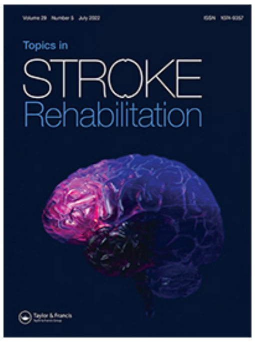

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RESEARCH ARTICLE

Use of artificial intelligence as an instrument of evaluation after stroke: a scoping review based on international classification of functioning, disability and health concept

AI applications for stroke evaluation

Gustavo José Luvizutto[a], Gabrielly Fernanda Silva[b], Monalisa Resende Nascimento[b], Kelly Cristina Sousa Santos[b], Pablo Andrei Appelt[b], Eduardo de Moura Neto[b], Juli Thomaz de Souza[c,d], Fernanda Cristina Wincker[c,d], Luana Aparecida Miranda[c,d], Pedro Tadao Hamamoto Filho[d], Luciane Aparecida Pascucci Sande de Souza[a], Rafael Plana Simões[e], Edison Iglesias de Oliveira Vidal[c], and Rodrigo Bazan[d]

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ABSTRACT

Introduction: To understand the current practices in stroke evaluation, the main clinical decision support system and artificial intelligence (AI) technologies need to be understood to assist the therapist in obtaining better insights about impairments and level of activity and participation in persons with stroke during rehabilitation.
Methods: This scoping review maps the use of AI for the functional evaluation of persons with stroke; the context involves any setting of rehabilitation. Data were extracted from CENTRAL, MEDLINE, EMBASE, LILACS, CINAHL, PEDRO Web of Science, IEEE Xplore, AAAI Publications, ACM Digital Library, MathSciNet, and arXiv up to January 2021. The data obtained from the literature review were summarized in a single dataset in which each reference paper was considered as an instance, and the study characteristics were considered as attributes. The attributes used for the multiple correspondence analysis were publication year, study type, sample size, age, stroke phase, stroke type, functional status, AI type, and AI function.
Results: Forty-four studies were included. The analysis showed that spasticity analysis based on ML techniques was used for the cases of stroke with moderate functional status. The techniques of deep learning and pressure sensors were used for gait analysis. Machine learning techniques and algorithms were used for upper limb and reaching analyses. The inertial measurement unit technique was applied in studies where the functional status was between mild and severe. The fuzzy logic technique was used for activity classifiers.
Conclusion: The prevailing research themes demonstrated the growing utility of AI algorithms for stroke evaluation.

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KEYWORDS
Stroke; artificial intelligence; machine learning; rehabilitation

Background

Stroke is the second leading cause of disability in adults, requiring long-term rehabilitation programs to prevent disability and enhance functional abilities.[1] During a rehabilitation program, therapists conduct neurological evaluation based on tests and measurements to determine better interventions.[2] In follow-up rehabilitations, therapists discuss patients' progress and periodically evaluate treatment outcomes to modify interventions as appropriate.[3]

Neurological clinical evaluation during the stroke rehabilitation process is essential for therapists to adjust interventions; however, this assessment relies on therapists' experiences.[4] In stroke evaluation, the International Classification of Functioning, Disability and Health (ICF) construct should be considered, including analysis of structure and body functions (such as motor, sensory, perceptual and cognitive impairments), and levels of activity and participations of the individual.[3,4] Additionally, several evaluations in health services

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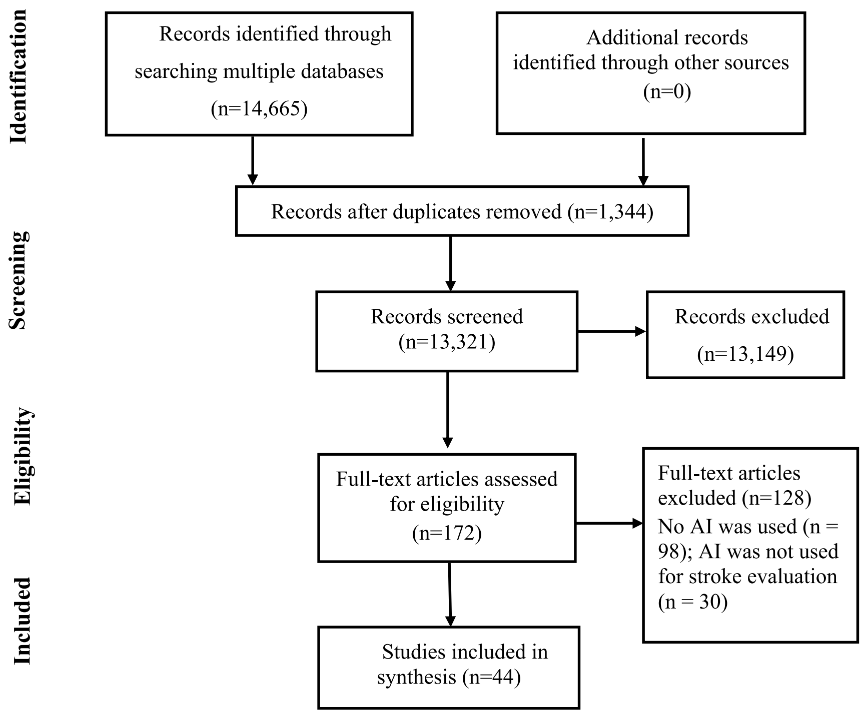

Figure 1. Flow diagram of the different phases of the scoping review.

do not present quantitative data on individual performance.[5] Therefore, it is difficult in several rehabilitation centers to systematically adjust interventions based on available assessments. With these problems in mind, there has been a growing increase in the use of artificial intelligence (AI) in health to assist therapists in decision-making and to facilitate clinical and functional assessment.

AI refers to any human-like intelligence exhibited by any type of machines, like a computer or a robot. Specifically, AI refers to the ability of a machine to mimic the capabilities of the human mind, i.e., the ability to solve problems and to make decisions based on a set of rules, logic conditions, or previous experience.[6,7] Machine Learning (ML) and Deep Learning (DL) are subsets of AI, which use computational algorithms that learn from training datasets and infer predictive models to make decisions.[8]

AI and decision support systems based on ML can help during stroke rehabilitation, mainly due to the high precision to predict long-term outcomes, assist in better therapeutic decision-making, as well as in the classification of neurological and functional tests.[9] To understand the current practices in stroke rehabilitation, the main clinical decision support system and AI technologies need to be mapped to assist the therapist. AI technologies could guarantee more accurate data about stroke evaluation and help solve problems and make better decisions during stroke rehabilitation. Therefore, this scoping review aims to map AI applications for functionality evaluation during stroke rehabilitation.

Methods

Protocol and registration

This review was registered in OSF (DOI 10.17605/OSF.IO/BCRHT). The methodological recommendations of the Joanna Briggs Institute for systematic scoping reviews[10] were followed and the Patient, Concept and Context framework was used to structure the eligibility criteria of our review. Our target patient population included persons with stroke, and the main concept of interest for this scoping review was the use of AI for functional evaluation during stroke rehabilitation. For the context of the review, we were interested in any setting where the

Table 1. Search terms and example search.

PubMed search example
("Artificial Intelligence"[tiab] OR "Machine learning" OR "Deep Learning" OR "Computational Intelligence" OR "Machine Intelligence" OR "Computer Reasoning" OR AI (Artificial Intelligence) OR "Computer Vision Systems" OR "Computer Vision System" OR "Knowledge Acquisition (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR Exoskeleton OR "Interactive motion technology" OR "Telepresence" OR "Social robots" OR "Smart environments" AND ("Rehabilitation"[Mesh] OR "Rehabilitation"[SH]) OR "Occupational Therapy"[tiab] OR "Occupational Therapy"[ot] OR "Physical Therapy"[tiab] OR "Physical Therapy"[ot] OR "Physiotherapy"[tiab] OR "Physiotherapy"[ot] OR "Rehabilitation"[tiab] OR "Rehabilitation"[ot] OR "Speech Language Pathology"[tiab] OR "Speech Language Pathology"[ot] OR "Physical Therapy Modalities"[Mesh] OR "Disability Evaluation"[Mesh] OR "Disability Evaluations"[Mesh] OR "Physical Examinations" OR "Physical Exam" OR "Physical Exams" OR "Physical Examinations and Diagnoses" OR "Neurological Examination" OR "Neurological Examinations" OR "Neurologic Examinations" OR "Neurologic Examination" AND ("Cerebral Vascular Accident"[tiab] OR "Cerebral Vascular Accident"[ot] OR "Cerebrovascular Accident"[tiab] OR "Cerebrovascular Accident"[ot] OR "CVA"[tiab] OR "CVA"[ot] OR "Stroke"[tiab] OR "Stroke"[ot] OR "Post Stroke"[tiab] OR "Post Stroke"[ot] OR "Poststroke"[tiab] OR "Poststroke"[ot] OR "Cerebrovascular Disorders"[Mesh])

Expanded search: ((("Artificial Intelligence"[tiab] OR "Machine learning" OR "Deep Learning" OR "Computational Intelligence" OR "Machine Intelligence" OR "Computer Reasoning" OR AI (Artificial Intelligence) OR "Computer Vision Systems" OR "Computer Vision System" OR "Knowledge Acquisition (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR Exoskeleton OR "Interactive motion technology" OR "Telepresence" OR "Social robots" OR "Smart environments") AND (("Rehabilitation"[Mesh] OR "Rehabilitation"[SH]) OR "Occupational Therapy"[tiab] OR "Occupational Therapy"[ot] OR "Physical Therapy"[tiab] OR "Physical Therapy"[ot] OR "Physiotherapy"[tiab] OR "Physiotherapy"[ot] OR "Rehabilitation"[tiab] OR "Rehabilitation"[ot] OR "Speech Language Pathology"[tiab] OR "Speech Language Pathology"[ot] OR "Physical Therapy Modalities"[Mesh] OR "Disability Evaluation"[Mesh] OR "Disability Evaluations"[Mesh] OR "Physical Examinations" OR "Physical Exam" OR "Physical Exams" OR "Physical Examinations and Diagnoses" OR "Neurological Examination" OR "Neurological Examinations" OR "Neurologic Examinations" OR "Neurologic Examination")) AND (("Cerebral Vascular Accident"[tiab] OR "Cerebral Vascular Accident"[ot] OR "Cerebrovascular Accident"[tiab] OR "Cerebrovascular Accident"[ot] OR "CVA"[tiab] OR "CVA"[ot] OR "Stroke"[tiab] OR "Stroke"[ot] OR "Post Stroke"[tiab] OR "Post Stroke"[ot] OR "Poststroke"[tiab] OR "Poststroke"[ot] OR "Cerebrovascular Disorders"[Mesh]))

rehabilitation of stroke may take place from its acute to chronic phase, ranging from its management in acute stroke units to the community setting and rehabilitation facilities, including experimental laboratories. With these elements in mind, the following criteria were adopted to select references for our review:

Eligibility criteria

Original and review studies published in English reporting on the empirical use of AI for functionality evaluation, based on the ICF construct, after stroke were included. Functionality evaluation includes all scales or tests, which analyze impairments and/or level of activity daily living (ADL) and participation in persons with stroke during rehabilitation. AI involves computational algorithms aiming to mimic human intelligence, and has been incorporated into many fields of stroke rehabilitation.[6,7] AI is an interactive process that refers to the capacity of machines to perceive information, retain it as knowledge, and apply it toward adaptive behaviors in an environment. Artificial intelligence is an umbrella concept with a virtual (informatics) and physical (robotics) branches. Machine learning (ML) is also included as a form of AI and refers to specific methods for building models that can be automatically improved.[8] AI has multiple applications in the field of stroke rehabilitation, including the evaluation of patients and a variety of approaches to treatment, such as exoskeletons, exercise and movement control by interactive motion technology, telepresence, social robots, and smart environments.[9]

We included studies using AI for the management of persons diagnosed with any type of stroke (ischemic or hemorrhagic), considering the period from the acute phase (within the first 24–72 h) to the chronic phase (> 6 months).[11]

Exclusion criteria

Studies involving non-human subjects and studies that used AI for the diagnosis of stroke or to assess its prognosis in humans were excluded. We also excluded all types of reviews, protocols, book chapters, editorial letters, guidelines, website, and other references not reporting empirical results.

Information sources and search

We (GJL and EIOV) searched the Cochrane Stroke Group Trials Register for eligible studies and the following electronic databases up to January 2021: CENTRAL, MEDLINE (through PubMed), EMBASE, LILACS, CINAHL, PEDRO, Web of Science, IEEE Xplore, AAAI Publications, ACM Digital Library, MathSciNet, and arXiv. We developed the MEDLINE search strategy based on Mesh terms and adapted it to other databases (Table 1).

Data collection and analysis

Selection of sources of evidence

Two reviewers (GFS and MRN) independently screened titles, abstracts, and full texts to ascertain the eligibility of the studies identified through the literature search. Disagreements were resolved through discussion with a third reviewer (RB). Multiple reports of the same study were collated so that each study (not each reference) was the unit of interest in the review.

All reviewers read several articles and checked that the results were consistent, recorded the selection method and completed the PRISMA flow diagram.[12]

Data charting process

Two reviewers independently extracted data from the included studies. A standardized data extraction form created by authors was used and the following details were recorded from each study: study design, characteristics of the study population (age, sex, functional status according to motor disability and from mild to severe deficits, type of stroke, phase of stroke, sample size), type of AI and its application, study outcomes, and setting.

Data items and synthesis of results

The number of participants included in each study was extracted. Stroke type was defined as ischemic (result of an atherothrombotic or embolic occlusion of the extracranial, intracranial cerebral artery, or small arteries of the subcortical white matter) or hemorrhagic (stroke that occurs when a blood vessel in the brain or on the surface of the brain leaks or breaks open, causing bleeding in or around the brain or into the subarachnoid space – subarachnoid hemorrhage). Specific brain areas were not considered.

The functional status classification was based on the scores of the main scales used in rehabilitation. The stroke disability was classified as mild (Fugl-Meyer Assessment Upper Extremity (FMA-UE): 66–35[13]; FMA-Lower Extremity (FMA-LE) >21[14]; Brunnström stages of stroke recovery from 6–7[15]; Chedoke McMaster Stroke Assessment (CMSA) from 1–3[16]; Functional Ambulation Category (FAC) score from 4–5[17]; Functional Independence Measure (FIM) score > 90[18]; Modified Rankin Scale (mRS) 0 to 1[19]; National Institutes of Healthy Stroke Scale (NIHSS) < 8), moderate (FMA-UE: 34–16[13]; FMA-LE < 21[14]; Brunnström stages of stroke recovery from 3–5[15]; CMSA from 4–5[16]; FAC score from 3–4[17]; FIM score from 54–90[18]; mRS 2 to 3[19], NIHSS 8 to 16), and severe (FMA-UE < 15[13]; FMA-LE < 21[14]; Brunnström stages of stroke recovery from 0–2[15]; CMSA from 6–7[16]; FAC score from 0–2[17]; FIM score < 54[18]; mRS 4 to 5[19], NIHSS > 16).

We charted the results around the phases of stroke as follows: acute (up to 72 h from stroke), subacute (from 73 h to 14 weeks), and chronic (from 15 weeks onwards). The second axis of the organization of the narrative synthesis was the type of AI used, and the third axis of the organization was the function of AI in the rehabilitation of stroke.

The type of AI and its application was extracted based on the type of technology used, the main function for stroke clinical evaluation, as well as ICF classification (s – structure; b – body function; d – activity and participation).

Data analyses

The data obtained from the literature review were summarized in a single dataset, wherein each reference paper was considered as an instance, and the study characteristics were considered as attributes. The attributes used for the multiple correspondence analysis (MCA) were: publication year, study type, sample size, age, stroke phase, stroke type, functional status, AI type, and AI function. MCA is an extension of the simple correspondence analysis and is also an exploratory technique for large datasets. Its application resulted in graphical representations of the instances and attributes of the initial dataset (with many attributes/instances) in the same factorial plane, allowing the inference

Table 2. Characteristics of included studies in the scoping review (n = 44 included studies).

Author (year)	Study type	Participants	Phase of Stroke	Stroke type	Functional status
Ang et al. (2008)[24]	Case-control	8 healthy individuals and 35 stroke individuals	Not reported	Not reported	Not reported
Lau et al.[25]	Case series	7 stroke individuals (2 women and 5 men) with a mean age of 45.6 years.	Chronic	Not reported	Mild and Moderate
Van Dijck et al.[26]	Case series	16 stroke individuals (10 men and 6 women) with a mean age of 65.2 years.	Acute, subacute and chronic	Ischemic and Hemorrhagic	Mild
Zhou et al.[27]	Case series	4 healthy individuals (3 men and 1 woman) with a mean age of 35.7 years; 2 stroke individuals (1 man and 1 woman) with a mean age of 55.5 years.	Not reported	Not reported	Not reported
Allin et al.[28]	Case series	7 stroke individuals with a mean age of 66 years.	Chronic	Not reported	Mild and Moderate
Parnandi et al[29]	Case report	1 stroke individual; no demographic information	Not reported	Not reported	Not reported
Yip[30]	Case series	110 stroke individuals; mean age was 72.8 years.	Acute until chronic	Ischemic and Hemorrhagic	Mild and Moderate
Dobkin et al[31]	Cohort study	6 healthy individuals (3 men and 3 women; age between 30 and 60 years); 12 stroke individuals (4 women and 8 men; age between 36 and 73 years.	Subacute and chronic	Not reported	Mild and Moderate
Fulk, and Sazonov[32]	Case series	8 stroke individuals (6 women and 2 men) with a mean age of 60.1 years.	Not reported	Not reported	Not reported
Lopez-meyer et al.[33]	Case series	16 healthy individuals (8 men and 8 women) with a mean age of 25 years; and 7 stroke individuals (2 men and 5 women) with mean age of 60.4 years.	Not reported	Not reported	Moderate
Fulk et al.[34]	Case series	12 stroke individuals (6 men and 6 women) with a mean age of 62.1 years.	Subacute and chronic	Not reported	Moderate
Scheffer, and Cloete[35]	Randomized control trial (RCT)	30 healthy individuals with a mean age of 22.6 years; and 28 stroke individuals with a mean age of 60.5 years	Not reported	Not reported	Not reported
Cesqui et al.[36]	Cohort study	9 healthy individuals and 7 stroke individuals	Not reported	Not reported	Not reported
Tedim Cruz et al[37]	Case series	5 men with stroke with age between 35 and 73 years	Not reported	Ischemic	Mild and Moderate
Leamy et al.[38]	Case-control	10 healthy individuals (8 men and 2 women), mean age 57.2 ± 17.6 years; and 5 stroke individuals (3 men and 2 women), mean age 59.0 ± 9.4 years.	Subacute and chronic	Ischemic	Mild and Moderate
Biswas et al[39]	Case series	4 healthy men (age, 24–40 years); 4 stroke individuals (age, 45–73 years).	Not reported	Not reported	Not reported
Massé et al[40]	Case series	12 stroke individuals (7 women and 5 men) with a mean age of 59.6 years.	Not reported	Ischemic and Hemorrhagic	Mild and Moderate
Munoz-Organero et al[41]	Cohort study	14 stroke individuals (7 men and 7 women; age, 66.43 years); 10 healthy individuals (3 men and 7 women; age, 48.8 years).	No reported	No reported	Mild and Moderate
Bochniewicz et al[42]	Cross-sectional	10 healthy individuals (6 women and 4 men); age, 43 years; 10 stroke individuals (2 women and 8 men); age, 56 years	Chronic	Ischemic and Hemorrhagic	Mild and Moderate
Lee et al[43]	Case series	10 stroke individuals (6 men and 4 women); age, 58 ± 16.5 years	Not reported	Ischemic and Hemorrhagic	Mild and Moderate
Liparulo et al[44]	Case series	9 stroke individuals (3 men and 6 women) with a mean age of 67.2 years	Not reported	Not reported	Mild and Moderate
O'brien et al.[45]	Cohort study	15 healthy controls and 30 stroke individuals	Chronic	Ischemic and Hemorrhagic	Mild until severe
Park et al.[46]	Cohort study	16 stroke individuals and 10 healthy controls with a mean age of 58.2 ± 17.8 years.	Not reported	Not reported	Mild and Moderate
Abdul Rahman et al.[47]	Case series	4 stroke individuals (1 man and 3 women), age between 49 and 63 years.	Acute and subacute	Not reported	Mild (upper limb paresis)
Chen et al[48]	Cross-sectional	5 stroke individuals and 8 healthy individuals; age between 45–75 years.	Subacute and Chronic	Not reported	Mild and Moderate

(*Continued*)

Table 2. (Continued).

Cui et al[49]	RCT	21 stroke individuals (16 men and 5 women); 21 healthy individuals (16 men and 5 women); age between 10 and 75 years.	Not reported	Not reported	Moderate
Zambrana et al[50]	Cross-sectional	6 stroke individuals (4 men and 2 women) with a mean age of 55.34 ± 16.85 years.	Not reported	Not reported	Mild and Moderate
Kim et al[51]	Case series	5 women with stroke with age between 55 and 66 years.	No reported	No reported	No reported
Kim et al.[52]	Cross-sectional	25 stroke individuals (16 women and 9 men) with a mean age of 67 years; 7 occupational therapists (3 women and 4 men), with a mean age of 28 years.	Not reported	Not reported	Mild and Moderate
Kopke et al.[53]	Case series	29 stroke individuals; mean age, 57.1 ± 9.2 years.	Chronic	Not reported	Moderate and Severe
Kopke et al[54]	Cross-sectional	12 healthy individuals; mean age, 59.1 ± 9.9 years; 12 stroke individuals; mean age, 60.8 ± 10.3 years.	Chronic	Not reported	Moderate and Severe
Lucas et al.[55]	Case series	4 stroke individuals (3 men and 1 woman), with a mean age of 51.75 years	Acute	Not reported	Severe
Panwar et al.[56]	Cohort study	2 stroke groups: 1) 10 individuals with a mean age of 61.4 ± 11.7 years; 2) individuals aged between 45 and 73 years.	Chronic	Not reported	Mild until Severe
Park et al[57]	Case series	31 stroke individuals (23 men and 7 women) with age between 33 and 88 years; 2 individuals with traumatic brain injury and 1 tumor.	Subacute and chronic	Not reported	Moderate
Van Ommeren et al.[58]	Cross-sectional	10 stroke individuals (5 men and 5 women) with a mean age of 61.0 years.	Chronic	Ischemic and Hemorrhagic	Mild and Moderate
Yang et al.[59]	Cohort study	33 stroke individuals (23 men and 10 women); mean age, 58.1 ± 11.8 years; and 12 healthy individuals (10 men and 2 women); mean age, 64.2 ± 3.2 years.	Not reported	Not reported	Mild and Severe
Zhang et al[60]	Cross-sectional	12 healthy individuals with age between 22 and 76 years; 15 stroke individuals with age between 39 and 80 years.	Chronic	Not reported	Mild and Moderate
Zhang et al[61]	Cross-sectional	11 stroke individuals; age between 33 and 71 years	Subacute	Ischemic and Hemorrhagic	Mild and Moderate
Cai et al.[62]	RCT	8 stroke individuals in two groups.	Subacute and Chronic	Not reported	Mild and Moderate
Hamaguchi et al.[63]	Cross-sectional	24 stroke individuals (5 women and 19 men); average age of 67 ± 12 years.	Not reported	Ischemic and Hemorrhagic	Mild to moderate
Kashi et al.[64]	Case series	30 stroke individuals (14 women and 16 men) with a mean age of 70.3 ± 9.4 years.	Not reported	Not reported	Mild until Severe
Mou et al.[65]	Cross-sectional	31 stroke individuals (19 men and 12 women) with a mean age of 56.74 ± 16.40 years; 42 healthy individuals (20 men and 22 women) with a mean age of 45.88 ± 13.24 years.	Not reported	Not reported	Not reported
Suzuki et al.[66]	Cohort study	177 stroke individuals with a mean age of 70.1 ± 11.0 years.	Acute	Ischemic and Hemorrhagic	Not reported
Wang et al[23]	Cross-sectional	15 stroke individuals (9 men and 6 women); mean age, 52.1 ± 15.1 years; and 15 healthy individuals (10 men and 5 women); mean age of 48.5 ± 13.1 years.	Not reported	Ischemic and Hemorrhagic	Mild and Moderate

of correspondence between the information from Euclidean distances between these data in the plane, forming clusters of corresponding information.[13–20]

All data analyses were performed using the R statistical program (R Foundation, Vienna, Austria). MCA calculations were performed using the "*FactoMineR*" and "*factoextra*" packages.[21,22] We excluded the variables that presented *cos2* < 0.05, i.e., the variables with low quality of representation on the factor map from the MCA results. Euclidean coordinates of the data (attributes and instances) in the dimension 1 (or Dim1) and dimension 2 (or Dim2) of the MCA factorial plane were clustered using the k-means method. The determinations of the optimal number of clusters were performed using the function "*fviz_nbclust*" from the "*factoextra*" package and the clustering analyses were performed using the "*cluster*" package.

Results

The flow diagram of the study selection process at the end of which 44 studies were included is presented in Figure 1.[23]

General study characteristics

Among these studies, there were 19 case series, 11 cross-sectional studies, eight prospective cohort studies, three randomized clinical trials, two case-control studies, and one isolated case report. Ischemic stroke was included in 13 studies, and hemorrhagic stroke in 11 studies. The stroke phase varied from acute (n = 5), subacute (n = 10), and chronic (n = 17), and not reported (n = 23). Some studies did not report the type of stroke. Functional status varied from mild (n = 27), moderate (n = 28), and severe (n = 5) (Table 2).

For stroke evaluation during rehabilitation, there was an increase in the use of a noninvasive brain–computer interface, a sensor wearable with an inertial measurement unit, and several algorithms to detect changes at specific rehabilitation scales, such as the filter bank common spatial pattern algorithm, Bayesian inference, artificial neural network, support vector machine, radial basis function network, random forest, and fusion-based probabilistic models. The use of AI was observed in 27 studies (61.4%) for only body functions evaluation, 14 studies (31.8%) for only activity/participation evaluation, and 3 studies (6.8%) for both body functions and activity/participation evaluation (Table 3).

For stroke evaluation during rehabilitation, the tests were concentrated for motor impairment and performance, with the activities of daily living as the primary focus, followed by spasticity evaluation (modified Ashworth scale), upper limb scales (Motor Assessment Scale and Wolf Motor Function Test), hand dysfunction, pronator drift test, cognitive screening, and gait analysis (Figure 2).

A graphical representation of the MCA grouping the characteristics of the instances (of different papers used in this review) that presented correspondence are summarized in Figure 3A. A graphical representation of the MCA applied over the attributes from the dataset previously described are presented in Figure 3B.

The analysis of the instances (Figure 3A) showed that spasticity analysis has been used for the cases of stroke in which the functional status was moderate (Cluster 1). Additionally, the techniques of DL and pressure sensors have been used for gait analysis (Cluster 2). Machine learning techniques and algorithms have been used for upper limb and reaching analysis (Cluster 3). The inertial measurement unit (IMU) technique has been applied in studies where the functional status was between mild and severe (Cluster 4).

Finally, the fuzzy logic technique was used for the activity classifiers. The attribute analysis (Figure 3B) resulted in three well-defined clusters. Cluster 1 grouped the attributes of stroke type, stroke phase, age, and functional status. Cluster 2 grouped the attributes of the AI type and study type. Finally, Cluster 3 grouped the attributes of AI function and sample size.

Discussion

Our results indicate a growing interest in the application of AI for the evaluation of the body functions and activity after stroke. Such research has gained greater interest and impact in recent years, as evidenced by the significantly higher number of publications in the last 5 years. While there is

Table 3. Characteristics of the main artificial intelligence technologies used for the assessment during the rehabilitation of individuals after stroke.

Author (year)	AI Type	AI function	ICF domain	
Ang et al. (2008)[24]	Noninvasive brain-computer interface and filter bank common spatial pattern algorithm	Quantify the skill to operate the interface based on motor images captured using electroencephalogram.	b	Laboratory
Lau et al.[25]	Support vector machine	Classify different walking conditions in hemiparetic individuals with dropped feet.	b and d	Laboratory
Van Dijck et al.[26]	Mechatronic platform and Bayesian inference mechanism	Activities of daily living tasks evaluation	d	Laboratory
Zhou et al.[27]	Support vector classifier; Classification and regression tree	Classify elbow intentions versus shoulder torque	b	Laboratory
Allin et al.[28]	Robust 3D parts-based tracking system	Probabilistic model of the arm to sequences of images taken from multiple angles.	b	Laboratory
Parnandi et al[29]	Sensor wearable with an inertial measurement unit	Automate Wolf Motor Function Test	d	Laboratory
Yip[30]	Cognitive intelligence assessment system and artificial neural network	Screening for cognitive deficits	b	Hospital
Dobkin et al[31]	Medical daily activity wireless network	Evaluation of lower limb activity and walking speed	b	Laboratory and home environment
Fulk, and Sazonov[32]	Support vector machine	The system identifies three postures in people with stroke (sitting, standing, and walking).	d	Laboratory
Lopez-meyer et al.[33]	Pressure sensors	Automatic gait analysis	d	Laboratory
Fulk et al.[34]	SmartShoe and artificial neural network	Classify different postures during daily living tasks	d	Laboratory
Scheffer, and Cloete[35]	Inertial motion capture and artificial neural network	Automatic gait analysis	d	Laboratory
Cesqui et al.[36]	Inmotion2 Robot (Interactive Motion Technologies, Watertown, MA, EUA); support vector machine	Reaching in a horizontal plane	d	Rehabilitation center
Tedim Cruz et al[37]	Sensor fusion algorithm with gyroscope, accelerometer, and magnetometer	Upper limb motor evaluation	b	Ambulatory
Leamy et al.[38]	Electroencephalogram-based brain–computer interface	Upper limb motor classification	b	Laboratory
Biswas et al[39]	Linear discriminant analysis, support vector machine, and inertial sensors	Real-time detection of arm movements	b	Laboratory
Massé et al[40]	Inertial measurement unit and a fuzzy logic-based activity classifier	Event-based activity classifier	b	Rehabilitation center
Munoz-Organero et al[41]	Pressure sensors	Automatic gait analysis	b	Laboratory
Bochniewicz et al[42]	Single wrist-worn sensor and machine learning	Measuring functional arm movement	d	Hospital
Lee et al[43]	Algorithm binary logic classifier and force-sensing resistor	Automate the scoring of Fugl-Meyer Assessment	b and d	Laboratory
Liparulo et al[44]	Fuzzy logic and algorithms	Automate the scoring of Brunnstrom stage of recovery	b	Rehabilitation center
O'brien et al.[45]	Activity recognition systems	Functional status at home	d	Home
Park et al.[46]	Support vector machine, radial basis function network, and random forest	Machine learning classification of pronator drift test using MATLAB (Mathworks)	b	Hospital
Abdul Rahman et al.[47]	Non-motorized device	Robotic assessment modules to predict the Motor Assessment Scale	d	Laboratory
Chen et al[48]	Fuzzy approximate entropy	Lower limb motor evaluation	b	Laboratory
Cui et al[49]	Decision fusion algorithms	Automatic gait analysis for the hemiparetic persons after stroke	b	Laboratory
Zambrana et al[50]	Sensores inerciais and hierarchical approach	Upper-limb kinematics evaluation	b	Laboratory
Kim et al[51]	Support vector machine, k-means method for machine learning, and rehabilitation robot.	Wrist evaluation to classify the Brunnstrom stage of recovery	b	Laboratory
Kim et al.[52]	Wearable device with accelerometer and machine learning algorithms	Monitor the upper limb movement	b and d	Hospital/Laboratory
Kopke et al.[53]	Haptic master robot with 6 degrees of freedom load cell and linear discriminant analysis-based classifier	Classify upper extremity movement intentions	b	Laboratory
Kopke et al[54]	Linear discriminant analysis-based classifier	Classify upper extremity movement intentions	b	Laboratory
Lucas et al.[55]	Support vector classifiers	Long-term motor assessment in persons with neurocritical care.	b	Hospital
Panwar et al.[56]	Deep learning 'Rehab-Net' and wearable sensors	Upper limb motor classification	b	Laboratory
Park et al[57]	Artificial neural network (AI algorithm)	Decision-making rule in the modified Ashworth scale	b	Hospital

(*Continued*)

Table 3. (Continued).

Van Ommeren et al.[58]	Inertial sensing and a support vector machine classifier	Classify the reach and grip movements	b and d	Laboratory
Yang et al.[59]	Machine learning and algorithms	Sit-to-Stand movement	d	Laboratory
Zhang et al[60]	Artificial neural networks	Upper limb motor evaluation	b	Laboratory
Zhang et al[61]	Machine learning algorithms	Evaluation of muscle spasticity	b	Hospital
Cai et al.[62]	*ReRobot platform*; support vector machine	Identify trunk compensations during reaching task	d	Laboratory
Hamaguchi et al.[63]	Support vector machine	Assessing recovery of hand dysfunction following stroke through the analysis of finger kinematics	b	Laboratory
Kashi et al.[64]	Machine machine-learning model; random forest algorithm	Identify compensations during reaching task	b	Laboratory
Mou et al.[65]	Artificial neural networks	Assessment of dysarthria	b	Laboratory
Suzuki et al.[66]	Support vector machine	Examine the relationships between grasping forces and self-care activities	b and d	Hospital
Wang et al[23]	Principal component analysis and k weighted angular similarity algorithm	Upper limb motor evaluation	b	Laboratory

ICF classification: b – body function evaluation; d – activity and participation evaluation.

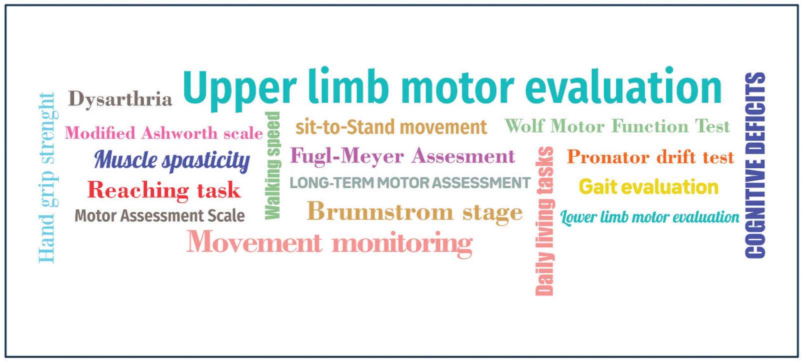

Figure 2. The main words found in the AI for stroke evaluation. The larger letters indicate a greater number of studies found.

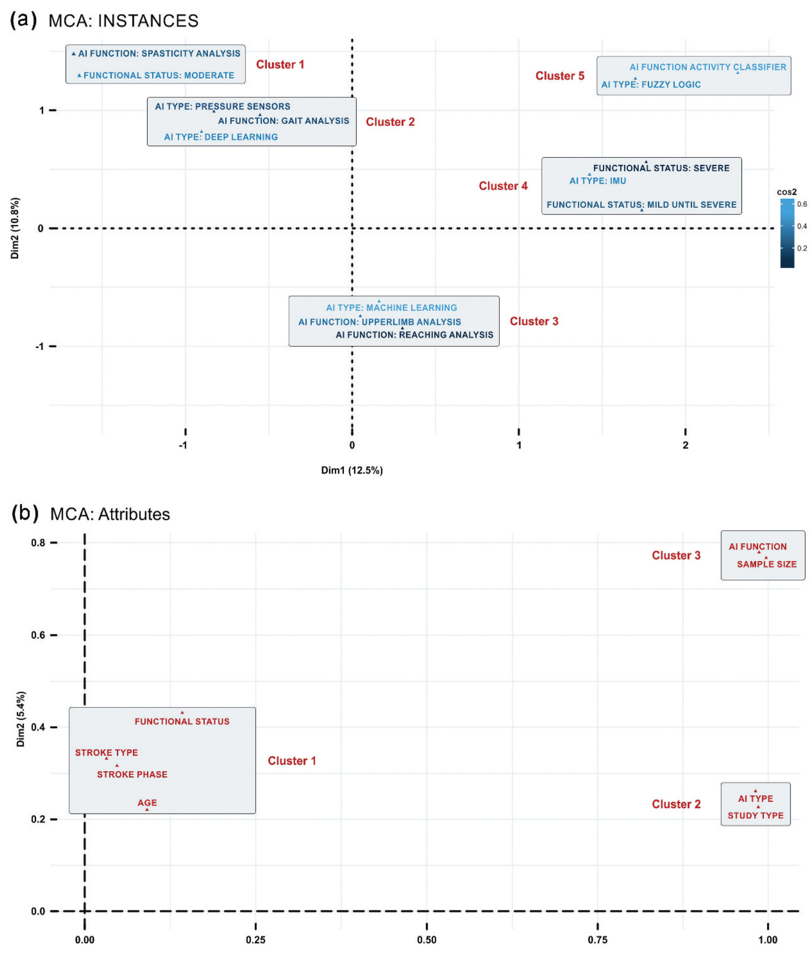

Figure 3. Graphical representation of **(A)** MCA grouping the characteristics of the instances; **(B)** MCA applied over the attributes from the dataset. MCA, multiple correspondence analysis.

a rapid increase in publications pertaining to AI for analyses of outcomes after stroke, our study is the first to provide a mapping of existing literature on the subject matter. The insight gained from this endeavor will hopefully influence the future rehabilitation programs.

Several trends were noted in this review. Topics with the most compelling growth were the application of AI for functional evaluation after stroke. For stroke evaluation during rehabilitation, there was an increase in the use of ML techniques/ algorithms, wearable sensors with IMU, DL, and pressure sensors.

Several MCA groupings were noted in our review. Spasticity analysis has been used for the cases of stroke in which the functional status was moderate. The influence of spasticity on motor control becomes greater in more severe cases. Spasticity is a limiting factor in motor and functional recovery, impairing the performance of daily living activities after stroke.[67] Furthermore, spasticity is one of the main factors contributing to the loss of selective motor control, especially in individuals who manifest severe motor impairment after stroke. Sunnerhagen[68] reported that spasticity was associated with more severe paresis at a median of 16 weeks poststroke.

Most of included studies in this review have shown that the use of AI assessed body function (disabilities) and few of them assessed activity and participation ICF domain. Some studies demonstrate that the evaluation of activity and participation based on ICF model after stroke helps in the optimal therapeutic planning, involving focus on specific goals, which are important and motivate patients to work toward them during stroke rehabilitation as well.[69–71] AI can provide a more accurate assessment of the limitations of the activities and participations restrictions in future studies. This technology can classify the main problems and potentials of individuals during rehabilitation and provide constant feedback on the clinical and functional status of the patient after stroke.

It was also observed that the techniques of DL (such as electroencephalogram (EEG)-based brain–computer interface (BCI)) and pressure sensors have been used for gait analysis. An EEG-BCI creates a new communication channel between the human brain and the computer.[72] BCI systems have used a variety of mental strategies and corresponding neural signals for this control, including motor imagery (MI), evoked potentials, steady-state evoked potentials, and/or slow waves. MI-based BCI systems are especially well suited for stroke rehabilitation. In this case, persons are asked to imagine a certain type of movement, which primarily affects their oscillations in the alpha or beta range of the EEG. Another approach with MI BCIs detects the motor-related cortical potential when the persons plan to perform a movement.[73,74] In our review, we showed that this technology can be used for quantifying the motor skills required to operate the machine interface based on motor images captured using EEG.

Machine learning techniques and algorithms have been used for upper limb and reaching analysis. Some studies have reported that ML techniques are being increasingly adapted for use in stroke evaluation because their high accuracy can improve the prediction of long-term outcomes in persons with ischemic stroke.[75] For evaluation tests, this technique can be used for a decision-making rule for upper limb spasticity degree[57] and for the classification of several neurological and functional reaching tests.[46] Most studies involve the evaluation of the upper limb and its functions owing to the ease of inclusion of study participants as well as greater adaptability of new technologies, as it requires less mechanical and technological devices.

The IMU technique has been applied in studies where the functional status is between mild and severe. This technology offers a source of data on the physical behavior of persons to assist in the management of chronic diseases, such as stroke.[76] Exercise adherence is often poor after stroke, despite being an important factor for successful rehabilitation.[76] The clinical applications of wearable sensors include remote monitoring,[77] mobile health,[78,79] and health metrics.[9] After a stroke, all persons benefit from the use of sensors to capture the level of physical activity from mild to severe, as the risk of stroke recurrence,[80] loss of muscle mass,[81] worsening mobility,[82] and cardiovascular dysfunction[83] is greater in sedentary individuals.

Additionally, MCA grouping was observed among the stroke type, stroke phase, age, and functional status. This grouping was expected since these are the characteristics that have already been reported as correlated in previous studies, and they were associated with stroke staging. Another cluster was observed between IA function and sample size. This latter grouping was also expected since ML and DL studies generally require a large sample size, which is why the number of persons tends to be higher. Studies involving sensors/robotics are more expensive and tend to be applied to smaller sample sizes.

We did not find studies on the use of AI for the assessment of the trunk after stroke, and there were few studies on lower limb motor control. Trunk control impairment in persons with stroke is multidirectional and can cause difficulties in many activities, such as breathing, speech, and movements of the upper and lower limbs.[84] Several studies have demonstrated the importance of trunk control for functional ability,[85] standing balance control, and walking, and as an important functional predictor in persons with stroke undergoing rehabilitation.[86] We believe that increased engineering research for the application of AI for trunk evaluation can generate long-term benefits for persons after stroke.

In our study, few studies were identified in the acute phase of severe strokes. Studies in the acute phase of stroke have reported the optimization of cognitive and motor recovery and reduction in long-term complications,[87] and we have recognized the difficulties in the implementation. We believe that the low number of IA studies in this phase is because of the increased difficulty in the clinical management of these persons. However, we believe that the earlier the rehabilitation, the better is the window of opportunity for brain plasticity. In contrast, the application of AI in hospitals and stroke units could facilitate the management of rehabilitation professionals.

Main limitations and clinical implication

While great effort has been devoted in conducting this bibliometric analysis through an intensive summary of keywords and research patterns, there are some limitations to this study. Scoping reviews do not formally evaluate the quality of evidence and often gather information from a wide range of study designs and methods.[88] This study only included English articles and may underreport trends and studies conducted in other languages. Additionally, the publication type was restricted to peer-reviewed publications, and this may influence the thoroughness of the analyzed results. AI studies have shown that post-stroke impairments and disabilities can be reduced by intensive, repetitive, and goal-directed rehabilitation, which improves motor function and cortical reorganization in persons with stroke with both acute and long-term (chronic) impairments.[89] The recovery process in traditional rehabilitation is typically slow and labor-intensive, usually involving extensive interaction between a therapist and a patient. One of the main motivations for developing AI studies and algorithms is to automate repetitive and physically demanding interventions during rehabilitation. The AI technologies make it possible for a single therapist to supervise multiple patients simultaneously and for home-based therapy, which can contribute to the reduction of health care costs.[90]

Conclusions

In summary, the findings of our study demonstrated the growing utility of ML techniques/algorithms, wearable sensors with IMU, DL, and pressure sensors for evaluation of body functions and activity during stroke rehabilitation.

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References

1. GBD. Stroke Collaborators. Global, regional, and national burden of stroke, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *Lancet Neurol*. 2019;18(5):439–458. doi:10.1016/S1474-4422(19)30034-1.
2. Lee MH, Siewiorek DP, Smailagic A, Bernardino A, Badia SB Opportunities of a machine learning-based decision support system for stroke rehabilitation assessment. 20202020ArXiv, Abs./2002.12261.
3. O'Sullivan SB, Schmitz TJ, Fulk G. Physical rehabilitation. *F A Davis*. 2019.
4. Smith DM, Brown SL, Ubel PA. Mispredictions and misrecollections: challenges for subjective outcome

measurement. *Disabil Rehabil*. 2008;30(6):418–424. doi:10.1080/09638280701625237.

5. Hendricks HT, Van Limbeek JV, Geurts AC, Zwarts MJ. Motor recovery after stroke: a systematic review of the literature. *Arch Phys Med Rehabil*. 2002;83 (11):1629–1637. doi:10.1053/apmr.2002.35473.
6. Dick S. Artificial Intelligence. *Harvard Data Sci Rev* [Internet]. 2019;1(1). Available from: https://hdsr.mitpress.mit.edu/pub/0aytgrau
7. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. *Nat Biomed Eng*. 2018;2(10):719–731. doi:10.1038/s41551-018-0305-z.
8. Collins GS, Moons KGM. Reporting of artificial intelligence prediction models. *Lancet*. 2019;393 (10181):1577–1579. doi:10.1016/S0140-6736(19)30037-6.
9. Barry DT. Adaptation, artificial intelligence, and physical medicine and rehabilitation. *PM R*. 2018;10(9): S131–S143. Suppl2. doi:10.1016/j.pmrj.2018.04.013.
10. Peters MD, Godfrey CM, Khalil H, McInerney P, Parker D, Soares CB. Guidance for conducting systematic scoping reviews. *Int J Evid Based Healthc*. 2015;13 (3):141–146. doi:10.1097/XEB.0000000000000050.
11. Bernhardt J, Hayward KS, Kwakkel G, et al. Agreed definitions and a shared vision for new standards in stroke recovery research: the stroke recovery and rehabilitation roundtable taskforce. *Int J Stroke*. 2017;12 (5):444–450. doi:10.1177/1747493017711816.
12. Moher D, Liberati A, Tetzlaff J. Altman DG, the PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: the PRISMA Statement. *PLOS Med*. 2008;6(7):e1000097. doi:10.1371/journal.pmed.1000097.
13. Woodbury ML, Velozo CA, Richards LG, Duncan PW. Rasch analysis staging methodology to classify upper extremity movement impairment after stroke. *Arch Phys Med Rehabil*. 2013;94(8):1527–1533. doi:10.1016/j.apmr.2013.03.007.
14. Kwong PWH, Ng SSM. Cutoff score of the lower-extremity motor subscale of Fugl-Meyer assessment in chronic stroke survivors: a cross-sectional study. *Arch Phys Med Rehabil*. 2019;100(9):1782–1787. doi:10.1016/j.apmr.2019.01.027.
15. Huang CY, Lin GH, Huang YJ, et al. Improving the utility of the Brunnstrom recovery stages in patients with stroke: validation and quantification. *Med (Baltim)*. 2016;95(31):e4508. doi:10.1097/MD.0000000000004508.
16. Gowland C, Stratford P, Ward M, et al. Measuring physical impairment and disability with the Chedoke-McMaster Stroke Assessment. *Stroke*. 1993;24(1):58–63. doi:10.1161/01.STR.24.1.58.
17. Elord C, Corrêa FI, Pereira GS, Silva SM, Corrêa JC. Translation into Brazilian Portuguese, cross-cultural adaptation, reliability and validation of the Functional Ambulation Classification for the categorization of ambulation following a stroke in a clinical setting. *Rev Neurol*. 2020;70(10):365–371. doi:10.33588/rn.7010.2019400.
18. Ancheta J, Husband M, Law D, Reding M. Initial functional independence measure score and interval post stroke help assess outcome, length of hospitalization, and quality of care. *Neurorehabil Neural Repair*. 2000;14 (2):127–134. doi:10.1177/154596830001400205.
19. Lee SY, Kim DY, Sohn MK, et al. Determining the cut-off score for the Modified Barthel index and the Modified Rankin Scale for assessment of functional independence and residual disability after stroke. *PLOS ONE*. 2020;15(1):e0226324. doi:10.1371/journal.pone.0226324.
20. Kassambara A Practical guide to principal component methods in R, n.d.
21. Kostov BA, Bécue-Bertaut MM, Husson F. Correspondence analysis on generalised aggregated lexical tables (CA-GALT) in the FactoMineR package. *R J*. 2015;7(1):109–117. doi:10.32614/RJ-2015-010.
22. Lê S, Josse J, FactoMineR: HF. An R package for multivariate analysis. *J Stat Soft*. 2008;25(1):1–18. doi:10.18637/jss.v025.i01.
23. Wang C, Peng L, Hou ZG, Li J, Zhang T, Zhao J. Quantitative assessment of upper-limb motor function for post-stroke rehabilitation based on motor synergy analysis and multi-modality fusion. *IEEE Trans Neural Syst Rehabil Eng*. 2020;28(4):943–952. doi:10.1109/TNSRE.2020.2978273.
24. Ang KK, Guan C, Chua KS, Ang BT, Kuah C, Wang C, Phua KS, Chin ZY, Zhang H. A clinical evaluation on the spatial patterns of non-invasive motor imagery-based brain–computer interface in stroke. Annu Int Conf IEEE Eng Med Biol Soc. 2008;4174–4177.
25. Lau HY, Tong KY. Zhu H yin. *Hum Mov Sci*. 2009;28 (4):504–514. doi:10.1016/j.humov.2008.12.003.
26. Van Dijck G, Van Vaerenbergh J, Van Hulle MM. Posterior probability profiles for the automated assessment of the recovery of patients with stroke from activity of daily living tasks. *Artif Intell Med*. 2009;46 (3):233–249. doi:10.1016/j.artmed.2009.03.001.
27. Zhou J, Yao J, Deng J, Dewald JP. EEG-based classification for elbow versus shoulder torque intentions involving stroke subjects. *Comput Biol Med*. 2009;39 (5):443–452. doi:10.1016/j.compbiomed.2009.02.004.
28. Allin S, Baker N, Eckel E, Ramanan D. Robust tracking of the upper limb for functional stroke assessment. *IEEE Trans Neural Syst Rehabil Eng*. 2010;18(5):542–550. doi:10.1109/TNSRE.2010.2047267.
29. Parnandi A, Wade E, Matarić M. Motor function assessment using wearable inertial sensors. *Annu Int Conf IEEE Eng Med Biol Soc Annu Int Conf IEEE Eng Med Biol Soc EMBC*. 2010;2010:86–89.
30. Yip CK, Man DW. Validation of the Intelligent Cognitive Assessment System (ICAS) for stroke survivors. Brain Inj. 2010;24(7-8):1032–8.
31. Dobkin BH, Xu X, Batalin M, Thomas S, Kaiser W. Reliability and validity of bilateral ankle accelerometer

algorithms for activity recognition and walking speed after stroke. *Stroke*. 2011;42(8):2246–2250. doi:10.1161/STROKEAHA.110.611095.
32. Fulk GD, Sazonov E. Using sensors to measure activity in people with stroke. *Top Stroke Rehabil*. 2011;18(6):746–757. doi:10.1310/tsr1806-746.
33. Lopez-Meyer P, Fulk GD, Sazonov ES. Automatic detection of temporal gait parameters in poststroke individuals. *IEEE Trans Inf Technol Biomed*. 2011;15(4):594–601. doi:10.1109/TITB.2011.2112773.
34. Fulk GD, Edgar SR, Bierwirth R, Hart P, Lopez-Meyer P, Sazonov E. Identifying activity levels and steps of people with stroke using a novel shoe-based sensor. *J Neurol Phys Ther*. 2012;36(2):100–107. doi:10.1097/NPT.0b013e318256370c.
35. Scheffer C, Cloete T. Inertial motion capture in conjunction with an artificial neural network can differentiate the gait patterns of hemiparetic stroke patients compared with able-bodied counterparts. *Comput Methods Biomech Biomed Eng*. 2012;15(3):285–294. doi:10.1080/10255842.2010.527836.
36. Cesqui B, Tropea P, Micera S, Krebs HI. EMG-based pattern recognition approach in post stroke robot-aided rehabilitation: a feasibility study. *J Neuroeng Rehabil*. 2013;10(1):75. doi:10.1186/1743-0003-10-75.
37. Tedim Cruz VT, Bento VF, Ribeiro DD, Araújo I, Branco CA, Coutinho P. A novel system for automatic classification of upper limb motor function after stroke: an exploratory study. *Med Eng Phys*. 2014;36(12):1704–1710. doi:10.1016/j.medengphy.2014.09.009.
38. Leamy DJ, Kocijan J, Domijan K, et al. An exploration of EEG features during recovery following stroke – implications for BCI-mediated neurorehabilitation therapy. *J Neuroeng Rehabil*. 2014;11(1):9. doi:10.1186/1743-0003-11-9.
39. Biswas D, Cranny A, Gupta N, et al. Recognizing upper limb movements with wrist worn inertial sensors using k-means clustering classification. *Hum Mov Sci*. 2015;40:59–76. doi:10.1016/j.humov.2014.11.013.
40. Massé F, Gonzenbach RR, Arami A, Paraschiv-Ionescu A, Luft AR, Aminian K. Improving activity recognition using a wearable barometric pressure sensor in mobility-impaired stroke patients. *J Neuroeng Rehabil*. 2015;12(1):72. doi:10.1186/s12984-015-0060-2.
41. Munoz-Organero M, Parker J, Powell L, Mawson S. Assessing walking strategies using insole pressure sensors for stroke survivors. *Sensors (Switzerland)*. 2016;16(10):10. doi:10.3390/s16101631.
42. Bochniewicz EM, Emmer G, McLeod A, Barth J, Dromerick AW, Lum P. Measuring functional arm movement after stroke using a single wrist-worn sensor and machine learning. *J Stroke Cerebrovasc Dis*. 2017;26(12):2880–2887. doi:10.1016/j.jstrokecerebrovasdis.2017.07.004.
43. Lee S, Lee YS, Kim J. Automated evaluation of upper-limb motor function impairment using Fugl-Meyer assessment. *IEEE Trans Neural Syst Rehabil Eng*. 2018;26(1):125–134. doi:10.1109/TNSRE.2017.2755667.
44. Liparulo L, Zhang Z, Panella M, Gu X, Fang Q. A novel fuzzy approach for automatic Brunnstrom stage classification using surface electromyography. *Med Biol Eng Comput*. 2017;55(8):1367–1378. doi:10.1007/s11517-016-1597-3.
45. O'Brien MK, Shawen N, Mummidisetty CK, et al. Activity recognition for persons with stroke using mobile phone technology: toward improved performance in a home setting. *J Med Internet Res*. 2017;19(5):e184. doi:10.2196/jmir.7385.
46. Park E, Chang HJ, Nam HS. Use of machine learning classifiers and sensor data to detect neurological deficit in stroke patients. *J Med Internet Res*. 2017;19(4):e120. doi:10.2196/jmir.7092.
47. Abdul Rahman HA, Khor KX, Yeong CF, Su ELM, Narayanan ALT. The potential of iRest in measuring the hand function performance of stroke patients. *Bio Med Mater Eng*. 2017;28(2):105–116. doi:10.3233/BME-171660.
48. Chen Y, Hu H, Ma C, et al. Stroke-related changes in the complexity of muscle activation during obstacle crossing using fuzzy approximate entropy analysis. *Front Neurol*. 2018;9(MAR):131. doi:10.3389/fneur.2018.00131.
49. Cui C, Bian GB, Hou ZG, et al. Simultaneous recognition and assessment of post-stroke hemiparetic gait by fusing kinematic, kinetic, and electrophysiological data. *IEEE Trans Neural Syst Rehabil Eng*. 2018;26(4):856–864. doi:10.1109/TNSRE.2018.2811415.
50. Zambrana C, Idelsohn-Zielonka S, Claramunt-Molet M, Almenara-Masbernat M, Opisso E, Tormos JM, Miralles F, Vargiu E. Monitoring of upper-limb movements through inertial sensors – Preliminary results. *Smart Health*. 2019;13:100059. https://doi.org/10.1016/j.smhl.2018.07.027
51. Kim J, Park W, Kim J. Quantitative evaluation of stroke patients' wrist paralysis by estimation of kinematic coefficients and machine learning. *Sens Mater*. 2020;32:981.
52. Kim Y, Jung H-T, Park J, et al. Towards the Design of a Ring Sensor-based mHealth System to Achieve Optimal Motor Function in Stroke Survivors. *Proc ACM Interact Mob Wearable Ubiquitous Technol Proc ACM Interact, Mobile, Wearable Ubiquitous Technol*. 2019;3(4):1–26.
53. Kopke JV, Hargrove LJ, Ellis MD. Applying. LDA-based pattern recognition to predict isometric shoulder and elbow torque generation in individuals with chronic stroke with moderate to severe motor impairment. *J Neuroeng Rehabil*. 2019;16(1):35. doi:10.1186/s12984-019-0504-1.
54. Kopke JV, Member S, Ellis MD, Hargrove LJ, Hargrove LJ, Hargrove LJ. Determining user intent of partly dynamic shoulder tasks in individuals with chronic stroke using pattern recognition. *IEEE Trans*

Neural Syst Rehabil Eng. 2019;28(1):1. PP(c). doi:10.1109/TNSRE.2019.2955029.
55. Lucas A, Hermiz J, Labuzetta J, Arabadzhi Y, Karanjia N, Gilja V. Use of accelerometry for long term monitoring of stroke patients. *IEEE J Transl Eng Heal Med*. 2019;7:2100310.
56. Panwar M, Biswas D, Bajaj H, et al. Deep learning framework for arm movement classification using wearable sensors for stroke rehabilitation. *IEEE Trans Bio Med Eng*. 2019;66(11):3026–3037. doi:10.1109/TBME.2019.2899927.
57. Park JH, Kim Y, Lee KJ, et al. Artificial neural network learns clinical assessment of spasticity in modified Ashworth scale. *Arch Phys Med Rehabil*. 2019;100(10):1907–1915. doi:10.1016/j.apmr.2019.03.016.
58. Van Ommeren AL, Sawaryn B, Prange-Lasonder GB, Buurke JH, Rietman JS, Veltink PH. Detection of the intention to grasp during reaching in stroke using inertial sensing. *IEEE Trans Neural Syst Rehabil Eng*. 2019;27(10):2128–2134. doi:10.1109/TNSRE.2019.2939202.
59. Yang N, An Q, Kogami H, et al. Temporal features of muscle synergies in sit-to-stand motion reflect the motor impairment of post-stroke patients. *IEEE Trans Neural Syst Rehabil Eng*. 2019;27(10):2118–2127. doi:10.1109/TNSRE.2019.2939193.
60. Zhang X, D'Arcy R, Menon C. Scoring upper-extremity motor function from EEG with artificial neural networks: a preliminary study. *J Neural Eng*. 2019;16(3):036013. doi:10.1088/1741-2552/ab0b82.
61. Zhang X, Tang X, Zhu X, Gao X, Chen X, Chen X. A regression-based framework for quantitative assessment of muscle spasticity using combined emg and inertial data from wearable sensors. *Front Neurosci*. 2019;13(MAY):398. doi:10.3389/fnins.2019.00398.
62. Cai S, Wei X, Su E, Wu W, Zheng H, Xie L. Online compensation detecting for real-time reduction of compensatory motions during reaching: a pilot study with stroke survivors. *J Neuroeng Rehabil*. 2020;17(1):58. doi:10.1186/s12984-020-00687-1.
63. Hamaguchi T, Saito T, Suzuki M, et al. Support vector machine-based classifier for the assessment of finger movement of stroke patients undergoing rehabilitation. *J Med Biol Eng*. 2020;40(1):91–100. doi:10.1007/s40846-019-00491-w.
64. Kashi S, Feingold-Polak R, Lerner B, Rokach L, Levy-Tzedek S. A machine-learning model for automatic detection of movement compensations in stroke patients. *IEEE Trans Emerg Top Comput*. 2020;16(1). doi:10.1109/TETC.2020.2988945.
65. Mou Z, Ye W, Chang C, Mao Y. The application analysis of neural network techniques on lexical tone rehabilitation of mandarin-speaking patients with post-stroke dysarthria. *IEEE Access*. 2020;8:90709–90717. doi:10.1109/ACCESS.2020.2994069.
66. Suzuki M, Sugimura S, Suzuki T, et al. Machine-learning prediction of self-care activity by grip strengths of both hands in poststroke hemiplegia. *Med (United States)*. 2020;99:e19512.
67. RdO C, Cacho EWA, Loureiro AB, GNdM C, Pereira SA. Freitas RPdA et al. The spasticity in the motor and functional disability in adults with post-stroke hemiparetic. *Fisioter Mov*. 2017;30:745–752.
68. Sunnerhagen KS. Predictors of spasticity after stroke. *Curr Phys Med Rehabil Rep*. 2016;4(3):182–185. doi:10.1007/s40141-016-0128-3.
69. Teixeira-Salmela LF, Neto MG, Magalhães LC, et al. Content comparisons of stroke-specific quality of life based upon the international classification of functioning, disability, and health. *Qual Life Res*. 2009;18(6):765–773. doi:10.1007/s11136-009-9488-9.
70. Schepers VP, Ketelaar M, Van De Port IG, et al. Comparing contents of functional outcome measures in stroke rehabilitation using the International Classification of Functioning, Disability and Health. *Disabil Rehabil*. 2007;29(3):221–230. doi:10.1080/09638280600756257.
71. Steiner WA, Ryser L, Huber E, et al. Use of the ICF model as a clinical problem-solving tool in physical therapy and rehabilitation medicine. *Phys Ther*. 2002;82(11):1098–1107. doi:10.1093/ptj/82.11.1098.
72. Guger C, Edlinger G, Harkam W, Niedermayer I, Pfurtscheller G. How many people are able to operate an EEG-based brain-com- puter interface (BCI)? *IEEE Trans Neural Syst Rehabil Eng*. 2003;11(2):145–147. doi:10.1109/TNSRE.2003.814481.
73. Guger C, Millán JR, Mattia D, Ushiba J, Soekadar SR, Prabhakaran V, Mrachacz-Kersting N, Kamada K, Allison BZ. Brain–computer interfaces for stroke rehabilitation: summary of the 2016 BCI Meeting in Asilomar. *Brain Comput Interfaces*. 2018;5(2-3):41–57. doi:10.1080/2326263X.2018.1493073.
74. Guger C, Schlögl A, Neuper C, Walterspacher D, Strein T, Pfurtscheller G. Rapid prototyping of an EEG-based brain–computer interface (BCI). *IEEE Trans Neural Syst Rehabil Eng*. 2001;9(1):49–58. doi:10.1109/7333.918276.
75. Heo J, Yoon JG, Park H, Kim YD, Nam HS, Heo JH. Machine learning-based model for prediction of outcomes in acute stroke. *Stroke*. May 2019;50(5):1263–1265.
76. Tack C. Artificial intelligence and machine learning | applications in musculoskeletal physiotherapy. *Musculoskelet Sci Pract*. 2019;39:164–169. doi:10.1016/j.msksp.2018.11.012.
77. Dobkin BH. Behavioral self-management strategies for practice and exercise should be included in neurologic rehabilitation trials and care. *Curr Opin Neurol*. 2016;29(6):693–699. doi:10.1097/WCO.0000000000000380.
78. Capela NA, Lemaire ED, Baddour N, Rudolf M, Goljar N, Burger H. Evaluation of a smartphone human activity recognition application with

able-bodied and stroke participants. *J Neuroeng Rehabil*. 2016;13(1):5. doi:10.1186/s12984-016-0114-0.
79. Sarfo FS, Ovbiagele B. Mobile health for stroke: a promising concept for research and practice. *Mhealth*. 2017;3:4. doi:10.21037/mhealth.2017.02.01.
80. Kramer SF, Hung SH, Brodtmann A. The impact of physical activity before and after stroke on stroke risk and recovery: a narrative review. *Curr Neurol Neurosci Rep*. 2019 April 22;19(6):28. doi:10.1007/s11910-019-0949-4.
81. Ryan AS, Ivey FM, Serra MC, Hartstein J, Hafer-Macko CE. Sarcopenia and physical function in middle-aged and older stroke survivors. *Arch Phys Med Rehabil*. 2017 March;98(3):495–499. doi:10.1016/j.apmr.2016.07.015.
82. Mansfield A, Aqui A, Centen A, et al. Perturbation training to promote safe independent mobility post-stroke: study protocol for a randomized controlled trial. *BMC Neurol*. 2015;15(1):87. doi:10.1186/s12883-015-0347-8.
83. Hasan SMM, Rancourt SN, Austin MW, Ploughman M. Defining optimal aerobic exercise param- eters to affect complex motor and cognitive outcomes after stroke: a systematic review and synthesis. *Neural Plast*. 2016;2016:1–12. doi:10.1155/2016/2961573.
84. Duarte E, Marco E, Muniesa JM, et al. Trunk control test as a functional predictor in stroke patients. *J Rehabil Med*. 2002;34(6):267–272. doi:10.1080/165019702760390356.
85. Van Nes IJ, Nienhuis B, Latour H, Geurts AC. Posturographic assessment of sitting balance recovery in the subacute phase of stroke. *Gait Posture*. 2008;28(3):507–512. doi:10.1016/j.gaitpost.2008.03.004.
86. Isho T, Usuda S. Association of trunk control with mobility performance and accelerometry-based gait characteristics in hemiparetic patients with subacute stroke. *Gait Posture*. 2016;44:89–93. doi:10.1016/j.gaitpost.2015.11.011.
87. Li Z, Zhang X, Wang K, Wen J. Effects. *J Stroke Cerebrovasc Dis*. 2018;27(5):1326–1337. doi:10.1016/j.jstrokecerebrovasdis.2017.12.021.
88. Sucharew H, Progress Notes: MM. Methods for Research Evidence Synthesis: the Scoping Review Approach. *J Hosp Med*. 2019;14(7):416–418. doi:10.12788/jhm.3248.
89. Fasoli SE, Krebs HI, Hogan N. Robotic technology and stroke rehabilitation: translating research into practice. *Top Stroke Rehabil*. 2004;11(4):11–19. doi:10.1310/G8XB-VM23-1TK7-PWQU.
90. Patel VL, Shortliffe EH, Stefanelli M, et al. The coming of age of artificial intelligence in medicine. *Artif Intell Med*. 2009;46(1):5–17.8. doi:10.1016/j.artmed.2008.07.017.