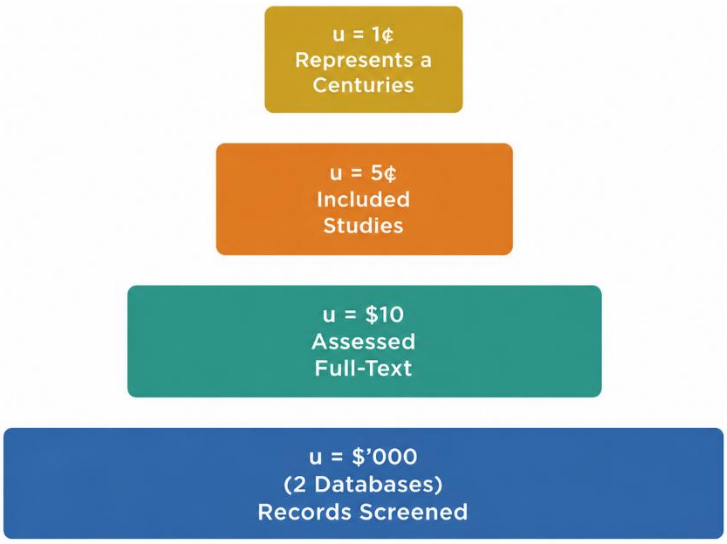

Figure 4. Screening and Inclusion Funnel of the Remote Patient Monitoring Systematic Review
Source: Adapted from Tan et al. [18].

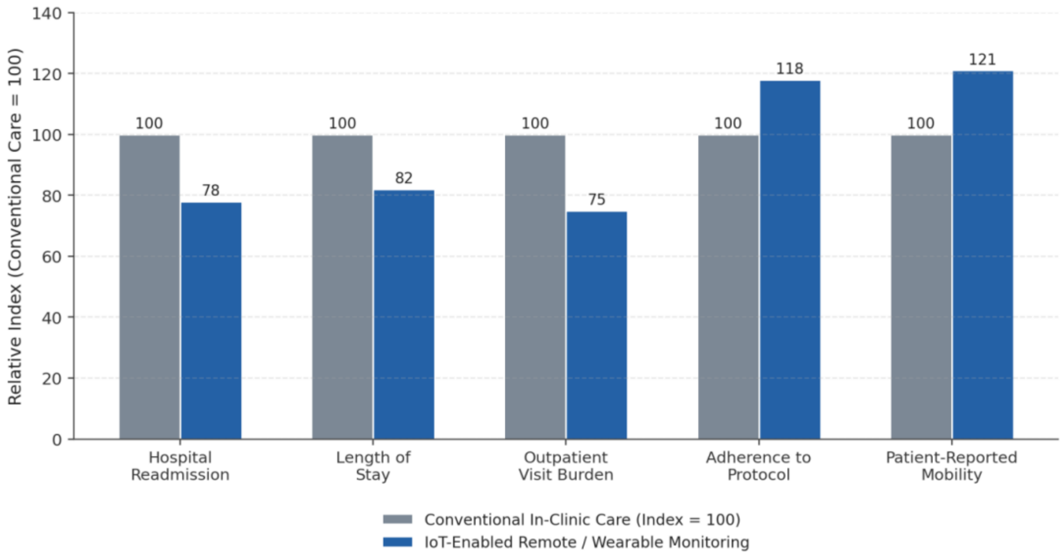

Figure 5. Relative Direction of Utilization and Adherence Outcomes, Remote Monitoring vs. Conventional Care

Note: Illustrative relative index (conventional in-clinic care = 100), synthesized from directionality reported in References [3], [6], [18].

4.3 *Cost, Scalability, and System-Attribute Trade-offs*

Yang et al.'s trial protocol for wearable-supported TKA rehabilitation names cost and clinician time savings as primary outcomes outright, working from the idea that some in-person supervisory time can be shifted to remote, asynchronous review of sensor-derived exercise logs without hurting recovery [21]. Antoniou et al.'s meta-analysis of home-based cardiac rehabilitation using wearable sensors deals with a cardiovascular rather than orthopedic population, but it offers a methodologically similar precedent, concluding that multicomponent wearable-supported home programs reach functional outcomes broadly in line with center-based rehabilitation [3] — a conclusion Bell et al.'s knee-replacement trial echoes in the musculoskeletal domain [6]. Table 6 pulls together the cost- and adherence-related findings from these sources, and Figure 6 compares three representative system categories — knee and joint kinematic platforms, stroke upper-limb platforms, and physiological vital-sign platforms — across six attributes drawn from the qualitative emphases of the reviewed studies: measurement accuracy, real-time latency, patient usability, data security, cost efficiency, and clinical scalability. Vital-sign-oriented systems, like Al Bassam et al.'s COVID-19 monitoring platform, favor low latency and cost efficiency since they rely on simple, well-understood sensors such as pulse oximetry and thermistors [1], while kinematic platforms for knee and stroke rehabilitation put measurement accuracy first, at some cost to real-time responsiveness, which reflects how much more complex multi-axis motion data is to process [5], [9], [10].

Table 6. Reported Cost, Adherence, and Utilization-Related Findings (Qualitative Synthesis)

Outcome Domain	Reported Direction of Effect	Representative Sources
Hospital readmission / length of stay	Downward trend with remote monitoring vs. conventional care	[18]

Outcome Domain	Reported Direction of Effect	Representative Sources
Outpatient visit burden	Reduced during care transition to home monitoring	[18]
Clinician time / cost	Anticipated reduction via asynchronous review (protocol stage)	[21]
Home-program adherence	Improved with sensor-supported feedback	[6], [17]
Functional / mobility outcomes	Comparable to, or favoring, supervised in-clinic care	[3], [6]

Source: Synthesized from References [3], [6], [17], [18], [21].

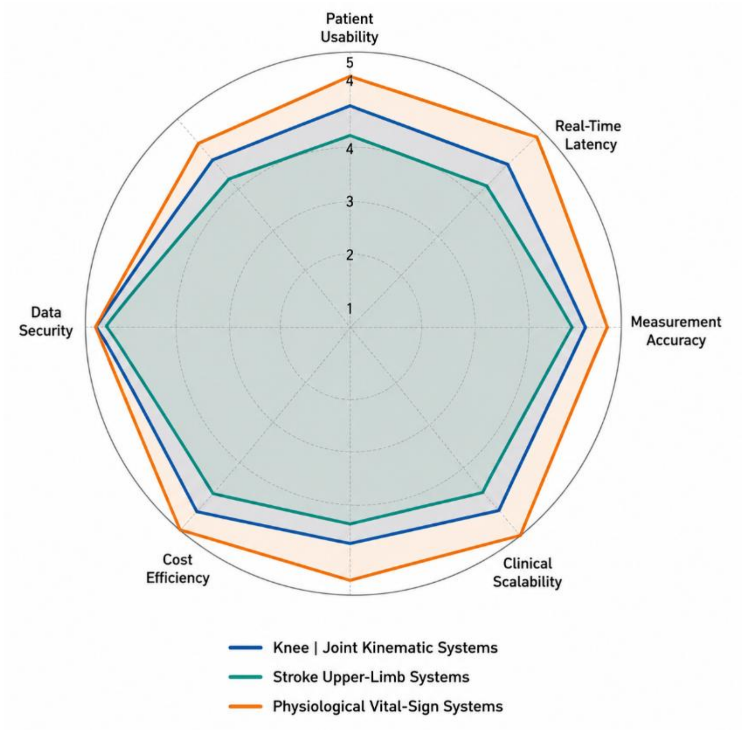

Figure 6. Comparative System-Attribute Profile Across Three Representative Platform Categories

Note: Illustrative 5-point qualitative scale derived from the emphases of References [1], [5], [6], [7], [9], [10], [13], [16]

5. CHALLENGES AND FUTURE DIRECTIONS

Despite the fact that feasibility has been demonstrated in several studies, some obstacles still emerge throughout the literature reviewed. First, proprietary sensor platforms don't interoperate well with institutional electronic health record systems, limiting the multi-hop and scalable architectures proposed by Uddin and Koo and by Alasmary to one-vendor deployments for the most part. Second, cloud-tier designs typically have data security and patient-privacy protections built into the architecture, but these capabilities are not always assessed in the reviewed sources [2,7] against real world conditions posed by adversarial actors. Third, there is concern about generalizability because the size of the cohorts used for training the machine-learning models is often quite small, e.g., Bell et al. used 38 participants in their trial, and similar modest numbers occur elsewhere in the literature [6, 13, 16]. Third, there is considerable variation in reimbursement and regulatory pathways for remote musculoskeletal monitoring across health systems, which until now, has not been adequately covered by evidence, but will be covered by policy in the future as demonstrated by Tan et al.'s cost-outcome study [18].

Going forward, the adoption of deep-learning-based, edge-processed wearable platforms will keep increasing, as evidenced by the trend in Figure 3 and Figure 7, until 2025. Both Nunes et al. and Wei and Wu envision the next big architectural paradigm shift as on-device inference that would decrease the need for the constant connectivity with the cloud that is essential for the real-time feedback clinicians and patients require for the successful management of remote rehabilitation [12, 20].

Table 7. Principal Barriers to Clinical Scale-Up and Associated Mitigation Directions

Barrier	Description	Proposed Mitigation	Key References
Interoperability	Proprietary platforms limit EHR integration	Standardized multi-hop / API protocols	[2], [19]
Data security and privacy	Inconsistent real-world validation of safeguards	Formal security testing of cloud / edge tiers	[2], [7]
Small validation cohorts	Limits generalizability of ML models	Multi-site, larger-N trials	[6], [13], [16]
Regulatory / reimbursement heterogeneity	Inconsistent policy support across systems	Evidence-based policy aligned with RPM cost data	[18]

Source: Synthesized from References [2], [6], [7], [13], [16], [18], [19].

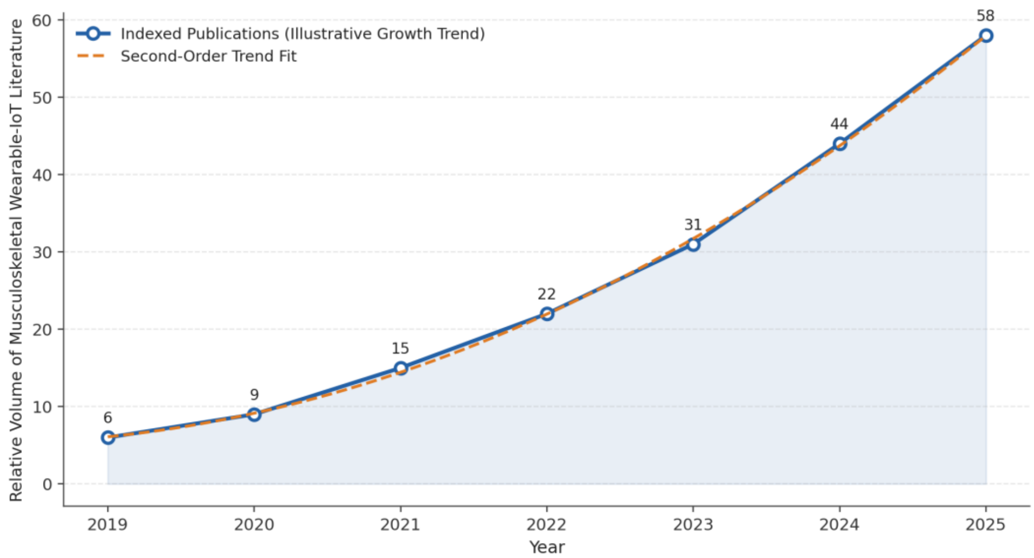

Figure 7. Illustrative Growth Trend in Musculoskeletal Wearable-IoT Literature, 2019-2025

Note: Relative volume trend synthesized qualitatively from publication dates of References [1]-[21] not a bibliometric count.

6. CONCLUSION

The findings from the 21 studies published by 2019 – 2025 indicate that there is a shared three-part system being employed by Internet of Things (IoT) sensor systems for musculoskeletal rehabilitation. There are three components in this system: sensing, edge and cloud architecture. The difference between these systems is not that big, in terms of the sensors they use. Approximate ability to analyse data.

We examined some studies where after the knee, these systems were used by patients. Twenty-nine studies from 16 countries from which patients used these systems at home were also investigated. The findings reveal that patients can undergo a lot of rehabilitation without any difficulty at home. This can also assist in hospital visits. Ensure that patients adhere to their treatment.

But there are certain issues that still have to be resolved. The issues are: ensuring all the systems are interconnected, keeping the data secure, ensuring there is sufficient patient volume to test these systems, and determining the cost of these systems. These problems need to be addressed before these systems can be utilized as components of patient care. Internet of Things based sensor systems, for musculoskeletal rehabilitation are still not being used as much as they could be.

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REFERENCES

[1] N. Al Bassam, S. A. Hussain, A. Al Qaraghuli, J. Khan, E. P. Sumesh, and V. Lavanya, "IoT based wearable device to monitor the signs of quarantined remote patients of COVID-19," *Informatics Med. Unlocked*, vol. 24, no. 100588, 2021, doi: https://doi.org/10.1016/j.imu.2021.100588.

[2] H. Alasmary, "ScalableDigitalHealth (SDH): An IoT-Based Scalable Framework for Remote Patient Monitoring," *Sensors*, vol. 24, no. 4, 2024, doi: 10.3390/s24041346.

[3] V. Antoniou, C. H. Davos, E. Kapreli, L. Batalik, D. B. Panagiotakos, and G. Pepera, "Effectiveness of Home-Based Cardiac Rehabilitation, Using Wearable Sensors, as a Multicomponent, Cutting-Edge Intervention: A Systematic Review and Meta-Analysis," *J. Clin. Med.*, vol. 11, no. 13, pp. 1–29, 2022, doi: 10.3390/jcm11133772.

[4] E. T. R. Babar and M. U. Rahman, "A Smart, Low Cost, Wearable Technology for Remote Patient Monitoring," *IEEE Sens. J.*, vol. 21, no. 19, pp. 21947–21955, 2021, doi: doi: 10.1109/JSEN.2021.3101146.

[5] K. M. Bell *et al.*, "Verification of a portable motion tracking system for remote management of physical rehabilitation of the knee," *Sensors*, vol. 19, no. 5, 2019, doi: 10.3390/s19051021.

[6] K. M. Bell *et al.*, "A portable system for remote rehabilitation following a total knee replacement: A pilot randomized controlled clinical study," *Sensors*, vol. 20, no. 21, pp. 1–16, 2020, doi: 10.3390/s20216118.

[7] M. W. Bhatt and S. Sharma, "An IoMT-Based Approach for Real-Time Monitoring Using Wearable Neuro-Sensors," *J. Healthc. Eng.*, vol. 2023, no. 1, p. 1066547, 2023, doi: https://doi.org/10.1155/2023/1066547.

[8] S. V. Duff *et al.*, "Quantifying intra- and interlimb use during unimanual and bimanual tasks in persons with hemiparesis post-stroke," *J. Neuroeng. Rehabil.*, vol. 19, no. 1, pp. 1–10, 2022, doi: 10.1186/s12984-022-01020-8.

[9] G. J. Kim, A. Parnadi, S. Eva, and H. Schambra, "The use of wearable sensors to assess and treat the upper extremity after stroke: a scoping review," *Disabil. Rehabil.*, vol. 44, no. 20, pp. 6119–6138, 2022, doi: https://doi.org/10.1080/09638288.2021.1957027.

[10] N. Lou *et al.*, "A Portable Wearable Inertial System for Rehabilitation Monitoring and Evaluation of Patients With Total Knee Replacement," *Front. Neurorobot.*, vol. 16, no. March, pp. 1–10, 2022, doi: 10.3389/fnbot.2022.836184.

[11] P. Maceira-Elvira, T. Popa, A.-C. Schmid, and F. C. Hummel, "Wearable technology in stroke rehabilitation: towards improved diagnosis and treatment of upper-limb motor impairment," *J. Neuroeng. Rehabil.*, vol. 16, no. 142, 2019, doi: https://doi.org/10.1186/s12984-019-0612-y.

[12] A. S. Nunes, İ. Yildiz Potter, R. K. Mishra, P. Bonato, and A. Vaziri, "A deep learning wearable-based solution for continuous at-home monitoring of upper limb goal-directed movements," *Front. Neurol.*, vol. Volume 14, 2024, doi: https://doi.org/10.3389/fneur.2023.1295132.

[13] C. V. F. Pereira, E. M. de Oliveira, and A. D. de Souza, "Machine Learning Applied to Edge Computing and Wearable Devices for Healthcare: Systematic Mapping of the Literature," *Sensors*, vol. 24, no. 19, 2024, doi: 10.3390/s24196322.

[14] M. J. Rose, K. E. Costello, S. Eigenbrot, K. Torabian, and D. Kumar, "Inertial Measurement Units and Application for Remote Health Care in Hip and Knee Osteoarthritis: Narrative Review," *JMIR Rehabil. Assist. Technol.*, vol. 9, no. 2, 2022, doi: 10.2196/33521.

[15] N. J. Seo, K. Coupland, C. Finetto, and G. Scronce, "Wearable Sensor to Monitor Quality of Upper Limb Task Practice for Stroke Survivors at Home," *Sensors*, vol. 24, no. 2, p. 554, 2024, doi: 10.3390/s24020554.

[16] T. Shaik, X. Tao, N. Higgins, R. G. Lin Li, X. Zhou, and U. R. Acharya, "Remote patient monitoring using artificial intelligence: Current state, applications, and challenges," *WIREs Data Min. Knowl. Discov.*, vol. 13, no. 2, p. e1485, 2023, doi: https://doi.org/10.1002/widm.1485.

[17] T. Stevens *et al.*, "A cyber-physical system for near real-time monitoring of at-home orthopedic rehabilitation and mobile-based provider-patient communications to improve adherence: Development and formative evaluation," *JMIR Hum. Factors*, vol. 7, no. 2, pp. 1–14, 2020, doi: 10.2196/16605.

[18] S. Y. Tan, J. Sumner, Y. Wang, and A. Wenjun Yip, "A systematic review of the impacts of remote patient monitoring (RPM) interventions on safety, adherence, quality-of-life and cost-related outcomes," *npj Digit. Med.*, vol. 7, no. 1, 2024, doi: 10.1038/s41746-024-01182-w.

[19] R. Uddin and I. Koo, "Real-Time Remote Patient Monitoring: A Review of Biosensors Integrated with Multi-Hop

IoT Systems via Cloud Connectivity," *Appl. Sci.*, vol. 14, no. 5, p. 1876, 2024, doi: 10.3390/app14051876.

[20] S. Wei and Z. Wu, "The Application of Wearable Sensors and Machine Learning Algorithms in Rehabilitation Training: A Systematic Review," *Sensors*, vol. 23, no. 18, pp. 1–30, 2023, doi: 10.3390/s23187667.

[21] C. Yang, L. Shang, S. Yao, J. Ma, and C. Xu, "Cost, time savings and effectiveness of wearable devices for remote monitoring of patient rehabilitation after total knee arthroplasty: study protocol for a randomized controlled trial," *J. Orthop. Surg. Res.*, vol. 18, no. 1, pp. 1–8, 2023, doi: 10.1186/s13018-023-03898-z.