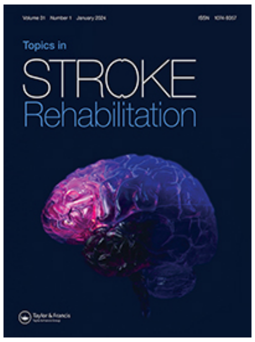

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Topics in Stroke Rehabilitation

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ytsr20

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To cite this article: Alex Martino Cinnera, Pietro Picerno, Alessio Bisirri, Giacomo Koch, Giovanni Morone & Giuseppe Vannozzi (2024) Upper limb assessment with inertial measurement units according to the international classification of functioning in stroke: a systematic review and correlation meta-analysis, Topics in Stroke Rehabilitation, 31:1, 66-85, DOI: 10.1080/10749357.2023.2197278

To link to this article: https://doi.org/10.1080/10749357.2023.2197278

Published online: 21 Apr 2023.

TOPICS IN STROKE REHABILITATION
2024, VOL. 31, NO. 1, 66–85
https://doi.org/10.1080/10749357.2023.2197278

Upper limb assessment with inertial measurement units according to the international classification of functioning in stroke: a systematic review and correlation meta-analysis

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ABSTRACT

Objective: To investigate the usefulness of inertial measurement units (IMUs) in the assessment of motor function of the upper limb (UL) in accordance with the international classification of functioning (ICF).
Data sources: PubMed; Scopus; Embase; WoS and PEDro databases were searched from inception to 1 February 2022.
Methods: The current systematic review follows PRISMA recommendations. Articles including IMU assessment of UL in stroke individuals have been included and divided into four ICF categories (b710, b735, b760, d445). We used correlation meta-analysis to pool the Fisher Z-score of each correlation between kinematics and clinical assessment.
Results: A total of 35 articles, involving 475 patients, met the inclusion criteria. In the included studies, IMUs have been employed to assess the mobility of joint functions ($n = 6$), muscle tone functions ($n = 4$), control of voluntary movement functions ($n = 15$), and hand and arm use ($n = 15$). A significant correlation was found in overall meta-analysis based on 10 studies, involving 213 subjects: ($r = 0.69$) (95% CI: 0.69/0.98; $p < 0.001$) as in the d445 ($r = 0.71$) and b760 ($r = 0.64$) ICF domains, with no heterogeneity across the studies.
Conclusion: The literature supports the integration of IMUs and conventional clinical assessment in functional evaluation of the UL after a stroke. The use of a limited number of wearable sensors can provide additional kinematic features of UL in all investigated ICF domains, especially in the ADL tasks when a strong correlation with clinical evaluation was found.

ARTICLE HISTORY
Received 26 June 2022
Accepted 24 March 2023

KEYWORDS
IMU; Accelerometer; Biomechanics; Wearable technology; Patient outcome assessment; Rehabilitation; Upper body

Introduction

Stroke is one of the leading causes of disability worldwide and can result in permanent motor impairment in 80% of cases.[1,2] Up to 85% of patients show an initial deficit in the upper limb (UL) and problems remain, 3–6 months later in 55% to 75% of patients.[3] Common manifestations of UL motor impairment include muscle weakness or contracture, changes in muscle tone, joint laxity, and impaired motor control. These impairments induce disabilities in common activities such as reaching, picking up objects, and holding onto objects[4] and consequently affect the ability to perform activities of daily living[5] and quality of life.[6,7] Despite the importance of UL motor recovery, in clinical and experimental settings, evaluation methods are subjectively scored by clinicians, and the assessment results vary individually[8] and present lack of sensitivity to subtle changes in motor performance throughout the rehabilitation process.[9] Understanding UL impairments is principally complex for two reasons: 1) the impairments are not static and change during time due to motor recovery and 2) multiple impairments may be observed simultaneously, i.e. a patient may present with weakness of the arm and hand immediately after a stroke, which may not have resolved when spasticity sets in a few weeks or months later, resulting in a chronic impairment.[10] In these chronic conditions, there is the need to apply a biopsychological model that considers the illness and health such as

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the result of an interaction between biological, psychological, and social factors.[11] above concept is the pillar of the World Health Organization's International Classification of Functioning Disability and Health (ICF) that aims to provide a comprehensive, universal, and international classification of health, health-related domains, and a list of environmental factors via a schematic coding scheme. This model tries to improve communication between health care workers, researchers, policy makers, and the public including people with disability and data comparison across countries. In this respect, this improved communication only slightly involved the assessment of motor function. In fact, while numerous measures are readily available for the evaluation of UL function, no single measure is available to encapsulate the entire range of activities performed by the UL according to the ICF.[12] The Fugl-Meyer Assessment scale (FMA) is the most commonly used measure for UL evaluation after a stroke.[13] Moreover, with respect to the ICF, the FMA only deals with the body function domain.[9] For this reason, more than one measurement scale is often used for evaluation in about 70% of studies (i.e., FMA-WMFT).[13] Nevertheless, in this multiple outcomes assessment, only a part of ICF domains is covered (body function and activity).[9,13] Moreover, relatively few studies have applied the ICF model to identify the contributions of specific UL impairments, such as muscular weakness, pain, and sensory loss, as predictors of activity and participation.[14]

To improve the accuracy of impairment assessment of UL, instrumental evaluation can be coupled with clinical assessment or clinical scales and tests can be sensorised. In this perspective, wearable sensors are useful, noninvasive, low-cost, and objective tools that are being extensively used to assess motor and functional impairment in many neurological diseases.[15–17] In the last decade, the use of inertial motion units (IMUs), a subclass of wearable sensors, for clinical purposes has moved from laboratory to ambulatory-based settings. More recently, we are witnessing a transition to unsupervised real-world environments thanks to their affordability, unobtrusiveness, and higher ecological validity with respect to conventional motion analysis.[18,19] Several fields of medicine, like orthopedic, neurological, physical medicine, and rehabilitation and occupational, have benefited from wearable IMUs for the assessment of the residual motor function both for the planning of the intervention and the assessment of the efficacy of the treatment over time.[20,21] In particular, research on clinical movement analysis in the past 5 years has focused on the use of IMUs for the assessment of neurological gait and balance disorders,[22] orthopedic gait disorders,[23] and neurological and orthopedic disorders of the upper limb in standardized laboratory or clinical settings.[24] While all this has led to significant benefits, the vast amounts of data generated by these sensors carry issues related to privacy and to the extraction of clinically relevant and interpretable information by practitioners, which may discourage their use in the clinical practice.[19] A recent review suggests that IMUs can be practical options to assess motor function during the execution of activities of daily life, as well as tracking of complex upper limb movements,[25] even though this aspect is not fully recognized in clinical practice, and a better understanding is necessary to guide future clinical applications of wearable technology.[26] Similarly, the effectiveness of wearable technologies for the treatment of stroke needs further investigations to solve the unsatisfactory sample sizes and the lack in the methodological approaches of studies currently available.[27]

The aim of the present review is to evaluate the usefulness of IMUs for the kinematics assessment of specific functions of the UL (in accordance with the ICF) in patients with stroke. Specifically, we reported an overview of kinematics variables and provided a first quantification of their correlation with clinical evaluation through meta-analysis.

Methods

The current systematic review was performed following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations[28] and was registered in the PROSPERO database

(CRD42021240847). We try to respond to the following research questions: Can IMUs objectively evaluate UL motor functions in clinical settings in people with stroke? Is there an association between IMUs assessment and clinical evaluation?

A literature search of multiple electronic databases (PubMed; Scopus; Embase; WoS and PEDro) was conducted from inception to 1 February 2022. We combined Mesh Terms and free-terms as keywords *"(wearable sensors) or (inertial sensors) or (accelerometers) or (sensor) or (IMUs) AND (upper limb) AND ((neurological disease) or (stroke)) AND (kinematics)"* (Complete search strategy is available in Appendix A). We selected articles that meet the following inclusion criteria: 1) stroke population; 2) upper extremity assessment through inertial measurement units; 3) English language. Exclusion criteria were: 1) other neurological disease; 2) other wearable sensors such as chemical, optical, and electrical sensors; 3) methodological study design (not involving humans); 4) gray literature.

All results have been uploaded to an online database and screened simultaneously and independently by three reviewers (AB, AMC, and PP). At the end of the process, in the event of no agreement, a fourth reviewer (GV) was consulted.

ICF classification

The ICF includes several domains that are organized in a hierarchical tree structure. The first classification level defines two categories: "functioning and disability" and "contextual factors." Functioning and disability subheading including "body functions and structures" and "activities and participation." In the first subheading, we included the following domains: b710, mobility of joint functions; b735, muscle tone functions; and b760, control of voluntary movement functions. In the second subheading, we included the d445, hand and arm use domain. Further ICF's subheading such as b730, muscle power functions; b740, muscle endurance functions; d440, and fine hand use were excluded because they were not directly investigable via IMUs. All selected studies were labeled with an ICF subheading according to the outcome goals: the relevant assignment criterion is reported in Table 1. The studies that reported data across two or more domains were labeled consistently (the complete allocation is available in Appendix B).

Kinematics parameters

For each ICF domain, we investigated the use of IMU-based indices such as spatiotemporal parameters and global features (i.e., smoothness, symmetry, and spectral parameters) of UL movements (Figure 1). The information on signal processing procedures is available in the fifth column of each synoptic table (Tables 2–5). In the abovementioned tables, we reported when the variable of interest has been estimated from the three-dimensional (3D) orientation of the sensor case (eventually mediated by a kinematic model). We also reported if sensor orientation has been computed using a sensor fusion algorithm either based on accelerometer, gyroscope, and magnetometer data (i.e., 9-axis) or on accelerometer and gyroscope only data (i.e., 6-axis). In the case of a custom-made sensor device, the sensor fusion

Table 1. Selected domains of the World Health Organization's International Classification of Functioning Disability and Health (ICF).

Subheading	ICF code	Domain	Definition	Classification criterion
Body functions (b)	**b710**	*Mobility of joint functions*	Functions of the range and ease of movement of a joint.	IMUs used to assess range of motion.
	b735	*Muscle tone functions*	Functions related to the tension present in the resting muscles and the resistance offered when trying to move the muscles passively.	IMUs used to assess spasticity.
	b760	*Control of voluntary movement functions*	Functions associated with control over and coordination of voluntary movements.	IMUs used to assess voluntary movements with or without object manipulation in a non-finalized task (i.e., Mingazzini test, finger-to-noise task).
Activities and participation (d)	**d445**	*Hand and arm use*	Performing the coordinated actions required to move objects or to manipulate them by using hands and arms, such as when turning door handles or throwing or catching an object.	IMUs used to assess daily activity task (i.e., making a cup of tea, turn a key).

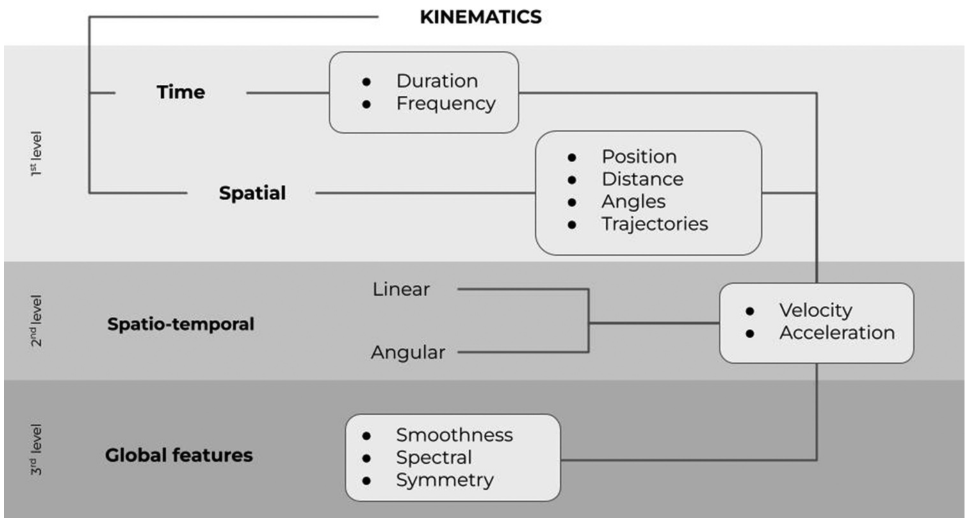

Figure 1. Schematic representation of spatio-temporal and kinematic parameters recorded through inertial measurement units. The investigated spatio-temporal and kinematics variables are reported into the white boxes.

algorithm is based on algorithms designed in previous studies.

Statistical analysis

All studies that reported a correlation between clinical assessment and IMU parameters in stroke population (linear or not linear) have been included in the meta-analysis. For the studies that reported more than one significant correlation result, we calculated the mean of the significant correlation coefficients. The correlation coefficient of each study has been transformed into the Fisher Z-score with the appropriate formula (linear or not linear). We pooled each Z-score and sample size with a random-effect model meta-analysis with a 95% of confidence interval (IC). Then, a reverse formula was used to transform the Z-score into an r value (rounded down). We used the following ranges for the interpretation of correlation coefficient: 0–0.10 negligible; 0.10–0.39 weak; 0.40–0.69 moderate; 0.70–0.89 strong; 0.90–1 very strong.[49] Heterogeneity between studies was assessed by computing the Q-statistics and I^2 index. Substantial statistical heterogeneity was assumed if the Q-statistic was significant (p-value < 0.05) and I^2 was higher by 75%. Characterization of variances across studies were calculated as no heterogeneity, low heterogeneity, moderate heterogeneity, and high heterogeneity, respectively, for the I^2 values<25%, 25% to 50%, 50% to 75%, and >75%. To investigate publication bias, we performed the Egger's regression test and the Begg-Mazumdar's test.[50] In addition, subgroup analysis has been performed with respect to ICF categories.

Results

A total of 711 articles were found. After the duplicate removal (137), 574 articles were screened. After screening of titles and abstracts, 530 articles have been excluded, because they do not meet the inclusion criteria. A total of 44 full-text articles have been examined. Eight studies have been excluded during full-text check, in conclusion, 35 articles have been included in the systematic review (flow chart of studies screening is available in Figure 2). The included studies have been divided, in one or more than one domain, with respect to preview ICF classification. IMUs have been employed to assess passive range of motion (ROM) (b710/n = 6), spasticity (b735/n = 4), motor control (b760/n = 15), and ability in performing activities of daily living (ADL)

Table 2. Synoptic table of studies included in the passive range of motion assessment (b710) of the ICF domain.

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signals (+ processing technique)	Procedure	Results
Bai 2020 (1)[29]	4 (3 M, 1F), 75.5 ± 2.5	(2) Humerus, Forearm	(a) "Xsens MTx, Xsens Technologies, the Netherlands," NR (b) "Sony Move," 30 Hz	(a) 3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm) (b) 3D sensor orientation as estimated by a 9-axis. (complementary filter/ Kalman filter)	Abduction test	IMUs are shown to be able to accurately measure upper limb joint orientation and position.
Bai 2020 (2)[30]	5 (4 M, 1F), 68.8 ± 8.7	(a) (4) Shoulder, Humerus, Forearm, Hand (b) (2) Humerus, Forearm	(a) "Xsens MTx, Xsens Technologies, the Netherlands," NR (b) "Sony Move," 30 Hz	(a) 3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm) (b) 3D sensor orientation as estimated by a 9-axis. (complementary filter/Kalman filter)	Shoulder f/e, shoulder abd/add, elbow f/e, forearm pronation/supination, wrist f/e, hand ulnar/radial deviation.	Low cost IMUs provide adequate accuracy in measurement UL orientation and position tracking.
Bertomeu-Motos 2018[31]	3 (NR) 61 ± 9.6	(2) Shoulder, Upper arm	"ShimmerSensing, Dublin, Ireland," 100 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	The wrist joint location has been computed during the exercise with a 7-DoF arm model fed with the segments orientation as provided by two magneto-inertial sensors and the wrist position as provided by an end-effector robot.	Higher estimated ROM's joints correlate with high FMA scores. The proposed algorithm can determine the ROM using only one accelerometer attached in the upper arm but reveals an instability when shoulder movements appear due to the inevitable trunk compensation in stroke patients.
Bhagubai 2020[32]	10 (6 M, 4F), 61.5	(7) Shoulder, Humerus, Forearm, Hand, Thumb, 2nd finger, 3rd finger	"Custom IMU based on ST LSM330DLC chip," 100 Hz	3D sensor orientation as estimated by a 6-axis. (gradient descent sensor fusion algorithm)	Arm-related tasks (A1, A2, A3, B1) from the FMA, with the affected and non-affected side.	The measurement system was adequately sensitive to show significant differences in stroke subjects' arm postures between the affected and non-affected side. The presence of pathological synergies can be analyzed using the measured joint angles.
Kang 2020[33]	18 (10 M, 8F), 49.78 ± 15.55	(6) Head, Sternum, Humerus BS, Forearm BS.	"Custom magneto-inertial measurement unit, MPU9250; InvenSense, San Jose, CA," 100 Hz	3D sensor orientation as estimated by a 9-axis. (gradient descent sensor fusion algorithm)	ROM, movement time and variability was recorded during three phases of shoulder movement (abduction, holding and adduction). Parameter extraction was performed on the Euler angles obtained from the frontal plane around the sagittal axis.	During the holding phase, MAC significantly increased the minimum Euler angle and decreased the ROM compared with the other types of cueing. Further, the root mean square error in the angle measurements was significantly smaller and the duration of movement execution was significantly shorter during the holding phase when MAC was provided than when the other types of cueing were used.
Li 2016[34]	35 (NR), NR	(4) Head, Upper arm, Forearm, Hand.	"Custom magneto-inertial measurement unit, MPU9150; InvenSense, San Jose, CA," NR	3D sensor orientation as estimated by a 9-axis. (Kalman filter sensor fusion algorithm)	shoulder flexion (90°) in a sitting position and held on for 2–3 seconds.	All kinematics showed a significant statistical difference between patients and healthy people, while the feature values showed a high correlation with FMA scores.

Abbreviations: NR = Not Reported; ROM = Range Of Motion; UL = Upper Limb; BS = Both Side; f/e = flexion/extension; abd/add = abduction/adduction; FMA = Fugl-Meyer Assessment; ARAT = Action Research Arm Test; ADL = Activities of Daily Living; IMU = Inertial Measurement Unit; MAC = Melodic Auditory Cueing. In Bai et al., 2020 (1) and (2), only configuration (b) was used to performed kinematic analysis. Column five reports the source signal from which the kinematic variable of interest has been derived: 6-axis = the sensor fusion algorithm runs using accelerometer and gyroscope data; 9-axis = the sensor fusion algorithm runs using accelerometer, gyroscope, and magnetometer data.

(d445/n = 15) (the complete allocation is available in Appendix B). Ten[33,36,37,42,44,46–48,51,52] out of 35 studies investigated the kinematics variables in both ULs applying IMUs on affected and unaffected side.

Passive range of motion assessment (b710)

Seven studies have assessed ROM through IMUs in a sample of 74 patients,[29–34] with a range of IMUs' number from two[30] to seven.[32]

The ROM test was performed in three different ways: active ROM (AROM),[29,33,34] passive ROM,[31,32] and robot-assisted ROM.[30]

The most used kinematic variables were the joint angles of shoulder, elbow, wrist, and fingers either in a single plane or in three dimensions (3D). The most investigated tasks were single shoulder and elbow flexion-extension. Linear trajectories and velocity of anatomical landmarks as well as UL's smoothness have also been investigated in a limited number of studies.

Muscle tone functions (b735)

Regarding the proposed ICF subdivision, spasticity is the least investigated domain through IMUs.

Four studies have used IMUs to assess muscle tone impairment on 82 stroke patients.[37–40.]

The number of IMUs ranged from one[53] to three.[54,55] Three studies[53,54,56] performed a passive stretch reflex of the elbow flexors; additionally, Kim and colleagues (2020)[53] tested the elbow extensors; and

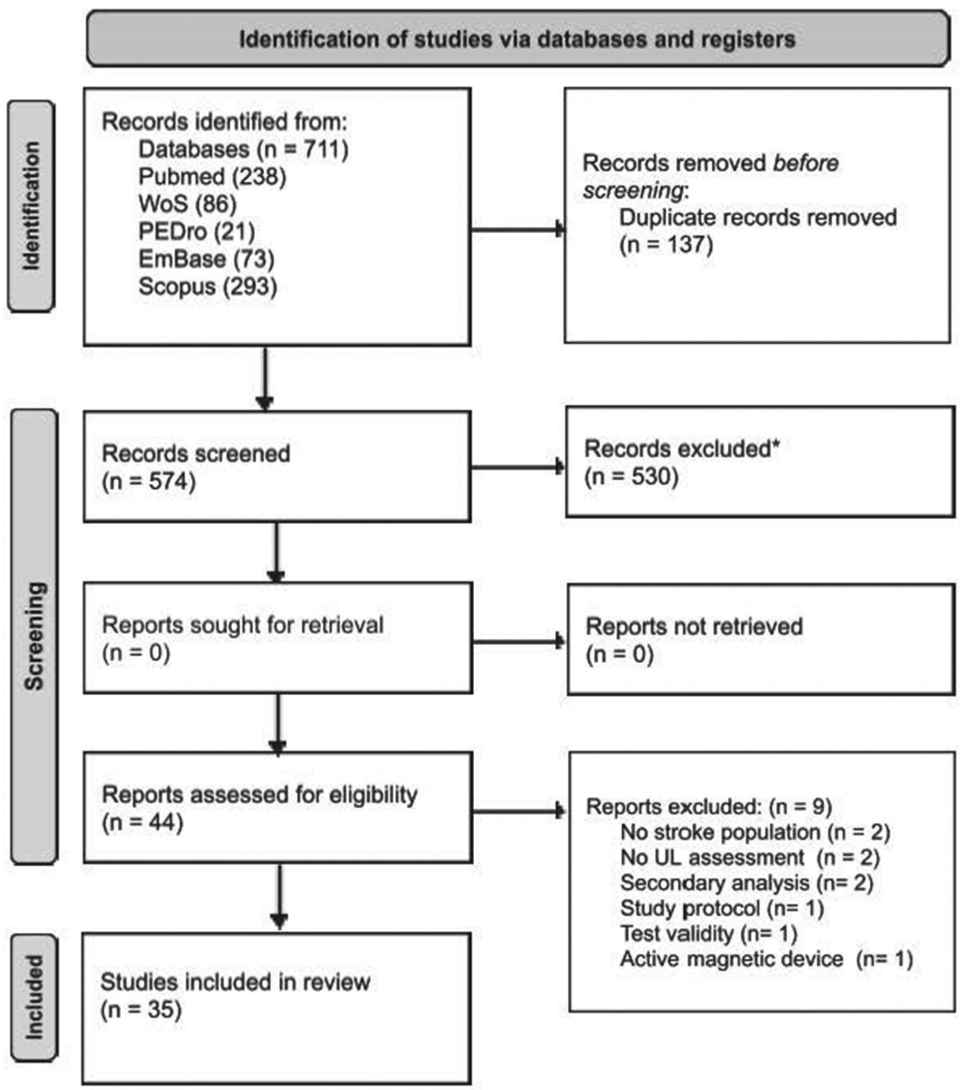

Figure 2. Flow diagram of studies selection process (PRISMA ver. 2020).[28] *All records were excluded by humans.

Table 3. Synoptic table of studies included in the muscle tone functions (b735) of the ICF domain.

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Ang 2018[54]	15 (7 M, 8F), 56.9 ± 10	(3) Thorax, Humerus, Forearm	"APDM Opal™ wireless," 128 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Joint torques have been computed using inverse dynamics with measurements from three IMUs to calculate the tonic stretch reflex threshold. Data have been subjected to correlation analysis with the EMG and MAS.	The estimated muscle activation profiles have a high correlation to the EMG signal profiles. Spasticity severity calculated with IMUs showed a high correlation with the MAS score.
Chen 2021[55] **(1)**	9 (8 M, 1F) 51.8 ± 12.4	(1) Forearm	"Custom magneto-inertial measurement unit, MPU9250; InvenSense, San Jose, CA, 200 Hz	3D sensor orientation as estimated by a 9-axis. (complementary filter sensor fusion algorithm)	f/e of the elbow supported by a guide-track has been performed. A slider was used to assist patients to achieve the maximum ROM.	The RF algorithms exhibited excellent classification performance in detecting and categorizing four grades of spasticity.
Kim 2020[53]	48 (26 M, 22F), 61.2 ± 13.7 (M) 77.8 ± 10.1 (F)*	(1) Wrist	"Shimmer Sensing, Dublin, Ireland," 256 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Results of an IMU device during a passive stretch test with Machine-learning algorithms (eg. RFs) have been combined. Measurement of elbow spasticity was based on the MAS.	Among the Machine-learning algorithms, a RF performed well, achieving up to 95,4% accuracy.
Paulis 2011[56]	13 (7 M, 6F), 70.2 ± 12.3	(2) Humerus, Wrist	"MTx, Xsens Technologies, Enschede, Netherlands," 100 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Tardieu Scale measurements have been performed in two sessions, using both IMUs and goniometry, to quantify spasticity in elbow flexors of stroke patients.	For goniometry, test – retest and inter-rater reliability proved to be excellent and fair to good, respectively. For IMUs, both test – retest and inter-rater reliability were excellent. IMUs are reliable and accurate to use in Tardieu Scale measurements to quantify spasticity in the elbow flexors of hemiplegic stroke patients.

Abbreviations: IMU = Inertial Measurement Unit; MAS = Modified Ashworth Scale; EMG = Electromyography; f/e = flexion/extension; RF = Random Forest.×45 stroke and 3 spinal cord injuries. Column five reports the source signal from which the kinematic variable of interest has been derived: 6-axis = the sensor fusion algorithm runs using accelerometer and gyroscope data; 9-axis = the sensor fusion algorithm runs using accelerometer, gyroscope, and magnetometer data.

Ang and colleagues (2018)[54] also tested shoulder, wrist, and thumb. Chen et al., 2021[55] performed a multimodal acquisition combining an IMU sensor with a surface EMG system (Ultium™ Biomechanics System, Noraxon Ltd, USA) during a guided flexion extension of the elbow.

Two studies used the Modified Ashworth Scale as clinical assessment,[53,54] and one of these performed a correlation analysis with kinematics data,[54] the other study used the Tardieu scale.[56]

The choice of the kinematic variable was heterogeneous among the selected studies. In particular, angular velocity and acceleration were used to assess the spasticity in two studies,[53,54] while elbow flexion-extension ROM was used in the study of Paulis and colleagues (2011).[56]

Voluntary movements assessment (b760)

Fifteen studies used IMUs to assess voluntary movements on 218 stroke patients[29,30,37,44,48,51,52,57–64] with a number of IMUs' ranging from one[64] to fourteen.[37]

A high heterogeneity with respect to the required tasks was found across studies. Generally, reaching tasks or clinical tests that mimic reaching and grasping tasks have been administered. Two studies used non-immersive virtual reality with exergaming.[29,64]

Regarding the required tasks, several kinematics variables were chosen to evaluate the voluntary movements. The most recurrent variables were timing, position, velocity (linear), acceleration, and smoothness. Additionally, angles, symmetry, and spectral analysis have also been investigated.

Table 4. Synoptic table of studies included in the voluntary movements assessment (b760) of the ICF domain.

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Bai 2020 (1)[29]	4 (3 M, 1F), 75.5 ± 2.5	(2) Humerus, Forearm	(a) "Xsens MTx, Xsens Technologies, the Netherlands," NR (b) "Sony Move," 30 Hz	(a) 3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm) (b) 3D sensor orientation as estimated by a 9-axis. (complementary filter/Kalman filter)	BBT and the NHPT have been performed.	IMUs are shown to be able to accurately measure upper limb joint orientation and position.
Bai 2020 (2)[30]	5 (4 M, 1F), 68.8 ± 8.7	(a) (4) Shoulder, Humerus, Forearm, Hand (b) (2) Humerus, Forearm	(a) "Xsens MTx, Xsens Technologies, the Netherlands," NR (b) "Sony Move," 30 Hz	(a) 3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm) (b) 3D sensor orientation as estimated by a 9-axis. (complementary filter/Kalman filter)	BBT and the NHPT have been performed.	Low cost IMUs provide adequate accuracy in measurement UL orientation and position tracking.
Chen 2021[57] **(2)**	37 (28 M, 9F) 49.8 ± 10.3	(4) Head, Upper Arm, Forearm, Hand	"IMU, Noraxon, USA Inc.," 100 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Finger-To-Nose task. UL motor function evaluated with FMA, ARAT and MBI.	Results showed that Finger-To-Nose task kinematic variables measured via IMU were associated with UL motor function.
Held 2018[37]	4 (NR), 48–55 range	(14) Shoulder BS, Humerus BS, Sternum, Sacrum, Feet BS, Lower leg BS, Upper leg BS.	"Xsens Technologies, Enschede, Netherlands," 20 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Kinematic data Have been recorded with a full body motion capture suit during clinical assessment (including FMA and ARAT).	These results demonstrate the feasibility of the method to meas- ure upper-limb kinematics, with an IMU-based motion capture system at different stages of stroke rehabilitation and during ADL and the concordance to standard clinical assessment.
Hesam-Shariati 2019[51]	24* (16 M, 8F), 57.9 ± 12.1	(6) Trapezius, Upper arm BS, Forearm BS, Hand	"Triaxial accelerometer Trigno, Delsys, USA," 148,15 Hz	gravity-free 3D linear acceleration and jerk as estimated from high-pass filtered measured sensor-embedded accelerations, as well as linear velocity as computed from numerical integration gravity-free 3D linear acceleration	Kinematic parameters have been investigated during Wii-baseball swing.	Increased acceleration magnitude and decreased normalized velocity during a complex movement.
Nikmaram 2019[58]	41(12)** (30 M, 11F), 67,6 ± 11,4	(2) Upper arm, Wrist	"Xsens MTx, Xsens Technologies, the Netherlands," 200 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	In the experiment the patients sit in front of a wooden frame labeled with musical note-pitch. The final goal was to teach them to play several simple nursery rhymes only by moving their affected arm in 3D sonification space.	IMUs data showed slight improvements in movement smoothness.

(*Continued*)

Table 4. (Continued).

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Nie 2021[59]	8 (6 M, 2F) 58 ± 12.6	(2) Upper Arm, Forearm	"Trigno IM Sensor, Delsys Inc.," 200 Hz	3D sensor orientation as estimated by a 9-axis. (improved explicit complementary filter)	3D reaching movements	Compared to a traditional optical tracking system, IMUs accurately tracked the wrist movement during reaching.
Pan 2021[60]	34 (26 M, 8F) 59.8 ± 11.2	(4) Middle of Waist, Upper Arm, Forearm, Hand	"Custom magneto-inertial measurement unit, MPU9150; InvenSense, San Jose, CA," 50 Hz	3D sensor orientation as estimated by a 9-axis. (particle filter)	IMU data and EMG signals have been collected from the UL during voluntary upward reaching. Five features have been assessed: max shoulder joint angle, peak and average speeds, and torso balance calculated from The FMA score of each patient.	Statistically significant differences were observed among severe, mild-to-moderate, and the control group. The features varied as the level of UL motor function changed since these features significantly correlated with the FMA. Moreover, the Bland – Altman method showed high consistency between the evaluation method of five features and the FMA scale.
Park 2020[52]	15*** (10 M, 5F) 68.6 ± 16.1	(4) Wrist BS, Lower Leg BS	NR	measured 3D linear acceleration	Mingazzini test upper limbs for 20 seconds.	The automatic grading system quantified proximal weakness in real time and assessed symptoms through automatic grading.
Rau 2013[61]	8 (5 M, 3F), 62.9 ± 13.8	(2) Acromion, Forearm	"Triaxial accelerometer (sensor chip is not reported) NR	NR	Five repetitions of forward-reaching movements.	High correlation has been found in reaching displacement, velocity, and acceleration measurements obtained using the tele-assessment system and the standardized kinematic system. Differences in the maximum reaching distance and the maximum reaching velocity of forward reaching movements were observed among the study groups.
Salazar 2014[62]	4 (2 M, 2F), 53.2 ± 6.5	(3) Back (T12), Acromion, Elbow	"Custom triaxial accelerometer (ADXL345), Analog Devices, Norwood, MA" 100 Hz	limb 3D rotation as estimated from measured tilt angles as derived from accelerometer signal (gravity-based)	Trunk, upper arm, and forearm angular displacements during a reach-press-return task.	Preliminary studies revealed acceleration profiles of stroke patients through which it is possible to quantitatively assess the functional movement, identify compensatory strategies, and help define proper movement.
Schwartz 2021[44]	26 (17 M, 9F) 62.2 ± 12.1	(9) Spina Scapulae BS, Sternum, Upper arm BS, Forearm BS, Wrist BS	"XSens MVN Awinda, Xsens Technologies, the Netherlands," 60 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	Four movements with both ULs: (1) isolated shoulder flexion, (2) pointing ahead, (3) reach-to-grasp a glass, and (4) key insertion. The validity of metrics compared to clinically measured interjoint coordination (FMA) has been done by correlation analysis.	The movement task and the tested arm showed significant effects on all kinematic parameters. Hand dominance resulted in significant effects on shoulder f/e and curve efficiency. Relations with the FMA revealed the strongest and significant correlation for curve efficiency, followed by shoulder f/e, elbow f/e, and shoulder abd/add. Curve efficiency additionally correlated significantly with the arm subsection, focusing on synergistic control.

(*Continued*)

Table 4. (Continued).

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Tedim-Cruz 2014[63]	5 (5 M), 35–73 range	(4) Acromion, Humerus, Forearm, Wrist	"Custom magneto-inertial measurement unit (sensor chip is not reported)" 50 Hz	3D sensor orientation as estimated by a 9-axis. (non-specified sensor fusion algorithm)	Patients have been tested on BS across five selected tasks of WMFT: forearm-to-table (task 1), forearm-to-box (task 2), extend-elbow (task 3), hand-to-table (task 4) and hand-to-box (task 5). Each task was evaluated according to performance time (seconds) and Func-tional Ability Score (FAS) based on joint kinematics.	The prototype tested was able to automatically classify UL movement, according to WMFT, in a clinical setting.
Wade 2014[48]	10 (8 M, 2F), 59.2 ± 15.3	(2) Wrist BS	"Triaxial accelerometers (Gulf Coast Data Concepts, LLC)." 40 Hz	measured 3D linear acceleration	Unimanual goal-directed movements using both hands, with and without task objects.	Main effects of the hand on all 3 temporal measures and main effects of objects on movement duration and peaks have been found. Spectral measures of accelerometry data are sensitive to performance differences with the nonparetic and paretic limbs and with the object present and absent, for ADL-inspired tasks.
Zollo 2011[64]	24 (15 M, 9F), 55.9 ± 15.4	(1) Forearm	"Xsens MTx, Xsens Technologies, the Netherlands" NR	Smoothness (i.e., jerk) as computed from the absolute (gravity-free) linear acceleration derived from the 3D sensor orientation (proprietary sensor fusion algorithm)	Point-to-point movements with robot-assisted movement.	Significant correlation has been found between kinematic variables and FMA and motor strength scores during unperturbed and resistive robot-assisted tasks.

Abbreviations: IMU = Inertial Measurement Unit; NR = Not Reported; BS = Both Side; BBT =Bean Bag Test; NHPT = Nine Hole Peg Test; FAS = Functional Ability Score; UL = Upper Limb; f/e = flexion/extension; abd/add = abduction/adduction; ARAT = Action Research Arm Test; FMA = Fugl-Meyer Assessment; MBI = Modified Barthel Index; EMG = Electromyography; WMFT = Wolf Motor Function Test; MARG = Magnetic, Angular Rate, and Gravity sensor.

*13 at follow-up; **12 patients analyzed, ***13 stroke patients, 1 myelitis, and 1 myasthenia gravis. In Bai et al., 2020 (1) and (2), only configuration (b) was used to performed kinematic analysis. Column five reports the source signal from which the kinematic variable of interest has been derived: 6-axis = the sensor fusion algorithm runs using accelerometer and gyroscope data; 9-axis = the sensor fusion algorithm runs using accelerometer, gyroscope, and magnetometer data.

Table 5. Synoptic table of studies included in the object manipulation and daily life activity assessment (d445) of the ICF domain.

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Bai 2020 (1)[30]	5 (4 M, 1F), 68.8 ± 8.7	(a) (4) Shoulder, Humerus, Forearm, Hand (b) (2) Humerus, Forearm	(a) "Xsens MTx, Xsens Technologies, the Netherlands," NR (b) "Sony Move," 30 Hz	(a) 3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm) (b) 3D sensor orientation as estimated by a 9-axis. (complementary filter/ Kalman filter)	Patient performed a "drinking" task.	This study demonstrates that multi-sensor inertial sensing systems can provide additional insights for motion quantification.
Biswas 2014[35]	4 (NR but both sexes), 45–73 range	(1), Wrist	"Shimmer, Dublin, Ireland," 50 Hz	Limb posture as estimated from measured tilt angles as derived from accelerometer signal (gravity-based)	Activities involved in a representative ADL: "making a cup of tea."	The results showed that the IMU can independently recognize all three of the elementary UL movements investigated (reach and retrieve, lift cup to mouth, rotation of the arm) with accuracy in the range 91%-99% for healthy subjects and 70%-85% for stroke patients.
Bochniewicz 2017[36]	10 (8 M, 2F), 56 ± 10.4	(2), Wrist-worn BS	"Custom magneto-inertial measurement unit (ADIS16400BMLZ, Analog Devices, Norwood, MA)." 200 Hz	Limb measured 3D linear acceleration and angular velocity	Series of ADL tasks (doing the laundry, kitchen activities, shopping and making the bed).	A significant correlation between ARAT scores of the stroke's patients and the percentage of time spent in functional use has been found.
Held 2018[37]	4 (NR), 48–55 range	(14) Shoulder BS, Humerus BS, Sternum, Sacrum, Feet BS, Lower leg BS, Upper leg BS	"Xsens Technologies, Enschede, Netherlands," 20 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	FMA, ARAT, and self-directed ADL.	A change in data kinematics from the daily-life recording was seen in all patients, increasing the number of reaches performed during daily life in their home environment.
Lin 2017[38]	15 (9 M, 6F), 59.3 ± 16.3	(16) Hand, Fingers (one for each side of the interphalangeal joint)	"Custom IMU (LSM330DLC, STMicroelectronics, Geneva, Switzerland)," NR	3D sensor orientation as estimated by a 6-axis. (gradient descent algorithm)	Grip task, thumb task, and card turning task.	The IMUs glove provides quantitative data useful for medical treatments.
Mahmoud 2021[39]	9 (NR) 58.2 ± 4.8	(2) Forearm, Hand	"Xsens DOT, Xsens Technologies, the Netherlands,"800 Hz	3D sensor orientation as estimated by a 9-axis. (proprietary sensor fusion algorithm)	To simulate the daily activity of moving objects to a high level. To simulate the action of cleaning the window. To control action 1, the actual main investigation of the patient's arm in the state of low-load movement. To simulate the situation of daily horizontal movement of objects.	The results showed a high overall accuracy. In addition, the fusing of Kinect and Xsens data revealed that muscle strength was highly correlated with the kinematics data.

(*Continued*)

Table 5. (Continued).

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Mazomenos 2016[40]	4 (NR -mixed gender-), 45–73 range	(2) Elbow, Wrist	"Shimmer, Dublin, Ireland," 50 Hz	3D sensor orientation as estimated by a 9-axis. (gradient descent algorithm)	3 elementary UL movements: reach and retrieve, bend the arm at the elbow, rotation of the arm about the long axis, such as subtasks of an ADL ("making a cup of tea").	The results showed a high overall accuracy for all three movements for the "preparation of a cup of tea" task.
Michaelsen 2013[41]	8 (4 M, 4F), 59.4 ± 6.9	(1) Forearm	"Triaxial accelerometer, EMG Systems, Brazil," 100 Hz	measured 3D linear acceleration	Ten reach-to-grasp movements of grabbing a 500 ml-size bottle.	The IMU allowed identification of changes in reaching-to-grasp movements of subjects with hemiparesis. Movements were slower in the paretic UL with increased movement time, time to peak acceleration and deceleration duration.
Repnik 2018[42]	28 (18 M, 10F), 57 ± 9.1	(7) Sternum, Humerus BS, Forearm BS, Hand BS	"Magneto-inertial measurement unit (brand/chip is not reported),"200 Hz	3D sensor orientation as estimated by a 9-axis. (unscented Kalman filter)	ARAT.	Movement quantification enables differentiation between different subject groups within movement phases as well as for the complete task. Strong correlations between ARAT scores and movement time as well as movement smoothness was found. Weak to moderate correlations were observed for parameters that describe hand trajectory similarity and trunk stability.
Schwarz 2020[43]	10 (6 M, 4F), 60.8 ± 11.4	(8) Sternum, Shoulder, Upper arm, Lower arm, Hand, Thumb, 2° and 3° fingers	"Custom IMU (ST LSM330DLC, ST Microelectronics, Geneva, Switzerland," 100 Hz (accelerometer) and 200 Hz (Gyroscope)	3D sensor orientation as estimated by a 6-axis. (not specified sensor fusion algorithm)	Reach-to-grasp activities with the affected and non-affected UL. It was investigated whether the factors, tested arm, object weight, and target height, affect the expressions of ROM in trunk compensation and f/e of the elbow, wrist, and finger during object displacement.	The tested arm and target height showed strong effects on all metrics, while an increased object weight showed effects on trunk compensation. High inter- and intrasubject variability was found in all metrics without clear relationships to clinical measures. Relating all metrics to each other resulted in significant negative correlations between trunk compensation and elbow f/e in the affected arm.
Schwartz 2021[44]	26 (17 M, 9F) 62.2 ± 12.1	(9) Spina Scapulae BS Sternum Upper arm BS Forearm BS Wrist BS	"XSens MVN Awinda, Xsens Technologies, the Netherlands," 60 Hz	3D sensor orientation and position as estimated by a 9-axis. (proprietary sensor fusion algorithm with a kinematic model)	Four movements with both ULs: (1) isolated shoulder flexion, (2) pointing ahead, (3) reach-to -grasp a glass, and (4) key insertion.	The movement task and the tested arm showed significant effects on all kinematic parameters. Hand dominance resulted in significant effects on shoulder f/e and curve efficiency. The level of UL function showed influences on curve efficiency and the factor age on the median slope. Relations with the FMA revealed the strongest and significant correlation for curve efficiency.
Thies 2009[45]	6 (4 M, 2F), 59.1 ± 16	(1) Forearm	"Xsens Technologies B. V., Enschede, Netherlands (sensor model not reported)," 4 Hz (cutoff)	measured 3D linear acceleration	ADL (drinking from a glass and moving a plate). These activities involved movements such as a forward reach, followed by hand opening, hand grasp, object manipulation and finally object release and arm retraction.	For "drinking from a glass" significant group differences were obtained on both days for the timing variability of the acceleration signals' characteristics; all stroke patients showed increased signal timing variability as compared to their corresponding control subjects. "Moving a plate" provided less distinct group differences.

(*Continued*)

Table 5. (Continued).

Author	Participants, (gender), age	IMUs number (N) and location	"IMUs device," Frequency acquisition	Source signal (+ processing technique)	Procedure	Results
Van Meulen 2015[46]	13 (8 M, 5F), 63.8 ± 8.5	(17) Head, Sternum, Sacrum, Shoulder BS, Upper arm BS, Lower arm BS, Hand BS, Upper leg BS, Lower leg BS, Feet BS	"Xsens MVN Awinda, Xsens Technologies, the Netherlands," 120 Hz	3D sensor orientation and position as estimated by a 9-axis. (proprietary sensor fusion algorithm with a kinematic model)	Multiple ADL. Each task was repeated three times.	Significant correlations with the FMA scores were found in the hand movements (working area, maximum reached distance, and the range in vertical hand elevation.
Van Meulen 2016[47]	2 (NR), NR	(12) Head, Sternum, Pelvis, Upper arm BS, Lower Arm BS, Upper Leg BS, Lower Leg BS, Feet BS	"Xsens MVN Awinda, Xsens Technologies, the Netherlands," 20 Hz	3D sensor orientation and position as estimated by a 9-axis. (proprietary sensor fusion algorithm with a kinematic model)	Clinical assessment consisted of 10-mWT for the P1 and a predefined arm task (patient had to reach as far as possible and to make a circle as wide as possible over a table) for the P2. The second session included a measurement session of 3 h of movement data, which was captured at the patient's home 4 weeks after discharge.	Quality of movement can be evaluated in a daily life setting. Differences between in-clinic measurements and measurements during daily life are observed by applying the presented metrics and visualization methods. For the upper extremities, the P2 was able to reach a larger area.
Wade 2014[48]	10 (8 M, 2F), 59.2 ± 15.3	(2) Wrist BS	"Triaxial accelerometers (Gulf Coast Data Concepts, LLC)," 40 Hz	measured 3D linear acceleration	Unimanual goal-directed movements using both hands, with and without task objects.	Spectral measures of IMUs data are sensitive to performance differences with the nonparetic and paretic limbs and with the object present and absent, for ADL-inspired tasks.

Abbreviations: IMU = Inertial Measurement Unit; NR = Not Reported; BS = Both Side; DAS = Disability Assessment Scale; NHPT = Nine Hole Peg Test; DAS = Disability Assessment Scale; MAS = Modified Ashworth Scale; ADL = Activities of Daily Living; UL = Upper Limb; BBT = Box and Block Test; SIS = Stroke Impact Scale; TLT = Thumb Localizing Test; ARAT = Action Research Arm Test; ROM = Range Of Motion; DoF = Degrees of Freedom; RF = Random Forest; FMA = Fugl-Meyer Assessment; OT = Occupational therapy; MARG = Magnetic, Angular Rate, and Gravity sensor; EMG = Electromyography; EEG = Electroencephalogram; 10mWT = 10 Meters Walking Test; P1 = First Patient; P2 = Second Patient. In Bai et al., 2020 (2), only configuration (b) was used to performed kinematic analysis. Column five reports the source signal from which the kinematic variable of interest has been derived: 6-axis = the sensor fusion algorithm runs using accelerometer and gyroscope data; 9-axis = the sensor fusion algorithm runs using accelerometer, gyroscope, and magnetometer data.

Object manipulation and daily life activity assessment (d445)

Fifteen studies have used IMUs to assess object manipulation or activity of daily life tasks on 154 stroke patients,[30,35–48] with a number of IMUs' ranging from one[35,41] to seventeen.[46]

Kinematic investigation during daily life tasks took into consideration a diverse number of variables. Despite the high heterogeneity in the choice of the observed variables, some parameters are more recurrent in many studies. Specifically, the number of repetitions, joint ROM, and the symmetry of movement (with respect to healthy subjects or with respect to the contralateral limb) were the most frequent kinematics variables selected. Secondly, the position, acceleration, and smoothness of the movements were investigated in about one-third of the selected studies. Additionally, trunk stability, trunk compensation, and spectral analysis have been investigated.

Clinical vs kinematics correlation meta-analysis

A total of 10 studies were included in the quantitative analysis of the correlation between IMUs parameters and clinical assessment, and the total sample size was 213. Six out of the ten studies included in the meta-analysis investigate the correlation of kinematics with the Fugl-Meyer Assessment (FMA) scale,[34,44,46,57,60,64] three studies with the Action Research Arm Test (ARAT),[36,42,57] two with the Modified Ashworth Scale (MAS),[30,54] and one with the Modified Barthel Index (MBI).[57] Meta analysis shows an overall Fisher Z-score of 0.83 (95% CI: 0.69/0.98; $p < 0.001$), Fisher Z-transformation (r 0.69) indicating a moderate correlation (Figure 3). With no heterogeneity across the studies (Q-s = 6.7; p = 0.7; $I^2 = 0$). Risk of bias assessed with Egger's test ($t = 3.23$, $p < 0.05$) and Begg-Mazumdar's test (t = 1.25, $p = 0.2$) indicated that there was a potential publication bias (Funnel plot in Appendix C). Subgroup analysis for ICF d445 domain performed on 51 stroke patients, showed an overall Fisher Z-score of 0.88 (95% CI: 0.58/1.18; $p <$ 0.001), Fisher Z-transformation ($r = 0.71$) indicating a strong correlation. With no heterogeneity across the studies (Q-s = 0.87; $p = 0.6$; $I^2 = 0$). Risk of bias assessed with Egger's test ($t = 1.41$, $p = 0.4$) and Begg-Mazumdar's test ($t = 0.52$, $p = 0.6$) indicated that there was not a potential publication bias. In the subgroup meta-analysis for ICF b760 domain performed on 107 stroke patients, show an overall Fisher Z-score of 0.76 (95% CI: 0.56/0.96; $p < 0.001$), Fisher Z-transformation (r = 0.64) indicating a moderate correlation. With no heterogeneity across the studies (Q-s = 0.14; p = 0.98; $I^2 = 0$). Risk of bias assessed with Egger's test ($t = -0.5$, $p = 0.3$) and Begg-Mazumdar's test (t = −2.04, $p = 0.04$) indicated that there was a potential publication bias. The subgroup meta-analysis for ICF b710 domain performed on 40 stroke patients shows an overall Fisher Z-score of 1.28 (95% CI: −0.03/2.59; $p < 0.056$), Fisher Z-transformation ($r = 0.85$) indicating a strong correlation. With high heterogeneity across the studies (Q-s = 3.59; $p = 0.058$; $I^2 = 72$).

	ES	95% CI	W	V	Sig.	N
Ang 2018/ICF b735	1.19	0.63 / 1.76	6.56%	0.08	0.000	15
Bai 2020/ICF b710	2.14	0.75 / 3.52	1.09%	0.50	0.002	5
Bochniewicz 2017/ICF d445	0.95	0.21 / 1.69	3.83%	0.14	0.012	10
Chen 2021/ICF b760	0.81	0.47 / 1.15	18.58%	0.03	0.000	37
Li 2016/ICF b710	0.76	0.41 / 1.10	17.49%	0.03	0.000	35
Pan 2021/ICF b760	0.75	0.40 / 1.10	16.94%	0.03	0.000	34
Repnik 2018/ICF d445	0.77	0.37 / 1.16	13.66%	0.04	0.000	28
Schwarz 2021/ICF b760	0.73	0.32 / 1.14	12.57%	0.04	0.000	26
Zollo 2011/ICF b760	0.69	-0.05 / 1.43	3.83%	0.14	0.067	10
van Meulen 2015/ICF d445	1.11	0.49 / 1.73	5.46%	0.10	0.000	13
Overall (random-effects model)	0.83	0.69 / 0.98	100.00%	0.01	0.000	213

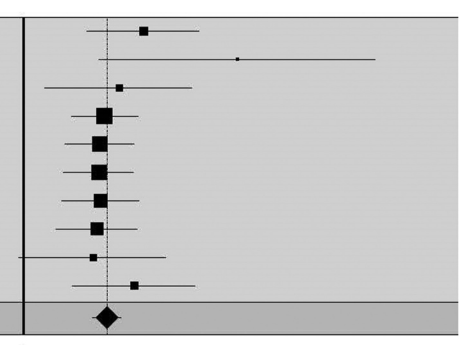

Figure 3. Forest plot for the random effect model correlation meta-analysis between kinematics and clinical data. The continuous line indicates no correlation (right and left, positive and negative correlation, respectively). The dashed line indicates the pooled Z-score. ES: effect size; CI: confidence interval; W: weight; V: variance; Sig.: statistical significance; N: sample number. Studies[30,44] allocated to more than one ICF' subgroups were considered for meta-analysis only in their dominant subgroup.

Discussion

The aim of the present systematic review was to give an overview of the use of wearable IMUs for the kinematic assessment of clinical features of the UL in accordance with the ICF in patients with stroke. The literature suggests that a limited number of sensors are functional in obtaining kinematic information on the functional activity of the upper limb in a simple and safe way. The use of IMUs alone or in association with other clinical or instrumental assessment tools has been used to collect objective data on the functions of the UL. The positive correlations with other instruments' acquisition and clinical tests, and the high precision in the test-retest and intra-test reliability, promote the adoption of wearables as appropriate solutions to assess UL functions, especially in the assessment of activity of daily living.

Regarding the assessment of the range of motion (ICF – b710), kinematic variables such as 2D and 3D angles are the most utilized to describe the movements of UL joints. Consistent with the evaluation aim, the angles recorded during passive, active, or robot-assisted movements provide useful information regarding the ROM performed. In this respect, even a limited number of sensors can be enough to assess this function. Trajectory, smoothness, and symmetry can be investigated to expose additional information about the quality of ROM. The scientific literature suggests some useful indications: (i) 3D sensor orientation estimated by a 9-axis can be used to calculate the joints' angles during passive or active mobilization; (ii) IMUs can detect the compensation during movement execution (i.e. trunk compensation); (iii) considering the individual variability of joints' angles, the assessment of both ULs through IMUs can provide a symmetry index between affected and unaffected side defining a tailored ROM measure.

Muscle tone (ICF – b735) of the UL is the least common aspect investigated via IMUs with heterogeneity in the protocols and kinematics variables selected. Clinically, spasticity is defined as a motor disorder characterized by a velocity-dependent increase in the tonic stretch reflex[65] often difficult to clinically evaluate. Therefore, it is acknowledged that quantified, instrumented methods should be used to provide a more accurate and valid assessment of spasticity.[66] In this respect, biomechanical and electrophysiological methods (i.e., isokinetic dynamometers) have been investigated as potential instruments, but none of these techniques provide an easy and reliable assessment of spasticity for the use in the clinical routine.[67] Interestingly, our investigation shows that angular velocity and accelerations recorded via IMUs during rapid mobilization of UL were fruitfully adopted. Three sensors, at most, are sufficient to measure spasticity in a joint target (i.e., the elbow). This information can support the use of wearables to objectively quantify spasticity on which assessment there are still many limits. To summarize, spasticity is often clinically hard to quantify and present a lower inter-rater reliability. Although limited, scientific literature reports encouraging suggestions about the use of IMUs in the assessment of spasticity: (i) angular displacement (velocity and acceleration) is the suitable kinematic variable recordable via 3D sensor orientation estimated by a 9-axis; (ii) an excellent inter-rater reliability was observed in kinematics investigations with respect to the fair result in clinical inter-rater reliability.

Voluntary movements assessment (ICF – b760) is, with the ADLs, the most investigated function of UL, and they share some similarities. In the included studies in this domain was observed a high heterogeneity of variables and protocols. Such movements are typically assessed during clinical tests or integrated in more complex setups, eventually including robot-aided therapies[64] or exergaming.[51] The kinematic data recorded during clinical evaluation showed a high statistical correlation with clinical score, favoring the increasing acceptability of wearable IMUs among clinical personnel. Noteworthy, IMU-based scores may provide additional information about the change in movement quality that clinical tools do not detect.[51] In different application contexts, either rehabilitation or home-monitoring,[61] a plethora of IMU-based parameters were fruitfully adopted to support clinical assessment and decision-making. In the context of voluntary movements, more than in other ICF categories, many global parameters have been proposed, such as spectral parameters, somewhere highlighted as better informative than traditional temporal or kinematics parameters. In brief, the assessment of voluntary movements via IMUs present high heterogeneity, moreover the literature provides useful information: (i) the investigation of voluntary movement was recurrently performed via instrumentation of clinical test (i.e. Mingazzini, finger-to-nose test); (ii) some IMUs variables (i.e. smoothness or trajectories) can reveal information about movement quality that cannot be recorded with timed or quantitative tests.

As mentioned above, the ability to perform activities of daily living and the manipulation of objects (ICF – d445) is one of the most investigated functions of UL. These skills are, in general, the elective goal of rehabilitation.[68] In fact, the capacity to reach and keep in mouth or explore the surroundings can be considered the hegemonic function of UL. Probably, for this reason, ADL skills were investigated more frequently in comparison to the other functions. Moreover, the improvement in the ability to perform ADL can be considered as the result of the recovery in the other skills, such as motor control, range of motion and muscle tone. The investigation of ADL skills can be useful when a comprehensive evaluation of UL is needed, without focusing on the subcomponents of movement. While it is recognized that the ADLs are complex tasks, the selected studies proposed to characterize them using simple kinematic scores such as the number of repetitions, joint angles, and symmetry (with respect to the healthy subjects or contralesional side). This information can be useful to quantify the use of impaired limb with respect to the non-lesioned limb, to evaluate the volume of space explored, and to assess the quality and quantity of movement during all-day life. David and colleagues (2021)[68] synthesized the UL functions during ADL in four aspects: (a) amount of use (duration and/or intensity), (b) hand preference, (c) type of task, and (d) quality of movement. As a result of the present systematic review, the most recurrent kinematics variables cited above can provide a satisfactory response to the main questions of investigation. Noteworthy, additional global features (such as smoothness) are also considered to investigate specific aspects of UL function. Quantitative analysis shows a strong correlation between kinematics variables and clinical assessment ($r = 0.71$ $p < 0.001$) recorded during activities of daily living tasks. The homogeneity across the studies and the low risk of bias indicate that wearables provide an objective measure with excellent compliance with clinical observations. To conclude, concerning the IMUs assessment of ADL, emerging evidence suggests: (i) kinematics variables establish high correlation with clinical assessment of every-day activities; (ii) simple and complex kinematics can be successfully used to evaluate linear or spatial components and global features, respectively; (iii) the investigation of both ULs can provide information about symmetry during movement sharing in bimanual tasks; (iv) IMUs can be used to quantify the UL use during daily life activities in their home.

Advantages

The use of IMUs allows us not only to objectively evaluate movement, ROM, spasticity, and ability in ADL skills but also to obtain information that is often not identified with the common clinical tests. Some parameters of global kinematics can broaden and/or deepen the evaluation of the functional capacity of the UL, often easily linked to the clinical observation of the clinical signs such as movement fluidity or symmetry. As shown for the lower limb, IMUs can provide clinically relevant data on movement quality in addition to the traditional outcome.[69]

The assumption that clinical performance is equivalent to real-world performance may not be true and new technologies are needed to objectively measure real-world activity.[70] In this respect, IMU technology represents an added value in terms of evaluation of the UL functions in the real world, having an impact in measuring free-living function in a more objective, realistic, and ecological way.[71]

The increased availability of inexpensive commercial devices might influence the clinical decision-making process.[12] In this respect, machine learning approaches could be used to detect specific characterization of UL movements to adapt treatments to subjects' disabilities. Specifically, these algorithms on a large kinematics dataset can be effective to identify patterns of activity recognition, movement classification, or clinical assessment emulation in stroke patients.[72]

Limitations and future perspectives

As a limitation of the study, less than a third of the studies performed a both-side IMUs detection, limiting the evaluation capacity of bimanual activities, especially in the ADL tasks. Moreover, in the literature are not provided the sensitivity of kinematics measures in the differentiation of minimal clinical difference. Finally, the current number of papers on the topic did not support a thorough meta-analysis especially when considering the papers falling in specific ICF domains. Noteworthy, the preliminary correlation meta-analysis clearly supported our conclusions , highlighting the increasing interest in using IMU technology to perform the functional assessment in and outside the clinical environment. As a matter of fact, functional UL evaluation with IMUs does not simply improve standard clinical evaluations, but radically changes their paradigm, providing information on functional domains and on subjects' motor behavior not previously explored. This powerful possibility opens the chance to deliver rehabilitation in different settings (home, inpatient, and outpatient), to measure treatment content (amount, quality, and efficacy of the movement) and to better personalize rehabilitation programs. In the future, the amount of data recognized from the IMUs might offer a unique opportunity to improve the continuum of therapy from hospital to home environment encoding single and bimanual ADLs tasks.

Conclusion

The literature provides information about the use of IMUs in all four investigated ICF domains. The results of the present review show that kinematics assessments by IMUs provide additional data (i.e., global features) on motor function, muscle tone, range of motion, and ability to perform the activity of daily living in a clinical or ecological setting. The most investigated domain is the functional capacity of the upper limb during the movements of daily activities. A limited number of IMUs devices are sufficient to provide useful information on UL performance. The strong correlation between clinical and kinematics variables supports the choice of IMUs to objectively evaluate UL movement. Indeed, IMUs can increase the knowledge on the real use of the UL during activities of daily life in the home-setting.

Author contributions

AMC and GV contributed to the conception of the study. AMC, PP, AB, and GV contributed to data collection. AMC carried out the data analysis. AMC and GV wrote the first draft of the manuscript. GM and GK revised the manuscript. All the authors reviewed and approved the final version of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research has not received financial support from any funding agency in the public, commercial, or not-for-profit sectors. No financial support was provided for the research, authorship, and/or publication of this article.

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