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The use of wearable sensors to assess and treat the upper extremity after stroke: a scoping review

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Abstract

Purpose: To address the gap in the literature and clarify the expanding role of wearable sensor data in stroke rehabilitation, we summarized the methods for upper extremity (UE) sensor-based assessment and sensor-based treatment.

Materials and methods: The guideline outlined by the preferred reporting items for systematic reviews and meta-analysis extension for scoping reviews was used to complete this scoping review. Information pertaining to participant demographics, sensory information, data collection, data processing, data analysis, and study results were extracted from the studies for analysis and synthesis.

Results: We included 43 articles in the final review. We organized the results into assessment and treatment categories. The included articles used wearable sensors to identify UE functional motion, categorize motor impairment/activity limitation, and quantify real-world use. Wearable sensors were also used to augment UE training by triggering sensory cues or providing instructional feedback about the affected UE.

Conclusions: Sensors have the potential to greatly expand assessment and treatment beyond traditional clinic-based approaches. This capability could support the quantification of rehabilitation dose, the nuanced assessment of impairment and activity limitation, the characterization of daily UE use patterns in real-world settings, and augment UE training adherence for home-based rehabilitation.

Keywords

Wearable sensors; accelerometers; IMU; upper extremity; stroke; sensor-based assessment; sensor-assisted treatment

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Disclosure statement

The authors declare that there is no conflict of interest.

Introduction

Wearable motion sensors are small, light, non-invasive electronic devices [1]. These sensors are worn on specific body segments, such as the wrist or chest, to capture motion data. Accelerometers and inertial measurement units (IMUs) are the two main sensors used to measure upper extremity (UE) motion [2]. Accelerometers capture linear acceleration data in 1–3 planes of motion [3]. IMUs capture three-dimensional (3D) linear accelerations from accelerometers, and angular velocities from gyroscopes [1]. The combination of linear and rotational data enables a more complete picture of UE motion, as it has many degrees of freedom that are insufficiently characterized by three dimensions of linear acceleration. Thus, IMU sensors are data-rich and are used when high classification performance is needed from the data [4]. Conversely, accelerometers are data-sparse and used when magnetic interference is a concern, i.e., in remote or uncontrolled environments [4]. Wearable sensor technology has widespread applications in sports, animation, and clinical settings [1,5]. Applications in clinical populations include quantifying tremor severity in individuals with Parkinson's disease, monitoring safety and fall risk in the elderly, and monitoring gait and habitual activity in older adults [3,5].

Researchers have also increasingly incorporated UE sensors into stroke rehabilitation research. Stroke is the leading cause of serious long-term disability in the USA [6]. Functional use of the affected UE after stroke is key for increased independence in basic and instrumental activities of daily living (ADLs), returning to work, and overall quality of life [7]. For individuals six months after a first-time ischemic stroke with severe hemiplegia, only 38% of patients demonstrate some hand dexterity (e.g., gross grasp, finger extension), and only 11.6% experience full recovery [8]. The implementation of effective UE rehabilitation approaches to reduce disability is therefore of critical relevance.

To address this need, clinical researchers have begun to using wearable sensors to capture UE motion in and outside of the clinic. The use of wearable sensors has the potential to expand existing methods for UE assessment and treatment after stroke. In principle, improved knowledge about impairment or activity limitation could enable therapists to better target their training, potentially improving functional return. The first publications in PubMed using accelerometers or IMUs in stroke appeared in 1983, with an exponential increase in publications in the last decade [2]. This sharp increase in the use of wearable sensors signals the need to understand how these modalities can be used for assessing and treating the affected UE [9].

Earlier studies largely focused on establishing sensor data as valid and reliable instruments for measuring UE motion. UE accelerometer metrics (activity counts) demonstrate excellent test-retest reliability and construct validity for assessing UE motion in acute and chronic stroke [10]. Accelerometer and IMU metrics demonstrate convergent validity [10–15] and divergent validity [14,16]. Accelerometer metrics demonstrate discriminant ability for UE use in healthy individuals versus stroke survivors, upper versus lower extremity use in stroke, and severity of UE impairment in acute stroke [10,14]. These clinimetric studies underscore the reliability and validity of using sensors to capture UE motion after stroke.

Three recent reviews examined the clinical application of sensors in rehabilitation. The first broadly overviewed clinical applications of wearable sensors in neurological (stroke, spinal cord injury, cerebral palsy), musculoskeletal (arthritis, frozen shoulder trauma), pain management, and general rehabilitation populations [2]. This review found that accelerometers and IMUs were commonly used to provide extrinsic feedback (knowledge of results, knowledge of performance) for posture and UE movements in stroke [2], but did not examine the methods used for data capture and analyses. The second presented a broad overview of the past, present, and future directions for the clinical use of IMU, EMG, and e-textile based technologies in UE stroke rehabilitation [17]. This review identified limited clinical utility, bulky equipment, and difficulties with device set up with these technologies [17], but did not review the methods used for data capture and analyses. The third focused on the feasibility of using accelerometers for UE assessment in real-world home and community settings [18]. This didactic review provided detailed background information on the methods for data capture and analysis for sensor-based assessment in home and community settings [18], but did not present a comprehensive review for other types of sensor-based assessments or sensor-based treatment approaches.

Since these reviews, there have been continued advancements in sensor technology and data analysis, which have expanded UE assessment and treatment methods. In addition to the limitations of the reviews noted above, there currently exists no detailed review of emerging sensor-based assessment and treatment approaches in UE stroke rehabilitation. We thus completed a scoping review to systematically map the research in this area. The aims of this study were to summarize UE sensor-based assessment and UE sensor-based treatment approaches in individuals with stroke.

Materials and methods

We followed the guidelines outlined by the preferred reporting items for systematic reviews and meta-analysis extension for scoping reviews to conduct this scoping review [19]. We used the population, concept, context (PCC) structure to identify the key elements to conceptualize the scoping review: stroke (population), UE wearable sensors (concept), and rehabilitation (context) [19,20].

Databases and systematic search

We completed a systematically search of PubMed, Embase, Web of Science, and CINAHL databases on 17 December 2020. We used the following key words and their iterations: accelerometry OR IMU OR stroke OR upper extremity. See Supplement Appendix A for detailed search strategies used for each database. We also reviewed the references of included articles to search for additional relevant articles.

Selection criteria

We used the following criteria to determine eligibility.

Inclusion criteria:

- adults with stroke;

- use of wearable sensors;
- measurement of UE motion;
- sensor data used to develop methods for UE assessment;
- sensor data used to augment UE training;
- studies published in peer-reviewed journals from 2009 to 2020.

Exclusion criteria:

- didactic papers, posters, book chapters, reviews;
- validation or reliability studies of sensor-based metrics (clinimetric properties – validity and reliability);
- studies examining the relationship between sensor data and clinical measures (clinimetric properties – concurrent validity);
- sensor data captured by robotic devices/gaming consoles;
- sensor data used to measure treatment outcomes (e.g., the effectiveness of robotics training or task specific practice).

Studies with stroke and healthy participants were included. Studies identified by the initial search were imported into Covidence, a review management software (https://www.covidence.org). Duplicates were removed and remaining abstracts were screened by ST and GK for eligibility. Abstracts without consensus were carried over into full text review. The remaining abstracts were advanced to full text review and examined independently by ST, GK, and AP. Any remaining uncertainty about eligibility was resolved by discussion between GK, AP, and HS.

Data extraction and analysis

The following data were extracted from each article: study aims, participant demographics, sensor characteristics, data collection methods, data processing methods, data analysis approaches, and study results. The extracted data were examined and studies were organized into assessment or treatment categories based on study aim. Studies in the assessment category were further analyzed and refined into three subcategories based on clinical application. Discrepancies with categorization were discussed with all co-authors until agreement was reached.

Results

We found 704 abstracts after searching the databases. The initial screen of titles and abstracts eliminated 575 abstracts, and 129 full text articles were reviewed. We excluded an additional 86 articles because they did not meet inclusion criteria, leaving 43 articles for full review. See Figure 1 for the PRISMA flowchart. We organized the results into assessment and treatment categories. In the assessment category, wearable sensor data were used to appraise three aspects of UE motion: functional motion, motor impairment/activity limitation, and real-world use. Functional motion is defined as any motion that is

goal-directed and volitional in the context of ADLs [21]. Motor impairment is partial or total loss of body function or structures, while activity limitation is difficulty with executing or completing activities [22] Real-world use is motion captured under non-standardized conditions for sustained time periods. In the treatment category, wearable sensors were used to trigger sensory cues or provide instructional feedback for the affected UE during training. We present summarized results for each category below. See Tables 1–4 for detailed information about each study including participant information, study sample size, sensor type and placement, data collection conditions, data processing and analyses, and study results.

Category 1a: identification of functional motion

We identified 10 studies that identified functional motion of the affected UE while participants completed typical ADLs. A taxonomy of UE function [21] was used to define functional motion terminology in this section. Functional motion is any purposeful motion/minimal-motion that engages the environment in the context of basic or instrumental ADLs [21]. Functional motion can be deconstructed in a hierarchical manner based on decreasing time durations and goals. Activities are long-duration motions with many goals (e.g., UE dressing); functional movements are moderate-duration motions with a few goals (e.g., putting arm through sleeve, zipping up jacket) [23,24]; and functional primitives are short-duration motions or minimal-motions with one goal (e.g., reach, stabilize, transport) [25]. Within this framework, one study identified activity [26], five studies identified functional movements [27–31], and one study identified functional primitives [32]. Three studies identified the presence or absence of functional motion rather than recognizing a specific hierarchical level of functional motion [33–35].

Data capture—All studies in this category used IMU sensor data with the exception of one study, which used a combination of accelerometers and surface electromyography [30]. The number of sensors varied from a single sensor affixed to the affected wrist [27,31,33] to 11 sensors affixed to the head, bilateral UE, trunk, and pelvis [32]. All studies collected data in outpatient settings, and two studies also collected data in the home setting [26,31]. All study participants completed functional activities or functional movements for a specific set of repetitions in standardized conditions. Two studies also collected non-standardized data in a home setting from healthy [26] and stroke [31] participants. Stroke participants were in the chronic phase of recovery [30–34] or it was not specified [26–29,35].

Data processing and analysis—Sensor data were pre-processed using low- and high-band pass filtering to remove noise at the minimum and maximum end of the frequency spectrum, typically 0.2–15 Hz. Supervised machine learning (ML) was used in seven studies to classify UE motion as functional movements or functional primitives [27,30–35]. Supervised ML entails training an algorithm with a motion dataset that has been labeled by human observers, then testing the trained algorithm on another labeled motion dataset to assess its classification performance [4]. It is beyond the scope of this paper to detail the specific methods of ML classification, but practical reviews can be found elsewhere [4,9]. ML approaches used to classify motion data included K-means cluster analysis [28], random forest [33–35], hidden Markov model with logistical regression [32], multi-layered neural

network and adaptive neurofuzzy system [30], convolutional neural network (deep learning) [31], radial basis function support vector machine [34], K-nearest neighbor, and support vector machines [35]. Once the algorithm was trained, out-of-subject testing was performed in all studies.

Three studies used non-ML approaches, including a threshold-based approach and a mathematical rule-based approach to classify UE motion as an activity or functional movement [26,27,29]. Rule-based or threshold-based approaches apply human-crafted rules and expert-determined thresholds to recognize functional motion, for instance identifying a reaching motion from a simultaneous increase in shoulder flexion and elbow extension. For non-ML approaches, algorithms were created to recognize kinematic patterns associated with functional movements or activities of interest [26,29], or to determine sensor orientation and movement sequences associated with specific functional movements [27].

Outcomes—The majority of studies assessed the performance of their algorithms by calculating sensitivity or accuracy. Sensitivity is calculated as the proportion of correct positive classifications relative to the total number of positive samples (true positive rate). Accuracy is calculated as the proportion of correctly classified samples (true positive and true negative) relative to the total sample [36]. The range for sensitivity or accuracy is 0–1, with 1 indicating perfect classification by the algorithms [4]. Unless noted, we report classification performance on out-of-subject data, where the algorithm assessed subject data that it had not previously seen.

The classification of three functional activities for controls and stroke had a high sensitivity of 1.0 [26]. The classification of functional movements had a sensitivity of 0.93 for stroke [30], and an accuracy of 0.83–0.99 for controls and 0.66–0.98 for stroke [27–29,31]. The classification of functional primitives had a sensitivity of 0.82 in controls and 0.75 in stroke [32]. The binary classification (functional versus non-functional motion) had an accuracy of 0.90–0.96 in controls and 0.61–0.93 in stroke [33–35].

Category 1b: identification of motor impairment and activity limitation

We identified 14 studies that classified UE motion at the motor impairment or activity limitation levels. Motor impairments are partial or total loss of body function or structures (e.g., strength, endurance, and motor control), while activity limitation is difficulty with executing or completing activities [22]. The purpose of the studies was to identify the presence of motor impairment [37–39] or to classify UE motion into distinct motor impairment/activity limitation levels [40–50].

Data capture—Various combinations of IMUs, accelerometers, and flex sensors were used to collect UE motion data. Flex sensors measure the amount of bend or deflection using thin strips of conductive materials and can be embedded into a glove or garment to capture movement of the wrist or fingers [51]. The number of sensors ranged from a single sensor at the affected wrist [42] to a 16-IMU hand glove [39,43]. Data were collected in the inpatient hospital [37,38,40,47–49], outpatient lab [43–45], outpatient clinic and home [46], or the location was not specified [42,50]. Data were collected during performance of standardized clinical assessments [40,42–46,50], study-specific shoulder/hand tasks [39,42,43,48,49],

or non-standardized arm motion [37,38,41,47,50]. Stroke participants were in the acute [37,38,40,41,47–49], subacute [46,50], or chronic phase of recovery [46,50], or chronicity was not specified [39,42–45].

Data processing and analysis—Sensor data were pre-processed using low- and high-band pass filtering. All studies extracted accelerometry signals from motion data to derive kinematic data such as velocity, smoothness, and magnitude.

Eleven studies used supervised ML methodology described above to classify levels of motor impairment. UE motion data were labeled using scores from the Oxford Motor Strength Scale [47], Fugl-Meyer Assessment (FMA) [40,46], Brunnstrom levels [39,42,43], Wolf Motor Function Test (WMFT) [44,45], and the National Institute of Health Stroke Scale (NIHSS) [41,48,49]. The investigators used various ML approaches to classify arm impairment levels, including decision tree [40], bagging forest [40], dynamic time warping [42], K-means clustering [43], K-fold validation [43], extreme learning and RRelief [46], naïve Bayes classifier [44], random forest [45], logistic regression [39], support vector machines [47], hierarchical discriminant analysis [48,49], and non-linear mixed effects models with Gaussian process [50]. Once the algorithm was trained, out-of-subject testing was performed [40,42,43,46–50] or testing procedures were not specified [39,44,45].

Three studies used a non-ML threshold-based approach to classify motion data into presence or absence of motor impairment [37,38] and multiple class impairment categories [41]. In these studies, investigators used expert-knowledge to generate thresholds for sensor data (e.g., acceleration value) or statistical metrics derived from sensor data (e.g., cross-correlation, energy). A reading above this threshold indicates a “match” (stroke patient) and a value below indicates “not a match” (healthy control). Studies using threshold-based analysis did not split the motion data into testing and training sets. They generated the threshold using domain knowledge and used the entire dataset to test the threshold-based classification.

Outcomes—Algorithm performance was evaluated using sensitivity, accuracy, coefficient of determination (R^2), and error estimate calculations (root mean square (RMS) values). The coefficient of determination is calculated as the proportion of variance of the predicted data that is explained by the observed data [42]. Values range from 0 to 1, with scores approaching 1 representing a better fit. Error estimates represent misclassifications that are both false positives (“false alarms”) and false negatives (“accidental misses”), and are considered the complement of accuracy [36]. Error estimates do not have a set score range and have the same units as their target value, but scores approaching zero reflect better fit [52].

The classification of functional dependence versus ability to move against gravity had a sensitivity of 0.87 and an accuracy of 0.82 [47]. The classification of the presence versus absence of impairment had a sensitivity of 0.87–0.98 [37–39,48,49], mild versus moderate/severe impairment had a sensitivity of 0.80 and an accuracy of 0.80 [49], and moderate versus severe impairment had a sensitivity of 0.82–0.88 and an accuracy of 0.87–0.96 [48,49]. FMA scores were predicted with an error rate of 0.025 ± 0.025 [40] and an R^2

of 0.92 [46]. Brunnstrom levels 3–6 were predicted with an accuracy of 0.82 [42], and Brunnstrom levels 4 and 5 were predicted with an accuracy of 0.70 [43]. WFMT scores were predicted with RMS values of 0.45 [44] and 2.25 [45]. NIHSS motor scores were predicted with an accuracy of 0.81 [41]. Chedoke Arm and Hand Activity Inventory (CAHAI) scores were predicted with RMS values of 6.9 for subacute and 3.4 for chronic participants [50].

Category 1c: quantification of real-world use

We identified 14 studies that quantified real-world use. This approach is considered "real-world" because data were captured under non-standardized conditions for sustained time periods in the home or hospital. This approach quantifies general arm motion rather than specific functional motion. These studies compared use of the affected UE to the unaffected UE of stroke participants or to the UEs of healthy participants.

Data capture—All studies in this group used accelerometer data to capture motion. Nine studies used a sensor on each wrist [53–61], whereas five other studies used bilateral wrist sensors plus 1 −3 sensors at the bilateral lower extremities and/or hip [62–66]. Sensor data were collected in community, outpatient, and inpatient settings. Participants did not complete any predetermined UE tasks. Observational UE motion data were captured continuously for durations ranging from daytime waking hours [56,66] to 30 contiguous days [59]. Four longitudinal studies collected UE data at multiple time points post-stroke, including at hospital admission and 3 weeks [62], at admission and 3 months [55], at hospital discharge and 12 months [63], and from start of outpatient therapy to discharge from therapy [54]. Stroke participants were in the acute [54,55,57,60–63,66], subacute [55], and chronic [53,54,56,58,59,63,64] phases of recovery.

Data processing and analysis—Studies with commercial accelerometers used built-in proprietary software for initial pre-processing of raw acceleration data [53,54,57,60–63]. Some studies reported little information on pre-processing and calculation of metrics [55,56,58,59,65]. Mathematical calculations determined common metrics including duration of use, activity counts, and acceleration magnitude. Activity counts are defined as the sum of acceleration signals over a pre-determined epoch or period of time [67]. Activity counts are specific for each study, and are often used as the basic unit representing UE use. Activity counts were reported [55,56,62,63,65] or further processed to characterize UE duration of use [53,54,57–61,64]. Acceleration magnitude, calculated as the sum of the vector magnitude for every second of activity, was used to characterize UE motion intensity [53,54,58,60,61,64,66]. Several studies calculated laterality indices – the ratio of affected to unaffected UE motion – examining duration of use (bilateral use ratio) or acceleration magnitude (bilateral magnitude ratio) [53,54,57,58,60–63,66].

Outcome—Individuals in the acute, subacute, and chronic phase of recovery used their affected UE significantly less than their unaffected UE or the UE of healthy controls, as measured by activity counts [55,62,63], duration of use [53,57,58,60,61,64], and acceleration magnitude [53,54,58,60,61,64,66]. In acute stroke, activity counts in the affected UE were 1.3 times lower than the unaffected UE and 2.4 times lower than in individuals with transient ischemic attack [65]. Activity counts in the affected UE were 4.0

times lower at 3 weeks and 3.0 times lower at 12 months compared to the unaffected UE [62,63]. Another study found activity counts in the affected UE to be 2.5 times lower at 2 weeks and 1.8 times lower at 3 months compared to the unaffected UE [55]. Mean activity counts for moderately impaired individuals were 3.5 times lower than mildly impaired individuals [56]. Duration of use ranged from 1.5 to 6.7 h on the affected side and 5.3–9.1 h on the unaffected side [57,58,60,61,64]. The use ratio was 0.22–0.86 in stroke and 0.89–0.95 in controls [54,57,60,61]. The bilateral magnitude ratio ranged from −2.2 to −7 in stroke participants and −0.1 to −0.26 in controls [53,54,60,61], and was significantly lower on weekends than weekdays in the acute rehabilitation setting [66]. A bilateral magnitude ratio score approaching zero indicates equal contribution of both UEs, while a negative ratio indicates more motion in the unaffected UE relative to the affected UE [53].

Category 2: sensor-assisted treatment

We identified five studies that used sensor-derived data to help with an aspect of treatment. Two studies used motion data to set the timing of vibration cues delivered to the affected UE during home-based arm training [68,69]. Two studies provided intermittent performance feedback to participants during home-based interventions, using UE motion data to calculate general UE use or to classify the type and quality of motion completed by participants [70,71]. One study assessed the initial feasibility of multiple types of performance feedback and stakeholder acceptance of the sensor-based training approach in preparation for a clinical trial [72].

Data capture—Three studies used accelerometers [68,69,71], while two studies used IMUs [70,72]. The studies used 1–2 sensors affixed to the affected or bilateral UEs. Data were collected during inpatient rehabilitation [68,69], in the home [68–71], or an outpatient lab [72]. Participants completed pre-determined functional tasks and UE exercises determined by research staff [70,72] or were instructed to complete their usual activities under non-standardized conditions [68,69,71]. Studies included participants with subacute [68,69] and chronic stroke [70–72].

Data processing and analysis—Sensor data were pre-processed using low- and high-band pass filtering [72] or procedures were not specified [68–71]. Two studies calculated acceleration magnitude every three days to set a threshold for vibration cues during an arm training protocol [68,69]. One study calculated general use metrics (duration of use, use ratio, acceleration magnitude) twice a week during a 3-week treatment period [71]. Two studies used a supervised ML approach to identify several aspects of UE motion [70,72]. The first of these studies classified whether assigned home exercises were performed (convolutional neural network) [70]. The second study determined performance feedback in multiple steps and classified UE motion as functional/non-functional (logistic regression), feedback or no feedback (nearest neighbor with dynamic time warping algorithm), and accuracy or compensatory (random forest) [72]. Once algorithms were trained, out-of-subject testing was performed for both studies [70,72].

Outcomes—Two studies delivered vibration cues based on acceleration magnitude thresholds to prompt UE activity, finding that they increased arm activity by 11–29%

[68] or increased the practice of assigned or self-chosen activities [69]. Three studies provided intermittent performance feedback based on sensor data [70–72]. The first study gave feedback based on general UE use metrics, improving scores on perceived actual arm use after a 3-week home intervention [71]. The second study gave feedback based on the classification of study-specific UE exercises (accuracy of 0.95–0.9) [70], significantly improving shoulder range of motion and WMFT scores for the treatment group compared to the control group. The third study demonstrated the feasibility of their multi-step approach by initially identifying functional/non-functional motion (accuracy of 0.87) [72]. Functional motion was then classified by whether it needed feedback or no feedback (sensitivity of 0.76), compensatory feedback (sensitivity of 0.67), or accuracy feedback (sensitivity of 0.76) [72]. Stakeholder willingness to use this proposed approach for home rehabilitation was 91.7% for therapists and 88.2% for stroke survivors [72].

Discussion

Publication trends reflect the growing interest in using wearable sensors to study stroke recovery and rehabilitation. We reviewed and discussed the current literature to showcase the potential applications of this technology for UE assessment and treatment. We summarized how sensors have been used to assess UE functional motion, motor impairment and activity limitation, and real-world use. We also summarized the use of sensors to deliver sensory cues to prompt UE training or provide intermittent performance feedback during the UE treatment.

The number and placement of sensors were variable in the assessment of functional motion, impairment, and activity limitation. While the optimal number and placement of sensors did not emerge, sensor data were collected at the affected wrist in all studies, indicating that this could be a sensible placement location. The complexity of data analysis methodologies used for assessment and treatment were dependent on the level of specificity needed. Studies that identified specific functional ADLs or level of motor impairment required more complex ML and non-ML classification approaches. Studies that quantified general UE use used straightforward mathematical calculation of acceleration kinematics. Studies that used sensor data to assist in UE training had the greatest variability, using all aforementioned approaches.

Sensor-based assessment

The first group of studies used advanced analyses (ML and non-ML) to identify UE motion data at the three levels of functional motion: activity, functional movement, and functional primitives. Classification performance was generally higher for healthy control data and decreased with stroke data. While overall performance was high in these studies, comparison is challenged by their use of variable sensor systems, data types, functional tasks, classification approaches (ML versus non-ML), and ML algorithms.

The classification of UE functional motion has the potential to objectively monitor training content. The calculation of training dose for remote UE training is currently based on self-report. This sensor-based assessment could be used to quantify the dose of rehabilitation training in terms of time spent in functional motion [33] or repetitions of functional motion

[26,32]. The classification of UE functional motion in non-standardized settings is more challenging than in standardized settings, but it is an important area for future work if measuring home-based rehabilitation is to be undertaken.

A limitation of the studies was the inconsistent terminology used to define the UE motion that was being classified. We suggest the adoption of a uniform language based on a functional motion hierarchy, which would facilitate the consistent identification and reporting of functional motion in future studies [21]. Future studies are also needed to systematically compare classification performance with different data capture, processing, and analysis methodologies and in standardized versus non-standardized (real-world) rehabilitation conditions.

The second group of studies used sensors to classify UE impairment and activity limitation by predicting scores of traditional standardized assessments such as the FMA [40,46], Brunnstrom stages [42,43], WMFT [44,45], and the CAHAI [50]. Studies used advanced analyses (ML and non-ML approaches) to classify data into impairment or activity limitation categories.

The classification of UE impairment and activity limitation has the potential for objectively monitoring recovery. This sensor-based assessment could quantify UE impairment and activity limitation with fewer items than the FMA and WMFT, reducing the need for time-consuming clinical testing. An additional advantage of this approach is that sensor data can be transmitted wirelessly to external work stations, enabling the monitoring of a patient's motor status in real-time [73]. One important consideration for implementation in the home would be having caretaker help to don the sensors. We are not suggesting that this approach should replace clinical outcomes; however, this approach may surmount the challenge of administering clinical tests in specific circumstances including the first few hours after stroke or in community settings where resources (e.g., trained assessors, testing kits) may be limited.

A limitation of these studies was their focus on recapitulating the scores of existing clinical tests. The FMA, WMFT, and Brunnstrom stages use ordinal scoring systems, which precludes the detailed appraisal of impairment or activity limitation. Sensors capture continuous kinematic data, and could provide a more nuanced assessment of impairment and activity limitations. This would require the establishment of new metrics that break from traditional bedside tests. Work on this type of measurement is its infancy [74]. An additional limitation of the studies was the lack of participants with severe arm impairment, who may require additional sensors (e.g., EMG) to detect subtle muscle activation. Future work could include severely impaired participants to expand the classification capabilities of the approaches, making their application more universal.

All studies in the third group used sensors to quantify UE use over a sustained period of time [53,54,62–65]. Results from this group demonstrated that healthy individuals use both UEs fairly equally during everyday activities regardless of hand dominance, while stroke survivors used their affected UE less than the unaffected UE in acute, subacute, and chronic stages of recovery.

The quantification of real-world use has provided a unique understanding of the patterns of bilateral and unilateral arm motion over extended periods in natural settings, but it does not identify UE functional motion. Measurements based on activity counts (duration of use and use ratios) are commonly reported as proxies for amount of functional UE motion; however, these measurements have been shown to significantly overestimate functional UE motion, even when presented as a use ratio [34]. Metrics based on acceleration magnitude may be more promising and less prone to overestimation [34,75].

Unlike earlier studies, recent work in the acute stroke setting has stratified real-world use by a patient's impairment level, which clarifies the full spectrum of general use patterns outside of therapy [60,61]. Studies that stratify real-world use by motor impairment are needed in subacute and chronic stroke. In addition, the reporting of data processing methods and the calculation of metrics varied widely in this category, which limits reproducibility. To increase methodological consistency, we suggest the standardized sensor set-up, motion data preprocessing, and selection of metrics discussed elsewhere [18].

Sensor-assisted treatment

The use of sensor data to facilitate UE training has recently emerged in the literature. The five studies in this category used motion data to increase training or to provide feedback to improve UE performance. The methodologies used in this category were based on an aspect of the intervention that the researchers wanted to facilitate using sensor data. For example, the straightforward mathematical calculation of acceleration magnitude was used to determine UE motion threshold levels to remind participants to move their arm [69] while complex ML approaches (deep learning algorithms) were used to identify the completion of assigned home exercises during a home-based protocol [70].

The use of sensors has the potential for increasing adherence to home-based interventions. Compared to traditional methods of adherence (activity diaries or checklists), sensor data have the potential to increase the frequency of arm training in real-time by triggering sensory reminders to move. They may also promote engagement and adherence by providing objective feedback about the type and amount of UE exercises completed in a home-based program. The same is likely true for in-clinic rehabilitation settings, where objective feedback to therapists and patients will keep training aligned with training and recovery goals. Future work with larger sample sizes is needed to validate the feasibility and clinical efficacy of these approaches for home-based rehabilitation. As the adoption of telerehabilitation and remote health care delivery increases in stroke rehabilitation [76], sensors are a promising tool to facilitate adherence and improve UE performance in home settings. The cost-effectiveness of sensor-based approaches will need to be systematically examined, as this area of research develops further.

Limitations

The aim of the review was to address the current gap in the literature for a detailed review of emerging assessment and treatment approaches in UE stroke rehabilitation. To map out emerging applications, we included a variety of research designs, including proof-of-concept and feasibility studies. We did not weigh the strength of the evidence or appraise efficacy of

the approaches, which is beyond the scope of this review. We included studies that examined function, impairment, and use, but not other contributors to UE disability such as spasticity or impaired energy expenditure.

Conclusions

Wearable sensors have the potential to greatly expand assessment and treatment, both early after stroke and later in home and community settings. As demonstrated by the studies discussed here, sensor data can be used to assess UE functional motion, motor impairment, activity limitation, and real-world use. Sensor data can also be used to facilitate UE training by delivering sensory cues, and providing objective performance feedback during home-based UE training. This capability supports several emerging areas of research relevant to UE recovery: the quantification of rehabilitation dose, the nuanced assessment of impairment and activity limitation, the characterization of daily UE use patterns in real-world settings, and the adherence to home-based rehabilitation. Wearable sensors could enable us to respond to changing needs in rehabilitation delivery, opening new horizons in the automated assessment and treatment of stroke disability.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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IMPLICATIONS FOR REHABILITATION

- Sensor data have been used to assess UE functional motion, motor impairment/activity limitation, and real-world use.
- Sensor-assisted treatment approaches are emerging, and may be a promising tool to augment UE adherence in home-based rehabilitation.
- Wearable sensors may extend our ability to objectively assess UE motion beyond supervised clinical settings, and into home and community settings.

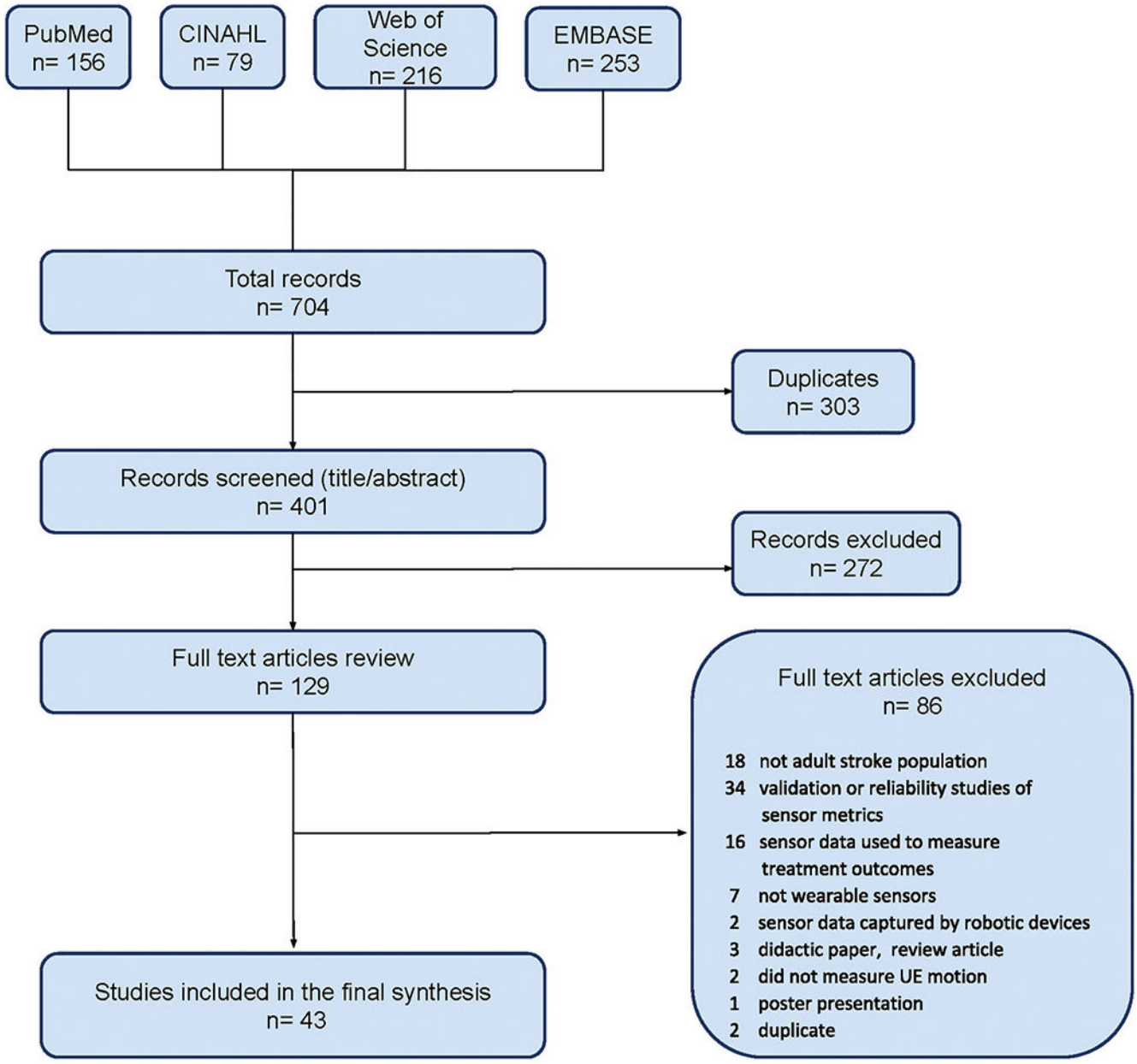

Figure 1.
Flowchart of the screening and review process for included studies.

Table 1.

Identification of functional motion.

Author	Participants	UE disability	Sensor information	Data collection	Data processing	Data analysis	Results
Biswas et al. [27]	*n*=4 control *n*=4 stroke, chronicity not specified	Not specified	Brand: Shimmer IMU Number: 1 Placement: affected wrist	Outpatient: "make cup of tea" activity consisting of reach and retrieve object, drinking, and pouring	Labeling: observation notes Preprocessing: band-pass filtering of ACC data only	Model type: non-ML, rule-based algorithm to determine sensor orientation, position transitions, and sequence detection Training: N/A Classification: functional movements (reach and retrieve object, drinking, pouring) Validation: N/A	Accuracy: 0.91–0.99 control 0.70–0.85 stroke
Biswas et al. [28]	*n*=4 control *n*=4 stroke, chronicity not specified	Not specified	Brand: Shimmer IMU Number: 1 Placement: affected wrist	Outpatient: reach and retrieve, drinking, pouring water	Labeling: observation notes Preprocessing: band-pass filtering	Model type: ML, supervised K means clustering Training: supervised Classification: functional movements (reach and retrieve object, drinking, pouring) Validation: out-of-subject testing	Accuracy: 0.88 control (ACC) 0.83 control (gyroscope) 0.70 stroke (ACC) 0.66 stroke (gyroscope)
Bochniewicz et al. [33]	*n*=10 control *n*=10 stroke, chronic	ARAT = 5–41	Brand: Analog Devices IMU Number: 1 Placement: affected UE	Outpatient: (mock apartment) laundry, shopping, kitchen activity, and making the bed	Labeling: video footage Preprocessing: band-pass filtering	Model type: ML, random forest Training: supervised Classification: functional vs. non-functional movement Validation: in-subject testing (intrasubject approach), and out-of-subject testing (inter-subject approach)	Accuracy: 0.91 control 0.70 stroke
Guerra et al. [32]	*n*=10 control *n*=6 stroke, chronic	FMA = 52.8 (mean)	Brand: XSens IMU Number: 11 Placement: head, sternum, pelvis, scapulae, BUEs	Outpatient: tabletop and shelf reaching tasks, feeding task, drinking task	Labeling: video footage Preprocessing: band-pass filtering	Model type: ML, sliding window approach, hidden Markov model, and logistical regression Training: supervised Classification: functional primitives (rest, reach, transport, retract) Validation: out-of-subject testing	Sensitivity: 0.82 control 0.75 stroke
Lemmens et al. [26]	*n*=30 control *n*=1 stroke, chronicity not specified	Not specified	Brand: Shimmer IMU Number: 7 Placement: bilateral hand, wrist, upper arm, and chest	Outpatient: drinking, eating, hair brushing Home: 30 min daily life recording (control, *n*=1)	Labeling: time borders of summed gyroscope data Preprocessing: band-pass filtering	Model type: non-ML, threshold-based approach, template matching algorithm using 2D convolution Training: N/A Classification: activity and functional movement (drinking, eating, hair brushing) Validation: out of subject testing	Sensitivity: 1.0 control 1.0 stroke Sensitivity, drinking: 1.0 control (non-standardized)
Lum et al. [34]	*n*=10 control *n*=10 stroke, chronic	ARAT = 23.5 (mean)	Brand: custom built IMU Number: 2 Placement: bilateral wrist	Outpatient: (mock apartment) laundry, shopping, kitchen activity, and making the bed	Labeling: video footage (functional, non-functional, unknown) Preprocessing: band-pass filtering	Model type: ML, random forest, radial basis function support vector machine Training: supervised Classification: functional vs. non-functional movement Validation: in-subject testing (intrasubject approach), and out-of-subject testing (inter-subject approach)	Accuracy, intra-subject approach 0.96 control 0.93 stroke Accuracy, inter-subject approach: 0.91 controls 0.74 stroke

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Author	Participants	UE disability	Sensor information	Data collection	Data processing	Data analysis	Results
Mazomenos et al. [29]	*n*=18 control *n*=4 stroke, chronicity not specified	Not specified	Brand: Shimmer IMU Number: 2 Placement: proximal affected wrist and elbow	Outpatient: reach and retrieve, pouring water, drinking	Labeling: pre-defined start/end positions during data collection Preprocessing: band-pass filtering	Model type: non-ML, rule-based detection algorithm to recognize kinematic patterns Training: N/A Classification: functional movement (reach and retrieve, drinking, pouring) Validation: N/A	Accuracy: 0.89–0.96 control 0.84–0.93 stroke
Panwar et al. [31]	*N*=14 stroke, chronic	Not specified	Brand: Shimmer IMU and Physilog IMU Number: 1 (outpatient), 3 (home) Placement: affected wrist (outpatient), bilateral wrist and sternum (home)	Outpatient: “make cup of tea” activity consisting of reach and retrieve, lift arm, rotate arm Home: 2 continuous hours during weekday, encouraged to use UE for daily activities (non-standardized)	Labeling: observational notes Data augmentation Preprocessing: band-pass filtering, signal length standardized, signal transformation	Model type: ML, convolutional neural network (deep learning), 10-fold cross validation Training: supervised Classification: functional movements (reach and retrieve object, drinking, pouring) Validation: Out-of-subject testing	Accuracy, 0.98 0.89 non-standardized condition
Roy et al. [30]	*N*=10 stroke, chronic	Brunnstrom levels 3–5	Brand: Analog Devices ACC Number: 8 (ACC), 8 (sEMG) Placement: thigh, trunk, bilateral shoulder, bilateral forearm	Outpatient: 11 ADL activities based on the FIM in the areas of: feeding, grooming, dressing, functional mobility	Labeling: not specified Preprocessing: band-pass filtering	Model type: ML, artificial neural network, adaptive neuro-fuzzy adaptive system, scaled conjugate gradient algorithm Training: supervised Classification: functional movements (feeding, brushing teeth, hair combing, buttoning shirt, sit to stand, walking, toileting) Validation: out-of-subject testing	Sensitivity: 0.95 ACC+sEMG 0.93 ACC Specificity: 0.99 ACC+sEMG 0.97 ACC
Zambrana et al. [35]	*n*=15 control, *n*=6 stroke, chronicity not specified	Not specified	Brand: BNO055 IMU Number: 2 Placement: bilateral wrist	Outpatient: eating, pouring water, drinking, brushing teeth, folding a towel, walking	Labeling: video footage Preprocessing: band-pass filtering	Model type: module 1 – non-ML, threshold-based analysis module 2 – ML, K-nearest neighbor, support vector machines, random forest Training: supervised Classification: module 1 – movement vs. non-movement module 2 – functional vs. non-functional movement Validation: in-subject testing (intrasubject approach), and out-of-subject testing (inter-subject approach)	Accuracy, module 1: 0.89 Accuracy, module 2: 0.91 intra-subject control 0.90 inter-subject control 0.61 stroke

ACC: accelerometer; IMU: inertial measurement unit; FIM: Functional Independence Measure; FMA: Fugl-Meyer Assessment; ML: machine learning; non-ML: non-machine learning; sEMG: surface electromyography. Participants: number of healthy and/or stroke participants, level of chronicity (acute: onset – 1 month, subacute 1–6 months, chronic >6 months); UE disability: motor impairment (FMA, Brunnstrom stages) or activity limitation (ARAT); sensor information: name and type of device, number and location of sensors placed on the UE; data collection: location of data collection, type of UE motion collected; data processing: methods for data labeling and preprocessing; data analysis: model type (machine learning or non-machine learning), training (supervised/unsupervised), classification of UE motion (activity, functional movement, functional primitive, functional vs. non-functional), and validation of the algorithm (out-of-subject, in-subject testing); results: performance of algorithm (sensitivity or accuracy), unless otherwise reported, results reflect out-of-subject testing and data collected under standardized conditions (controlled environment with pre-set tasks).

Table 2.

Identification of motor impairment and activity limitation.

Author	Participants	UE disability	Sensor information	Data collection	Data processing	Data analysis	Results
Chaeibakhsh et al. [40]	*N*=8 stroke, acute	FMA = 4–53	Brand: ADPM Opal IMU Number: 5 Placement: sternum, bilateral wrist, bilateral arm	Inpatient: FMA items	Labeling: video Preprocessing: band-pass filtering	Model type: ML, decision tree algorithm and bagging forest algorithm Training: supervised Classification: movement categories – synergy, out of synergy, wrist/hand function, fine motor coordination (based on FMA scores) Validation: out-of-subject testing	Error rate: 0.03 ± 0.03 bagging forest 0.18 ± 0.01 decision tree
Datta et al. [48]	*n*=15 control *n*=32 stroke, acute	NIHSS 1–4	Brand: Eoxys, ACC Number: 2 Placement: bilateral wrist	Acute: finger tapping and swiping, hand opening/closing, wrist torsion, elbow flexion and extension, 3 min of spontaneous movement	Labeling: NIHSS scores (control, moderate, severe) Processing: band-pass filtering, marker-based segmentation for structured and spontaneous motion	Model type: ML, hierarchical discriminant analysis, AUC and ROC (classification performance) Training: supervised Classification: healthy or stroke, moderate or severe Validation: out-of-subject testing	Sensitivity: 0.87 overall 0.91–0.93 healthy or stroke 0.82–0.86 moderate or severe Accuracy: 0.91 overall 0.92 healthy or stroke 0.87–0.96 moderate or severe
Datta et al. [49]	*n*=15 control *n*=40 stroke, acute	NIHSS 1–4	Brand: Eoxys, ACC Number: 2 Placement: bilateral wrist	Acute: finger tapping and swiping, hand opening/closing, wrist torsion, elbow flexion and extension, 3 min of spontaneous movement	Labeling: NIHSS scores (control, mild, moderate, severe) Processing: band-pass filtering, segmentation for short-term activity	Model type: ML, hierarchical discriminant analysis, the Kruskal–Wallis test (feature extraction), AUC and ROC (classification performance) Training: supervised Classification: healthy or stroke, mild or moderate-to-severe, moderate or severe, mild-to-moderate or severe Validation: out-of-subject testing	Sensitivity: 0.78 overall 0.87 healthy or stroke 0.80 mild or moderate-to-severe 0.88 moderate or severe 0.92 mild-to-moderate or severe Accuracy: 0.78 overall 0.94 healthy or stroke 0.80 mild or moderate-to-severe 0.95 moderate or severe 0.87 mild-to-moderate or severe
Gubbi et al. [38]	*n*=7 control *n*=15 stroke, acute	Not specified	Brand: Crossbow iMote2 ACC Number: 2 Placement: bilateral wrist	Inpatient: non-standardized motion – 4h immediately post stroke, 1 h after day 1	Labeling: not specified Preprocessing: band-pass filtering	Model type: non-ML, threshold-based algorithm using cross correlation of ACC magnitude and difference in cross correlation of ACC magnitude of 3 axes Training: N/A Classification: impaired or not impaired Validation: N/A	Sensitivity: 0.87 cross correlation of ACC magnitude 0.95 correlation of 3 axes

Author	Participants	UE disability	Sensor information	Data collection	Data processing	Data analysis	Results
Gubbi et al. [41]	*n*=10 control *n*=15 stroke, acute	NIHSS >0	Brand: Crossbow iMote2 ACC Number: 2 Placement: bilateral wrist	Inpatient: non-standardized motion – 4h immediately post stroke, 1 h after day 1	Labeling: not specified Preprocessing: band-pass filtering	Model type: non-ML, threshold-based algorithm correlation of activity indices to NIHSS motor score Training: N/A Classification: NIHSS motor score Validation: N/A	Accuracy: 0.72 norm-based 0.73 SMA-based 0.81 energy-based
Heron et al. [37]	*n*=10 control *n*=30 stroke, acute	NIHSS, motor UE = 2 (median)	Brand: Crossbow iMote2 ACC Number: 2 Placement: bilateral wrist	Inpatient: non-standardized motion – 5 h over 25 h period	Labeling: not specified Preprocessing: band-pass filtering	Model type: non-ML, threshold-based algorithm, ICC, ROC curve analysis (diagnostic threshold) Training: N/A Classification: impaired or not impaired Validation: N/A	Sensitivity: 0.95 NIHSS and ICC correlation: −0.53, $p = 0.02$ Spearman's rho
Lin et al. [43]	*n*=15 control *n*=15 stroke, chronicity not specified	Brunnstrom levels 4–6	Brand: custom built IMU glove Number: 16 Placement: affected hand	Outpatient: grasp and release, thumb task, card turning	Labeling: Brunnstrom levels Preprocessing: band-pass filtering	Model type: ML, K-means clustering, K-fold cross validation algorithm, twofold, 10-fold, and leave-one-out Training: supervised Classification: Brunnstrom categories 4, 5, 6 Validation: out of subject testing	Accuracy: 0.73 B6 (healthy), 0.70 B5, 0.75 B4
Lin et al. [39]	*n*=15 control *n*=15 stroke, chronicity not specified	Brunnstrom levels >3	Brand: custom built IMU glove Number: 16 Placement: affected hand	Outpatient: thumb task, grip task, card-turning	Labeling: Brunnstrom levels Preprocessing: band-pass filtering	Model type: ML, logistic regression, principle component analysis (feature extraction), AUC and ROC (classification performance) Non-ML, the Kruskal–Wallis test Training: supervised Classification: impaired or not impaired, Brunnstrom levels 4, 5 and healthy subject (non-ML, the Kruskal–Wallis test) Validation: not specified	Sensitivity, impaired or not impaired: 0.98
Lucas et al. [47]	*N*=4 stroke, acute	Oxford Motor Scale, 0–5	Brand: Axivity AX3, ACC Number: 4 Placement: bilateral wrists and ankles	Inpatient: non-standardized motion for duration of ICU stay (up to 14 days)	Labeling: Oxford Motor Scale scores 0–2 = dependent 3–5 = antigravity Preprocessing: band-pass filtering	Model type: ML, support vector machines Training: Supervised Classification: dependent or antigravity UE Validation: out-of-subject testing	Sensitivity: 0.87 Accuracy: 0.82
Parnandi et al. [44]	*N*=1 stroke, chronicity not specified	Not specified	Brand: IMU custom built Number: 1 Placement: affected wrist	Outpatient: 15 WMFT tasks	Labeling: video Preprocessing: band-pass filtering	Model type: ML, naïve Bayesian classifier Training: supervised Classification: WMFT-FAS score Validation: not specified	RMS value (error estimate): 0.45
Patel et al. [45]	*N* = 24 stroke, chronicity not specified	WMFT-FAS = 47.2 (mean)	Brand: not specified, ACC Number: 6 Placement: Index finger, thumb, trunk,	Outpatient: 8 WMFT tasks – 4 reaching, 4 manipulation	Labeling: digital markers, performance videotaped Preprocessing: band-pass filtering	Model type: ML, random forest, RRelief algorithm and Davies Bouldin index (feature selection) Training: supervised Classification: WMFT-FAS score Validation: not specified	RMS value (error estimates): 0.056 for 8 tasks 0.091 for 4 tasks

Author	Participants	UE disability	Sensor information	Data collection	Data processing	Data analysis	Results
			hand, forearm, upper arm				
Tang et al. [50]	*N*=59 stroke, *n*=26 subacute, *n* = 33 chronic	Not specified	Brand: Axivity AX3, ACC Number: 2 Placement: bilateral wrist	Setting not specified: 9 CAHAI items, non-standardized motion of 3-day period for 8 weeks	Labeling: not specified Processing: band-pass filtering, day time activity only (9 am–9 pm)	Model type: ML, Gaussian Mixture Model and principle component analysis (feature clustering and extraction), linear mixed effects model, non-linear mixed effects model with Gaussian process (NMM-GP) Training: supervised Classification: CAHAI scores Validation: out-of-subject testing	RMS value (error estimates) for NMM-GP: 6.9 (subacute stroke) 3.4 (chronic stroke)
Yu et al. [46]	*N*=24 stroke, subacute and chronic	FMA = 18 (mean)	Brand: Analog Devices ACC, not specified, flex sensors Number: 2 (ACC), 7 (flex sensors) Placement: forearm, upper arm (ACC); wrist and hand (flex sensors)	Outpatient: 7 FMA items – 4 proximal and 3 distal 10x Home: 7 FMA items every week for 3 months (*n*=5)	Labeling: FMA scores Preprocessing: band-pass filtering	Model type: ML, Extreme Learning Machine algorithm (feature extraction and selection), RRelief algorithm (feature selection refinement) Training: supervised Classification: FMA scores for each item Validation: out-of-subject testing.	Coefficient of determination, overall: 0.92 (R^2)
Zhang et al. [42]	*n*=9 control *n*=21 stroke, chronicity not specified	Brunnstrom levels ≥3	Brand: InvenSense IMU Number: 1 Placement: wrist	Setting not specified: single shoulder touching task completed 5x	Labeling: Brunnstrom levels Preprocessing: band-pass filtering	Model type: ML, constrained dynamic time warping algorithm, Naïve Bayes, quadratic discriminant analysis, K-nearest neighbor (KNN) Training: supervised Classification: Brunnstrom levels 3, 4, 5, 6 Validation: out-of-subject testing	Sensitivity (most accurate using KNN): 0.93 B3, 0.88 B4, 0.80 B5, 0.93 B6, 0.82 overall

ACC: accelerometer; B4–6: Brunnstrom stage 4–6; AUC: area under the curve; CAHAI: Chedoke Arm and Hand Activity Inventory; FMA: Fugl-Meyer Assessment; ICC: intra-class correlation; IMU: inertial measurement unit; ML: machine learning; N/A: not applicable; NIHSS: National Institute of Health Stroke Scale; non-ML: non-machine learning; ROC: receiver operating characteristic; RMS: root mean square; WMFT-FAS: Wolf Motor Function Test, Functional Ability Scale.

Participants: number of healthy and/or stroke participants, level of chronicity (acute: onset – 1 month, subacute 1–6 months, chronic >6 months); UE disability: motor impairment (Brunnstrom stages, FMA, NIHSS, Oxford Scale) or activity limitation (WMFT-FAS); sensor information: name and type of device, number and location of sensors placed on the UE; data collection: location of data collection, type of UE motion collected; data processing: methods for data labeling and preprocessing, and wireless data transfer for real time processing (if applicable); data analysis: model type (machine learning or non-machine learning), training type (supervised/unsupervised for machine learning models), classification of UE motion (presence/absence of impairment, motor impairment, or activity limitation levels), and validation of algorithm (out-of-subject, in-subject testing for machine learning models); results: reported outcomes vary based on machine learning or non-machine learning approach (sensitivity, accuracy, error estimates).

Table 3.

Quantification of real-world use.

Author	Participants	UE disability	Sensors information	Data collection	Data processing	Data analysis	Results
Bailey et al. [53]	*n*=74 control, *n*=48 stroke, chronic	ARAT = 10–48	Brand: Actigraph, ACC Number: 2 Placement: bilateral wrist	Home: 24 h	Preprocessing: built-in ActiLife Software	Metrics: Activity count (proprietary software) Bilateral acceleration magnitude (sum of accelerations for all 3 axes) Magnitude ratio	Duration of use (hours): 7.2 control 4.1 stroke Unilateral duration of use (hours): 1.5 non-dominant UE control 1.9 dominant UE control 0.8 affected UE stroke 3.4 unaffected UE stroke Bilateral acceleration magnitude: 132.6 control 82.4 stroke Bilateral magnitude ratio (score range: +7, unilateral affected UE use to −7 unilateral unaffected UE use): −0.1 control −2.2 stroke
Barth et al. [57]	*n*=12 control, *n*=24 stroke, acute	FMA = 35.4 (mean)	Brand: Actigraph GT9X Link, ACC Number: 2 Placement: bilateral wrist	Inpatient: 24 h	Preprocessing: built-in ActiLife Software	Metrics: Activity count (proprietary software) Duration of use Use ratio	Duration of use (hours): 6.2 non-dominant UE (control) 7.0 dominant UE (control) 3.7 affected UE (stroke) 6.9 unaffected UE (stroke) Unilateral duration of use (hours): 1.1 non-dominant UE (control) 2.2 dominant UE (control) 0.93 affected UE (stroke) 3.9 unaffected UE (stroke) Bilateral movement (hours): 5.0 control 2.8 stroke Duration of use ratio: 0.89 control 0.56 stroke
Bhatnagar et al. [58]	*N*=20 stroke, chronic	FMA = 36.1 (mean)	Brand: Actigraph GT3X+, ACC Number: 2 Placement: bilateral wrist	Home: 3 contiguous days	Preprocessing: not specified	Metrics: Activity counts Duration of use Use ratio Acceleration magnitude Magnitude ratio	Duration of use (hours): 5.3 affected UE 9.1 unaffected UE Unilateral duration of use (hours): 0.6 affected UE 4.3 unaffected UE Bilateral movement (hours): 4.8 Magnitude ratio (negative values indicate greater nonparetic activity, 0 score indicates equal arm contribution) −1.1
Chin et al. [60]	*N*=12 stroke, acute	Mild: FMA = 65 (mean) Moderate:	Brand: Actigraph GT3X+, ACC Number: 2	Inpatient: 24 h	Preprocessing: built-in ActiLife Software	Metrics: Activity count (proprietary software)	Duration of use, affected UE (hours): 5.4 mild 4.1 moderate

Author	Participants	UE disability	Sensors information	Data collection	Data processing	Data analysis	Results
		FMA = 32 (mean) Severe: FMA = 5 (mean)	Placement: bilateral wrist			Duration of use Use ratio Bilateral acceleration magnitude Magnitude ratio Variation ratio	1.5 severe Duration of use unaffected UE (hours): 8.7 mild 8.5 moderate 7.1 severe Use ratio (duration of use): 0.59 mild 0.45 moderate 0.22 severe Magnitude ratio (score range: +7 unilateral affected UE use to −7 unilateral unaffected UE use): −2.79 mild −5.25 moderate −7 severe
Chin et al. [61]	*n*=30 control, *n*=60 stroke, acute	Mild: FMA = 61 (mean) Moderate: FMA = 36 (mean) Severe: FMA = 8 (mean)	Brand: Actigraph GT3X+, ACC Number: 2 Placement: bilateral wrist	Inpatient: 24 h	Preprocessing: built-in ActiLife Software	Metrics: Activity count (proprietary software) Duration of use Use ratio Bilateral acceleration magnitude Magnitude ratio Variation ratio	Duration of use, non-dominant, affected UE (hours): 8.72 control 6.71 mild 4.49 moderate 1.67 severe Duration of use dominant, unaffected UE (hours): 9.43 control 7.92 mild 7.68 moderate 6.97 severe Use ratio (duration of use): 0.93 control 0.86 mild 0.50 moderate 0.25 severe Magnitude ratio (score range: +7 unilateral affected/non-dominant UE use to −7 unilateral unaffected/dominant UE use): −0.26 control −2.79 mild −5.25 moderate −7 severe
Doman et al. [54]	*N*=15 stroke, acute and chronic	Not specified	Brand: Actigraph, ACC Number: 2 Placement: bilateral wrist	Home: 24 h at baseline, every 10th outpatient therapy visit, discharge	Preprocessing: built-in ActiLife Software	Metrics: Activity counts (proprietary software) Bilateral use ratio Bilateral acceleration magnitude Bilateral magnitude ratio	Bilateral use ratio: 0.95 control 0.57 stroke Bilateral magnitude ratio (score range: +7 unilateral affected UE use to −7 unilateral unaffected UE use): −0.1 control −4.04 stroke
Lee et al. [55]	*N*=16 stroke, acute and subacute	Not specified	Brand: Actiwatch ACC Number: 2 Placement: bilateral wrist	Inpatient: 24 h × 4 timepoints (onset to 3 months) Not specified if any of these	Preprocessing: not specified	Metrics: Raw activity count	Mean activity counts (10^4 counts/day): Onset: 8 affected, 20.5 unaffected 1-month: 27.1 unaffected, 10.8 affected 2-month: 28.3 unaffected, 14.1 affected 3-month: 34.5 unaffected,19.4 affected

Author	Participants	UE disability	Sensors information	Data collection	Data processing	Data analysis	Results
				timepoints were collected at home			
Lee et al. [59]	*N*=29 stroke, chronic, right hemiparesis *n*=14 non-dominant UE affected, *n*=15 dominant UE affected	FMA = 45.3 (mean)	Brand: Fitness Tracker Mi Band-3, ACC Number: 2 Placement: bilateral wrist	Home: 30 contiguous days	Preprocessing: not specified	Metrics: Activity counts Differential activity (non-dominant activity counts minus dominant activity counts) Asymmetry index	Activity counts, dominant UE (counts/day): 4126 non-dominant affected group 3053 dominant affected group Activity counts, non-dominant UE (counts/day): 3365 non-dominant affected group 4505 dominant affected group Differential activity (counts/day): 761 non-dominant affected group −1450 dominant affected group Asymmetry index (positive or negative index represents more contributions from dominant or non-dominant hand, respectively): 4.2 non-dominant affected group −30.5 dominant affected group
Michielsen et al. [64]	*n*=18 control *n*=38 stroke, chronic	Brunnstrom levels 3–5	Brand: ULAM, ACC Number: 5 Placement: sternum, bilateral thigh, bilateral wrist	Home: 24 h	Preprocessing: band-pass filtering	Metrics: Duration of use Movement intensity (root mean square values of acceleration)	Duration of use (hours): 5.1 non-dominant UE (control) 5.3 dominant UE (control) 2.4 affected UE (stroke) 5.3 unaffected UE (stroke) Movement intensity (g/min): 0.04 dominant and nondominant UE (control) 0.02 affected UE (stroke) 0.04 unaffected UE (stroke)
Alt Murphy et al. [66]	*n*=10 controls *n*=28 stroke, acute	FMA = 35 (median)	Brand: Shimmer 3, ACC Number: 5 Placement: bilateral wrist and ankles, trunk	Inpatient: 8 am–8 pm for 2 days during weekdays and weekend	Preprocessing: visual inspection, band-pass filtering	Metrics: Signal magnitude area (SMA) Signal magnitude area ratio	Signal magnitude area, weekday, (m/s^2): 2.51 non-dominant UE (control) 1.20 affected UE (stroke) 2.51 dominant UE (control) 2.34 unaffected UE (stroke) Signal magnitude area, weekend, (m/s^2): 2.45 non-dominant UE (control) 0.91 affected UE (stroke) 2.74 dominant UE (control) 2.10 unaffected UE (stroke) Signal magnitude area ratio (0 value indicated perfect symmetry between UEs, negative value indicates lower magnitude of affected UE or non-dominant UE): −0.07 weekday control −0.33 weekday stroke −0.04 weekend control −0.36 weekend stroke
Rand and Eng [62]	*n*=40 control, *n*=60 stroke, acute	Not specified	Brand: Actical ACC Number: 3 Placement: bilateral wrist, hip	Inpatient: 3 contiguous days at admission and at 3 weeks	Preprocessing: built-in software	Metrics: Activity counts (proprietary software) UE motion during ambulation removed	Change in activity counts (admission to 3 weeks): no difference affected and unaffected UE Change in use ratio (admission to 3 weeks): no change Activity count (at 3 weeks): unaffected UE 4x more than affected UE

Author	Participants	UE disability	Sensors information	Data collection	Data processing	Data analysis	Results
Rand and Eng [63]	*N*=32 stroke, acute, and chronic	FMA = 51 (median)	Brand: Actical ACC Number: 3 Placement: bilateral wrist, hip	Inpatient: 3 contiguous weekdays at discharge Home: 3 contiguous days at 12 months	Preprocessing: built-in software	Metrics: Activity counts- proprietary software UE motion during ambulation removed	Change in activity counts (discharge to 12 months): no difference in affected and unaffected UE Activity count (at 12 months): Unaffected UE 3x more than affected UE
Shim et al. [56]	*N*=40 stroke, chronic	Mild: FMA >45 Moderate: FMA = 19–44	Brand: Fittmeter ACC Number: 2 Placement: bilateral wrist	Inpatient: 8 am–11 pm × 5 days	Preprocessing: not specified	Metrics: Raw activity counts Use ratios	Mean activity count (m/s^2): Moderate impairment group- 552–734 (therapy time) 540 (free time) Mild impairment group – 1831–2191 (therapy time) 1868 (free time)
Strommen et al. [65]	*N*=100 stroke, acute	Not specified	Brand: Actical, ACC Number: 5 Placement: bilateral wrist, bilateral ankle, hip	Inpatient: contiguously until discharge or up to 7 days (0–7 days)	Preprocessing: Not specified	Metrics: Activity counts (proprietary software)	Activity count: 71% lower for stroke vs. TIA 80% less in affected UE vs. unaffected UE

ACC: accelerometer; ARAT: Action Research Arm Test; FMA: Fugl-Meyer Assessment; TIA: temporary ischemic attack.

Participants: number of healthy and/or stroke participants, level of chronicity (acute: onset – 1 month, subacute 1–6 months, chronic >6 months); UE disability: UE motor impairment (FMA, Brunnstrom levels) or activity limitation (ARAT); sensor information: name and type of device, number and location of sensors placed on the UE; data collection: location and duration of time of data collection; data processing: methods for motion data labeling and preprocessing; data analysis: motion data metrics calculated; results: duration of use, activity counts, acceleration magnitude, laterality indices (ratio of affected to unaffected UE motion).

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Table 4.

Sensor-assisted treatment.

Author	Participants	UE disability	Sensor information	Data collection/treatment	Data processing	Data analysis	Results
Chae et al. [70]	*N*=23 stroke, chronic *n*=6 control group (no feedback) *n*=17 treatment group (feedback)	FMA = 29 (control group), 36.6 (treatment group)	Brand: LG smartwatch, IMU Number: 1 Placement: affected wrist	Home: sensor data collected whenever smartphone app used by participants. Treatment: completed 4 home exercises daily over 12-weeks, treatment group received weekly feedback on type and amount of exercises they completed	Labeling: Home exercise tasks, observation notes Preprocessing: not specified	Model type: ML, convolutional neural network (deep learning), cross-validation testing Training: supervised Classification: home exercise tasks (shoulder flexion, wall pushups, scapular exercise, towel slides) Validation: out-of-subject testing	Accuracy: 0.99 (personal data) 0.95 (total data) Training time for home exercises (minutes per day): 13.6 control group (self-report) 22.6 treatment group(sensor data) Change in WMFT scores, baseline to discharge: 3.4 control 2.8 treatment Change in shoulder flexion, baseline to discharge (degrees): 5.5 control 20.2 treatment Change in shoulder internal rotation, baseline to discharge (degrees): 6.5 control 13.1 treatment
Da-Silva et al. [68]	*N*=11 stroke, acute, and subacute	ARAT = 39 (mean)	Brand: CueS, ACC Number: 1 Placement: affected wrist	Inpatient: 1 week to set prompt levels Home: 12 h/day ×4 weeks. Treatment: provided external vibration cue if UE activity did not reach customized threshold level	Labeling: NA Preprocessing: not specified	Metrics: Median signal vector magnitude (calculated every 3 days to set threshold for vibration cues)	Adherence to wearing sensors = 89% 11–29% increase in mean activity one-hour post vibration cue Cueing frequency preference higher for severe group and lower for mild group
Da-Silva et al. [69]	*N*=33 stroke, subacute *n*=19 control group(no vibration) *n*=14 treatment group (vibration)	ARAT = 15 (control group), 37 (treatment group)	Brand: CueS, ACC Number: 1 Placement: affected wrist	Inpatient and home: Sensors worn 12 h/day ×4 weeks. Treatment: provided external vibration cue if UE activity did not reach customized ACC threshold level	Labeling: NA Preprocessing: not specified	Metrics: Median signal vector magnitude (calculated every 3 days to set threshold for vibration cues)	Adherence to wearing sensors = 79% Responses to receiving wrist vibration cue (self-report): 43% practiced activities from daily activities list 38% practiced their own self-chosen activity 17% ignored the cue Cueing frequency preference: 8 cues per day, hourly basis
Lee et al. [72]	*n*=10 control *n*=20stroke, chronic	FMA = 37 (mean)	Brand: Shimmer, IMU Number: 2 Placement: bilateral wrist	Outpatient: ADLs targeting unilateral, bilateral and stabilization skills, strength and range of motion exercises Stakeholder survey of therapists (*n*=13) and stroke survivors (*n*=17) on user feasibility of proposed approach	Labeling: video Preprocessing: band-pass filtering	Model type: ML, logistic regression, nearest neighbor with dynamic time warping algorithm, random forest algorithm Training: supervised Classification: functional/ non-functional movement, feedback/no feedback,	Accuracy, functional/non-functional movement classification: 0.87 control and stroke unaffected UE Sensitivity, feedback/no-feedback classification: 0.83 stroke Sensitivity, type of feedback, compensatory classification: 0.64 stroke Sensitivity, type of feedback, accuracy

Author	Participants	UE disability	Sensor information	Data collection/treatment	Data processing	Data analysis	Results
						types of feedback categories (compensatory or accuracy) Validation: out-of-subject testing	classification: 0.76 stroke Survey, therapists: 91.2% willing to use in clinical practice Survey, stroke survivors: 76.5% willing to use the system 88.2% willing to use the system with therapist recommendation Survey, stroke survivors, preferred method of receiving UE feedback: 29.4% visual 23.5% vibration 35.3% sound and vibration
Whitford et al. [71]	*N*=8 stroke, chronic	FMA = 32 (mean)	Brand: Actigraph, ACC Number: 2 Placement: bilateral wrist	Home: sensors worn for 3-week treatment period Treatment: 7 feedback sessions provided over 3 weeks on duration of use, acceleration magnitude, use ratio	Labeling: NA Preprocessing: built-in software	Metrics: Activity counts (proprietary software) Duration of use Use ratio Acceleration magnitude	Adherence to wearing sensors: 100% Perceived UE use at home: 1.93 MAL AOU baseline 2.84 MAL AOU discharge

ACC: accelerometer; ARAT: Action Research Arm Test; FMA: Fugl-Meyer Assessment; IMU: inertial measurement unit; MAL AOU: Motor Activity Log, Amount of Use Subscale; ML: machine learning; WMFT: Wolf Motor Function Test.

Participants: number of healthy and/or stroke participants, level of chronicity (acute: onset – 1 month, subacute 1–6 months, chronic >6 months); UE disability: motor impairment (FMA) or activity limitation (ARAT); sensor information: name and type of device, number and location of sensors placed on the UE; data collection/treatment: location and type of UE motion collected; summary of study intervention; data processing: methods for data labeling and preprocessing; data analysis: motion data metrics calculated OR model type (machine learning or non-machine learning), training type (supervised/unsupervised), classification of UE motion (performance feedback categories), and validation of algorithm (out-of-subject, in-subject testing); results: UE training augmentation, performance of algorithm (sensitivity or accuracy).