What about the use of Wearable Sensors to assess Fall Risk in Neurological Disorders? A Systematic Review.

Mirjam Bonanno, Augusto Ielo, Paolo De Pasquale, Antonio Celesti, Alessandro Marco De Nunzio, Angelo Quartarone, Rocco Salvatore Calabrò

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Abstract

Background: The fall risk assessment, especially in neurological disorders, is essential to prevent hospitalization, hypomobility and reduced functional independence. Nowadays, the use of wearable sensors is catching on in the field of neurorehabilitation, as they allow an unsupervised fall risk assessment, providing continuous monitoring during daily functional tasks and thus reflecting subject's real fall risk.

Objective: We systematically reviewed literature on reliable biomechanical gait parameters detected with wearable devices to assess fall risk in neurological disorders, focusing on Parkinson's disease, multiple sclerosis, and post-stroke patients. Additionally, we examined the latest advancements in wearable sensor technology, including best practices for device positioning and data processing techniques.

Methods: Our comprehensive systematic review search was conducted for all peer-reviewed articles published up to 31 December 2023, using the following databases: PubMed, Web of Science, Embase, and IEEE Xplore, which are the most used databases in the context of health and bioengineering field.

Results: The 16 included studies involved 2.465 neurological patients, including 189 patients with MS (7 studies), 2.246 patients with PD (9 studies), and 30 patients with stroke (2 studies).

Conclusions: This review highlights the role of wearable technologies in assessing fall risk in neurological patients. While studies showed variation in methods and a focus on technology over clinical context, the lack of standardization reflects ongoing advancements, which may be seen as a strength. Clinical Trial: PROSPERO registration ID: CRD42023463944

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Review

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Keywords: fall risk assessment; wearable sensors; neurological disorders; Neurorehabilitation.

Introduction

Neurological disorders often present gait and balance alterations, thus exposing patients to an increased risk of falls. Consequently, falls in this fragile patient population can worsen the quality of life, due to hospitalisation, hypomobility and reduced functional independence [1]. Fall-related injuries not only entail substantial medical costs but also determine patients' mortality risk. Among neurological disorders, Parkinson's disease (PD), multiple sclerosis (MS), and cerebrovascular accidents are some of the most common, causing important motor disability. It is noteworthy that these neurological patients are considered as recurrent fallers, due to their gait features. In particular, it is estimated that PD patients have a frequency of 39% of falls, while 40-60% of MS people show recurrent falls [2]. Similarly, post-stroke patients have a high risk of falling, reporting 27% to 39% fall frequency in rehabilitation hospitals [2]. However, each disorder is characterised by great heterogeneity of gait disturbances, in relationship to the different aetiology [3]. For example, neurodegenerative disorders (like PD and MS) can show different gait patterns, characterized by reduced gait speed, step length, and increased muscle weakness [3]. In addition, PD patients' ambulation is characterized by shorter steps, loss of dissociated arm and trunk movements during gait, and postural instability [4]. On the other hand, MS patients manifest pathological gait features related to the presence of spasticity, ataxia, muscle weakness, and sensory and proprioceptive deficits, causing a progressive disability [5]. Differently from neurodegenerative disorders, post-stroke patients are characterized by a great temporal and spatial asymmetry between steps, which substantially increases the risk of falls [6]. This is the reason why gait and balance assessment in patients affected by neurological disorders is fundamental, in all phases of the rehabilitation path.

To this aim, both clinical scales (i.e., Timed Up and Go, Tinetti Scale, Falls Efficacy Scale-International, Berg Balance Scale) and innovative technologies, including wearable sensors and non-wearable devices, are used. In detail, wearable sensors (WS) are growing in popularity both in clinical and research contexts for their suitable features [7]. WS represent an optimal solution for health monitoring due to their small size, affordability, and user-friendly nature [8,9]. Unlike traditional laboratory-based monitoring systems, they can facilitate the constant monitoring of motor activity, obtaining physiological data during daily life routines [10]. In addition, fall risk assessment with laboratory-based systems is generally performed in supervised conditions, in which the behaviour adopted by test subjects may not be representative of the one adopted in everyday life, as the subjects might be performing their “best effort” during the experimental tasks [11]. Generally, fall events occur in unpredictable situations, during the context of everyday life [12]. In this sense, WS allow an unsupervised fall risk assessment, providing continuous monitoring during daily functional tasks and thus reflecting the subject’s real fall risk [10,11,13].

Thus, the interest in WS has been increasing considering the monitoring of the fall risk among the elderly community [11]. Among the prevalent wearable technologies utilized for health monitoring are inertial measurement units (IMUs), which gather data from accelerometers and gyroscopes. IMUs can be strategically positioned on the body to capture motion data for subsequent analysis, integration, and interpretation [14]. Some examples of gait characteristics that can be analysed include stride length, stance/swing phase ratio, and many other spatial and temporal parameters of gait [11,15,16]. Additionally, insole-based devices have been meant for fall risk assessment and detection. These wearable systems are embedded within the shoe sole to capture data related to plantar pressure distribution [11]. The features extracted from these devices are used to quantify objectively the risk of falling in the neurological population. However, the selection of the most reliable biomechanical parameters of gait related to the risk of falling is still an open question [11]. In addition, the information acquired from WS, data processing, data fusion, and various analysis techniques such as machine learning models or manual data analysis, are employed to obtain meaningful information from the parameters investigated [17].

To this aim, some authors investigated the role of deep learning (DL) in the context of neurorehabilitation. The DL-based approach can be used to extract data about stride-specific gait parameters from IMUs [18]. This approach could be useful in the field of telemedicine as a potential in-home gait monitoring tool since alterations in gait function can be a biomarker to predict the risk of falls.

In this context, our first objective was to systematically review the literature about the most reliable biomechanical parameters of gait, detected with wearable devices (WD), to evaluate the risk of falls in neurological disorders. Therefore, we selected studies on PD, MS, and post-stroke patients, since they collectively represent a significant proportion of neurological conditions worldwide and are associated with substantial gait impairment and a high risk of falls. Secondly, we aimed to investigate the current literature on WS technology, the best practices used for the device positioning, processing and analysis techniques.

Methods

We conducted a comprehensive systematic review to explore the existing evidence about fall risk assessment in patients affected by neurological disorders. We summarised the results of all published studies following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines **[19]**. (PRISMA checklist is available in the supplementary material S2). The protocol was registered in the prospective register of systematic reviews (PROSPERO) with the following ID (CRD42023463944).

PECO question

We used the PECO model (Population, Exposure, Comparison, Outcome) to define the search strategy [20]. The PECO tool was employed to respond to the research question: "What are the most reliable biomechanical gait parameters detected with wearable devices to assess fall risk in neurological disorders?" (Table 1).

Table 1. PECO table for included studies.

PECO elements	Expected search results	Search strategy
P (patients/population)	Patients affected by neurological disorders, including cerebro-vascular diseases, Parkinson's disease, multiple sclerosis	"stroke" OR "Parkinson's disease" OR "multiple sclerosis"
E (exposure)	Fall risk assessment using wearable devices, gait analysis using wearable devices	"wearable"
C (comparison)	studies with healthy controls comparison	/
O (outcome)	Fall risk parameters	"Fall"

Search Strategy and Eligibility Criteria

A systematic search was conducted for all peer-reviewed articles published up to the 31 of March 2024, using the following databases: PubMed, Web of Science, Embase, and IEEE Xplore, which are the most used databases in the context of the health and bioengineering field. The full search queries are available in the supplementary material (S1). We included all studies on the adult population (>18 years) affected by stroke, Parkinson's disease (PD), and multiple sclerosis (MS). Specifically, the inclusion criteria were: i) adult patients with cerebrovascular impairments, PD, and MS; ii) fall risk assessment using WD; iii) written in the English language; and iv) published in a peer-reviewed journal. We have excluded articles describing theoretical models, methodological approaches, algorithms, and basic technical descriptions. We excluded: i) animal studies; ii) conference proceedings and reviews; iii) studies involving children; and iv) case reports. The list of articles was refined for relevance, revised, and summarised, with the key topics identified from the summary based on the inclusion/exclusion criteria. Considering the limited literature available, we included multiple study designs for qualitative synthesis: i) Randomised Controlled Trials (RCT); ii) Observational studies; iii) Cross-sectional studies; iv) Case-control studies; and v) cohort studies. All search' results were imported into an online database (RYYAN) [21] and screened by two blinding reviewers (A.I. and M.B.). After screening based on titles and abstracts, the blind was opened and in case of disagreement, the two reviewers discussed the inclusion/exclusion of the undecided articles.

Data Extraction and Analysis

After full-text selection, the data extraction from the included studies was reported in a sheet. Data were summarised considering the following information: assigned ID number, the title of study, year of publication or presentation and first author, study aims and design, study duration, method and setting of recruitment, inclusion/exclusion criteria, use of a control group, use of devices, informed consent, conflict of interest and funding, type of intervention/evaluation and control, number of participants, characteristics at the baseline, setting of intervention, type of biomechanical parameters related to fall risk, results and key conclusions. Data extraction was performed independently and blindly by two reviewers. In case of disagreement, a third reviewer was consulted.

Risk of bias

The risk of bias for the studies included in this systematic review was assessed through the National Institutes of Health (NIH) Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies [22]. It consists of 14 questions, in which the reviewers answered with "Yes", "No", "Cannot Determine", "Not reported", "Not applicable". Results are interpreted as good, fair, poor. The risk of bias was assessed independently and blindly by two reviewers. In case of disagreement, a third reviewer was consulted.

Results

We found a total of 106 articles (PubMed = 18, Web of Science = 53, Embase = 19, and IEEE Xplore = 16). After duplicate removal (n = 42), 64 articles were screened. After the screening 61 articles met the inclusion criteria and 3 articles were excluded. From the full-text analysis, 45 articles were excluded. Finally, 16 studies involving 4.604 subjects were included in the review synthesis (Figure 1). The included studies were published from 2016 to 2023.

Quality of the studies and risk of bias assessment

The risk of bias of the included studies was assessed through the NIH Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies, which comprises 14 questions (Figure 2).

We found that all the included studies had an overall good quality level (as shown in Figure 2), and there was homogeneity among the methodologies, and procedures administered to detect the risk of falls in neurological disorders. However, some concerns were found in the following domains: 3, 5, 12 and 13. Specifically, 13 studies out of 16 did not report if the participation rate of eligible persons was at least 50%, while in the other three studies [13,23–25], it was not possible to determine this information. Regarding domain 5, all the included studies, apart from Sturchio et al. [26], did not mention or report sample size justification, power description, or variance and effect estimation. In domain 12, ten studies out of sixteen did not report blindness to the exposure of participants, while unclear information, it was not possible to determine in the other four studies [13,23,25,27]. In this sense, only Meyer et al. [24], reported the information regarding the blindness of participants. In addition, we found that five studies [26,28–30] out of sixteen did not report if there was a loss to follow-up. Finally, Meyer et al. [27] did not assess patients more than once over time, thus reducing the accuracy of their results.

Study population

The included studies involved 2.465 neurological patients, including 189 patients with MS (7 studies), 2.246 patients with PD (9 studies), and 30 patients with stroke (2 studies). The other 2.139

participants were healthy controls. Regarding the neurological level, we found that studies conducted in the MS population have an EDSS mean of 3.4, whereas PD patients showed a UPDRS-III (motor part) mean of 26.6 and a Hoehn & Yahr (H&Y) mean of 2.58. Regarding stroke patients both studies [31,32] considered chronic patients with five years at least after the cerebrovascular accident (Table 2).

Table 2. Descriptive summary of the selected studies.

Reference	Study design	Sample size and aetiology	Demographics	Study aim	Major findings
Hildebrand et al. (2021) [33]	Observational	25 subjects with MS.	F:17; M: 8; EDSS (median and IQR) 6.0 (5.5 – 6.0); RR (n=11), SP (n=8); PP (n=6)	The study compares the sensitivity and false discovery rates of three fall detection methods—prospective paper fall calendars, real-time self-reporting, and automated detection using a body-worn device—in patients with MS.	Fall calendars likely underestimate fall frequency by about 40%, whereas the evaluated automated detector misses very few falls but likely overestimates the number of falls by approximately one per day.
Tulipani et al. (2022) [13]	Observational	37 subjects with MS; Non fallers: 17; Fallers: 21;	EDSS (mean and SD) Non-fallers: 2.0 (0.8); fallers: 3.3 (1.4)	Participants with MS completed the 30CST in both supervised (laboratory) and unsupervised (home) settings while wearing a thigh-mounted triaxial accelerometer, and in the unsupervised setting, they also performed bi-hourly 30CSTs and rated their balance confidence and fatigue over 48 hours.	Short periods of instrumented unsupervised monitoring, in addition to regular clinical assessments, could enhance the accuracy of fall risk prediction in patients with MS.
Tulipani et al. (2020) [34]	Observational	38 subjects with MS; Non-fallers:17; Fallers:21.	EDSS (mean and SD) Non-fallers: 2.3 (1.2).: 3.4 (1.2).	Subjects with PwMS completed self-report measures and performed the 30CST, with triaxial acceleration data collected from sensors on the thigh and chest. The study assessed the relationship between accelerometer metrics and clinical measures and developed a logistic regression model to classify fall status.	Accelerometer-derived metrics were linked to clinically relevant measures of disease severity, fatigue, and balance confidence during balance-challenging tasks, suggesting that inertial sensors could improve functional assessments and fall risk identification in PwMS, with their simplicity aiding community-based monitoring.
Meyer et al. (2022)	Observational	38 subjects with MS;	M:12; F:27. EDSS (mean	Participants, categorized as fallers or non-fallers based on self-reported	Deep learning models performed better than feature-based models when

[24]		Non-fallers:17; fallers:21.	and SD) non fallers: 2.3 (1.0); fallers: 3.3 (1.4).	falls, underwent clinical assessments, completed balance and fatigue surveys, performed lab-based mobility tests while wearing MC10 BioStamp sensors to collect accelerometer and EMG data, and continued to wear the sensors at home for 48 hours to monitor acceleration.	analyzing home data, particularly when using all walking bouts for deep learning and shorter bouts for feature-based models in individual bout evaluations. Longer free-living walking bouts showed more pronounced differences between fallers and non-fallers compared to shorter bouts, and aggregating data from all free-living walking bouts resulted in the highest accuracy for fall risk classification.
Meyer et al. (2021) [27]	Observational	37 subjects with MS; Non fallers: 19; Fallers:18.	M:11; F:26. EDSS (mean and SD); Non-fallers: 2.0 (0.8); fallers: 3.3 (1.4) 2.99 (1.47)	Distinguishing fallers from non-fallers based on a one-minute walking task. Participants were evaluated using wearable sensors to collect accelerometer data.	The BiLSTM deep learning model achieved the highest performance with an AUC of 0.88, suggesting that deep learning using gait acceleration data is effective for classifying the fall status of PwMS.
Kushner et al. (2023) [23]	Observational	25 subjects with MS.	M:8; F:17. EDSS (median and IQR) 6.0 (5.5 – 6.0). RR (n=11), SP (n=8); PP (n=6).	Subjects were monitored over eight weeks using an inertial sensor equipped with a triaxial accelerometer and time-of-flight radio transmitter, communicating with beacons placed throughout the home, to assess associations between home locations and movement behaviors before falls compared to periods without falls.	Movement metrics obtained from WS, and smart-home tracking systems are correlated with fall risk in PwMS, where increased pauses during walking and more complex, longer movement paths indicate higher fall risk.
Arpan et al. (2022) [25]	Prospective cohort study	26 subjects with MS; Non-fallers:	EDSS (mean and SD); Non fallers: 4.3	The study computed the area under the receiver operating characteristic (ROC) curve (AUC) for each gait	Objective monitoring of gait and turning in daily life among individuals with MS identifies those at risk of

		13; Fallers: 13.	(0.23); Fallers: 4.2 (0.18).	measure that differentiated fallers from non-fallers, and then ranked these measures from highest to lowest AUC value to assess their effectiveness in predicting falls based on instrumented measures of mobility using a univariate model.	future falls, with the pitch at toe-off identified as the most significant predictor, suggesting potential benefits from interventions targeting plantarflexion muscle strength, range of motion, and proprioceptive input.
Greene et al. (2021) [28]	Longitudinal and cross-sectional	15 Subjects with PD; 27 subjects with PD; 1015 controls.	PD subjects: M: 10; F:5; M:17; F:9. UPDRS-III 15.1 (9.6) and 22.56 (10.25). Healthy controls: M:344; F:671.	The study analyzed data using two statistical approaches to predict falls counts: a previously reported falls risk assessment algorithm and elastic net and ensemble regression models.	The study found a robust correlation between falls counts and a previously established inertial sensor-based falls risk estimate, as well as significant associations between falls counts and various individual gait and mobility parameters, suggesting that falls predicted from inertial sensor data during a basic walking task could serve as a promising digital biomarker for PD warranting further validation in clinical settings.
Pallavi et al. (2023) [29]	Observationa l	28 subjects; 14 subjects with PD; and 14 healthy controls.	PD subjects: M:11; F3; 14. UPDRS (mean and SD) 35.5 (19.4); H&Y 2.2 (0.7). Healthy controls: M:11; F:3.	Participants were asked to walk overground on a 10m pathway, both without turns (Path0) and with turns (Path180), under varying task conditions of increasing complexity (Single, Dual, and Multiple task conditions).	The knee flexion and gait-related indices strongly aligned with clinical measures of fear of falling especially in the PD group, providing valuable predictive information for clinicians.
Silva de Lima et al. (2020)	Prospective cohort study	4126 subjects. 2063 with	PD subjects: M:48.3%; F: 51.7%;	A PERSok was used, which included a device worn as a necklace with multiple embedded sensors for	This study utilized wearable sensors to collect fall data, revealing that PD nearly doubles the incidence of falls in

[35]		PD; 2063 healthy controls.	Healthy controls: M:48.1%; F:51.9%;	automatic fall detection and manual fall reporting. Fall events were reported either by a button-push or automatically detected by the fall detector.	everyday life, underscoring PD as a significant falling risk. Additionally, monitoring fall events in over 4000 participants using a wearable sensor connected to a PERS suggests the potential of body-worn sensors for continuous home monitoring.
Sturchio et al. (2021) [26]	Observational	26 subjects with PD and OH.	M:19; F:7; UPDRS III (mean and SD) 40.1 (13.4).	The study aimed to estimate their association with the risk of falls, capturing fall frequency through a diary over 6 months.	Kinematic measures, rather than clinical assessments, predicted falls in PD with OH, suggesting that orthostatic mean arterial pressure ≤75 mmHg may indicate a hemodynamic threshold associated with increased fall risk, advocating for proactive corrective interventions.
Nouriani et al. (2023) [36]	Observational	21 subjects; PD:11; healthy controls:10.	UPDRS pull test (mean and SD) 0.56 (0.96).	The study validated the activity recognition algorithm through video footage of patients wearing sensors at home.	These findings suggest that incorporating the detection of near falls into home monitoring data significantly enhances the effectiveness of current methods for fall prediction algorithms.
Ullrich et al. (2023) [30]	Observational	35 subjects with PD; Non-fallers: 25; Fallers:10.	M:26; F:10. UPDRS non fallers: 12.9 (6.2); fallers: 21.7(9.1); H&Y: non fallers 2.3 (0.5); fallers 2.9 (0.5).	The study compares various data aggregation methods and machine learning models for predicting fall risk using gait parameters obtained from continuous real-world recordings and unsupervised gait tests.	These findings indicate that combining two weeks of real-world gait data provides the most accurate prediction of fall risk, surpassing predictions based solely on unsupervised gait tests (balanced accuracy of 68.0%), thereby advancing understanding in fall risk prediction.
Ma et al.	Observational	51 subjects	M:33; F:18.	This study aimed to comprehensively	Increased gait variability is a notable

(2022) [37]	l	with PD.	UPDRS III: 33.6 (13.5); H&Y 2.4 (0.8).	and objectively evaluate gait characteristics in PD patients who fall using wearable sensors, and to explore the relationship between spatiotemporal gait parameters, gait variability, and falls over a six-month follow-up period.	characteristic among Parkinson's disease fallers and proves more sensitive in identifying PD patients at elevated risk of falls compared to spatiotemporal parameters.
Taylor-Piliae et al. (2016) [31]	Feasibility study	20 subjects; Stroke patients: 10 (Ischaemic stroke: 6; Haemorrhagic stroke: 4). Healthy controls: 10.	Post-stroke patients: F:70%; M:30%; Healthy controls: F:89%; M:11%. Months post-stroke: 42 (25).	The study aimed to assess the feasibility of using a kinematic motion sensor (PAMSys) to monitor fall risk and gait in community-dwelling stroke survivors by evaluating the acceptability of wearing the sensor for 48 hours, identifying fall risk indicators and gait parameters, and comparing these metrics with data from age-matched non-frail controls.	Stroke survivors found 48 hours of continuous PAMSys monitoring highly acceptable, suggesting that in-home wearable technology could be valuable for monitoring fall risk and gait, potentially aiding in recovery efforts.
Botonis et al. (2022) [32]	Observational	35 subjects; Stroke patients:20; healthy controls:15.	Post-stroke patients: M:10; F:10; Years after stroke:7.47 (4.58). Healthy controls: M:8; F:7.	This study investigated whether population-specific training data and modelling parameters were necessary to pre-detect falls in a chronic stroke population.	These findings underscore the significance of population-specific sensitivity, utilization of non-fall data, and optimal lead time for machine learning-based pre-impact fall detection tailored for stroke patients, suggesting a need for inclusion of neurologically impaired individuals in model development for effective fall detection in other high-risk populations.

Legend: MS (multiple sclerosis), EDSS (Expanded Disability Status Scale), IQR (interquartile range), RR (relapsing remitting) PP (primary progressive), 30-CST (30 seconds chair stand test), PwMS (people with MS), EMG (electromiography), AUC (area under curve), ROC (receiver operating characteristic), PD (Parkinson’s disease), UPDRS (Unified Parkinson’s Disease Rating Scale), PERS

(Personal Emergency Response System), OH (orthostatic hypotension), H&Y (Hoen and Yahr).

We classified our results according to technological equipment used, motor task (supervised vs unsupervised), biomechanical parameters extracted, and artificial intelligence approach, used in the included studies.

Motor task for risk of fall detection

We found that nine studies assessed fall risk through supervised motor tasks, administered in clinical and laboratory settings. The remaining seven studies evaluated fall risk through unsupervised gait tasks, recording in the real world.

Supervised motor tasks

Generally, supervised motor tasks consisted of instrumented Timed-Up-Go (TUG) [24,26,28,34,37], 30-second chair stand test (30CST) [13,24,34], simulated daily activities [26,27]. However, Tulipani et al. [13] compared supervised 30CST with unsupervised 30CST, in a home-based setting. These authors reported a substantial statistical difference between the two types of motor tasks, suggesting that the laboratory setting could influence the fall risk rate. Some authors [24,26,27,34,37] administered a specific assessment protocol to quantify the risk of falls in neurological patients, while Pallavi et al. [29], and Greene et al. [28], quantified the risk of falls using solely TUG or gait tasks. Interestingly, Sturchio et al. [26] conducted an instrumented assessment of ADLs in a standardized home-like environment, in addition to clinical tests (e.g., TUG, 2-minute walking test, and similar) (see Table 2 for more details). Similarly, Meyer et al. [27], acquired sensor data from simulated daily activities in addition to several standard functional assessments. In the end, Botonis et al. [32], evaluated the risk of falling in stroke patients through the reactivity of balance responses in the laboratory setting.

Unsupervised motor tasks

In the remaining eight studies, authors [23,25,30,31,33,35,36] performed an unsupervised risk of falling assessment through recordings in the real world. In general, the unsupervised assessment was detected during ADLs [31,33,36], or gait tasks [23,25,30]. In particular, Silva de Lima et al. [35], detected fall events automatically from the WD, without monitoring the ADLs or gait.

Fall risk biomechanical parameters

From the included papers, we analysed the extracted features from WS related to the quantification of supervised/unsupervised motor tasks in patients suffering from MS, PD, and post-stroke. We found that some authors [23,24,26,29–31,34,37] extracted specific gait parameters from WS. These parameters consisted mainly of spatial-temporal parameters of gait [29,30,37], anteroposterior and mediolateral acceleration [34], lower limb joint angles, and cadence [29]. In particular, Arpan et al. [25] extracted some specific gait parameters to differentiate fallers from non-fallers. These biomechanical parameters reflect the quality of gait (gait speed, stride length, cadence, swing), and also turning function during gait [25]. Only two authors [26,31] extracted balance features in addition to gait parameters. In particular, Sturchio et al. [26], evaluated oscillation in centre of pressure (CoP) and mass (CoM), frequency of oscillations, and jerkiness in PD patients. Interestingly, these authors evaluated also the upper limb range of motion during motor tasks. Similarly, Arpan et al. [25], evaluated upper body kinematics, in addition to quality of gait through spatial and temporal parameters, calculating also specific parameters during gait turning. In particular, gait turning, and postural transfers were also extracted by Greene et al. [28], while Tulipani et al. [13,34] considered in their analysis specific biomechanical parameters during 30CST (Table 3).

Table 3. Biomechanical features extracted from wearable devices, according to the selected literature.

Reference	Motor task	Parameters analysed
Multiple sclerosis		
Hildebrand et al. (2021)[33]	Unsupervised tasks during daily life activities.	- Acceleration signals from tri-axial accelerometers mounted on the waist. - Impact forces and postural changes to identify patterns indicating a fall. - Gait analysis for differentiating between falls and activities of daily living (ADL). - Timed-Up-and-Go (TUG) measurements for assessing balance and mobility in participants. - Location tracking using GPS and time-of-flight sensors to associate falls with specific movements or environments.
Tulipani et al. (2022) [13]	30-second chair stand test (30CST), in which the participant is encouraged to complete as many full stands as possible within 30 seconds.	Metrics for sit-to-stand and stand-to-sit transitions: - Sit-to-stand time (average of 30CST, maximum time of 30CST, minimum time of 30CST). - stand-to-sit time (average of 30CST, maximum time of 30CST, minimum time of 30CST). - Total number of 30CST repetitions.
Tulipani et al. (2020)	The participants	Metrics for sit-to-stand and stand-

[34]	performed a series of functional assessments including one trial each of the 30CST, T25W, and TUG, a 30-second static standing trial with instructions to maintain a tall posture with their feet facing forward, wearing inertial sensors on the anterior right thigh and chest.	to-sit transitions: - mean and coefficient of variation (CV) of sit-stand time, stand-sit time. - peak cranial-caudal (CC), anterior-posterior (AP), and medial-lateral (ML) acceleration during transitions.
Meyer et al. (2022) [24]	Supervised activities completed in the following order: TUG, timed 25-foot walk test, 30-CST, lying to standing transition, three separate two-minute standing tests: tandem standing, feet shoulder-width apart eyes open, and feet shoulder-width apart eyes close, one-minute hallway walk at a self-selected pace including one turn, 30-second normal standing, 30-second upright sitting, 30-second slouch sitting, and 30 seconds each lying on back, left side, right side, and prone.	Gait parameters extracted: - stance time, swing time, stride time, variability measures (coefficient of variation of stride and duty factor). - Non-linear measures (entropy ratio and Lyapunov exponent). - Root mean square of the anterior-posterior acceleration. - Medial-lateral frequency dispersion.
Meyer et al. (2021) [27]	Data from these sensors were recorded during a variety of simulated daily activities and several standard functional assessments.	Spatial-temporal parameters of gait stride.

Kushner et al. (2023) [23]	Unsupervised tasks during daily life activities (e.g., gait quality and turning).	- Gait initiation time. - Spatial temporal parameters of gait (e.g., average step length; average walking speed; percentage of time spent turning while walking). - Time spent moving. - Movement length. - An entropy-based metric quantifying movement complexity through transitions between rooms. - Mean length of a path when walking around the house.
Arpan et al. (2022) [25]	Unsupervised tasks during daily life activities (e.g., gait quality and turning).	Instrumented measures of mobility as predictors of future falls: - pitch at toe-off. - Gait speed. - Stride length. - Double support. - Swing. - pitch at initial contact. - Turn angle.
Parkinson's disease		
Greene et al. (2021) [28]	Supervised TUG test, instrumented with inertial sensors.	71 different calculated parameters quantifying gait, mobility, turning, and transfers, along with a statistical falls risk estimate and frailty estimate based on inertial sensor data: - TUG time - gait velocity - Falls Risk Estimate (FRE) - Frailty Estimate (FE) - Mobility impairment scores
Pallavi et al. (2023) [29]	Gait singles task, dual task and multiple task.	Gait parameters: - Knee flexion during heel-strike event - Knee flexion during toe-off event. - Cadence. - Double Limb Support Time.

Silva de Lima et al. (2020)[35]	Unsupervised: Fall events were collected either automatically using the wearable falls detector or were registered by a button pushes on the same device.	- Fall event (manually detected). - Fall event (automatically detected). - Changes in height. - Changes in orientation. - Impact during fall.
Sturchio et al. (2021) [26]	Subjects performed the following activity: lying-to-standing test (standing up without assistance after 10 minutes of supine resting and keeping the upright position for 5 minutes); tests of gait and postural stability (TUG, two-minute-walk-test, and sway eyes opened/closed, and ADLs conducted in a standardized home-like environment.	Balance parameters: - Oscillations in the CoP. - Oscillations in the CoM. - JERK sway (jerkiness). - RMS sway (magnitude of acceleration). - CF sway (frequency of oscillation). Gait parameters: - Turn duration. - Total duration. - Peak turn velocity. - Waist sway during TUG. - Gait speed. - Stride length. - Number of steps during turning. - Upper limbs range of motion. - Cadence.
Nouriani et al. (2023) [36]	Unsupervised tasks during daily life activities.	IMUs values: - Time spent lying down per day (lie down frequency, i.e., lying duration/total time). - The total number of ambulatory bouts at home. - The frequency of sitting at home (e.g., sitting duration/ total time). - Walking frequency at home. - The peak acceleration of the chest at home.
Ullrich et al. (2023) [30]	Unconstrained real-world gait analysis and unsupervised gait tasks.	Spatio-temporal gait parameters, including: - Stride time. - Stance time.

		- Swing time. - Stride length. - Gait speed. - Initial contact foot angle. - Final contact foot angle. - Maximum foot lift
Ma et al. (2022)[37]	Patients were required to complete a seven-meter TUG twice (stand up from an armless chair, walk at own comfortable pace for seven meters, turn 180, then walk back and sit down).	Spatiotemporal gait parameters including: - Stride length. - Gait cycle time. - Gait phase (swing and double support percentages). - Range of motion (RoM) of the trunk in the sagittal plane. - Gait variability measures.
Post-stroke		
Taylor-Piliae et al. (2016) [31]	Unsupervised tasks during daily life activities.	Parameters related to postural transitions (e.g., sit-to-stand, standing-to-sitting, lying-to-sitting, and sitting-to-lying): - Duration (in seconds). - The Number of unsuccessful attempts. Gait parameters (detected based on the peaks in the vertical accelerometer data, following predefined conditions): - Number of steps taken. - Speed of walking (meters per second). - Duration of walking activities (% of total activity).
Botonis et al. (2022) [32]	Participants were instructed to respond to loss of balance using any natural technique, such as using an arm to catch themselves or taking multiple steps, to encourage realistic behaviour.	The pre-impact data: - Fall impact and the acceptable intervention time. Statistical features from raw IMU signals, including: - Minimum. - Median. - Maximum. - Interquartile range. - Standard deviation.

		- Skew. - Kurtosis.

Legend: Biomechanical features were analysed to quantify the risk of falls in patients with MS, PD, and post-stroke. 30-CST (30-seconds chair stand test), TUG (Timed up and go), COP (Centre of Pressure), COM (centre of Mass), ADL (activity of daily living), IMU (inertial measurement unit).

As shown in Table 3, the majority of the included studies analysed gait parameters, such as spatio-temporal features. These features were mostly considered in patients with PD and MS. In addition, some authors extracted biomechanical features from clinical tests, such as 30CST and TUG (e.g., TUG time, turning activity, 30CST average time, and repetitions). Concerning post-stroke patients, it was difficult to define a common pattern of extracted biomechanical features because we found only two studies. However, the authors considered fall characteristics and parameters related to postural changes, as done by other authors in PD and MS [23,36].

Technological equipment, data processing, and analysis approaches

This section details the technological equipment and data processing methods used across the included studies. Seven of the studies [13,23–25,27,33,34] focused on fall risk assessment in people with multiple sclerosis (pwMS) using wearable sensors. Four of these used the MC10 BioStamp system (MC10 Inc., Lexington, MA, USA), which includes triaxial accelerometers, gyroscopes, and EMG sensors capable of capturing a wide range of motion data [13,24,27,34]. Tulipani et al. (2020) examined accelerometer metrics from thigh and chest sensors and applied logistic regression models to distinguish fallers from non-fallers, achieving an AUC of 0.78 and an accuracy of 74%[34]. In [13], a single sensor placed on the thigh was used to record data during tests, and the authors applied ROC analysis to optimize classification thresholds. This improved predictive performance in unsupervised settings, with an AUC of 0.79 and an accuracy of 78.4%.
Meyer et al. (2021) used BioStamp in conjunction with APDM Opal wearable sensors. Data were acquired from triaxial accelerometer sensors secured to the sternum (below the clavicle) and to the anterior part of the right thigh. In addition, these authors recorded data from accelerometer and angular rate gyroscope secured to the lower sternum, lower back at the belt line, and anterior right and left shanks. The authors demonstrated that a bidirectional long short-term memory (BiLSTM) deep neural network could identify pwMS who had recently fallen, achieving an AUC of 0.88 and 86% accuracy, based on data collected from two wearable sensors during a one-minute task [27].
In [24], accelerometer and EMG data were collected from the right and left tibialis anterior, while accelerometer and angular rate gyroscope data were collected from the chest and lower back as well as bilaterally from the anterior thighs, proximal lateral shank, and dorsal aspect of the feet. EMG was collected to allow the investigation of foot drop. The models tested in this study showed that short walking bouts were the best predictor of fall risk in free-living conditions (AUC of 0.63). In contrast, medium and long walking bouts had lower predictive performance, with AUCs of 0.52 and 0.54, respectively. Deep learning models, especially LSTM models that utilized up to 22 strides, outperformed traditional feature-based models, with the LSTM model achieving

an AUC of 0.76, showing its robustness in discerning fall risk from complex gait patterns. Hildebrand et al. [33] and Kushner [23] et al. used an automated fall detection system consisting of a body-worn IMU (placed on the waist) with a button for participants to self-report falls and a machine learning algorithm trained to evaluate falls on real-world in PwMS [38]. Specifically, the algorithm used an auto-encoder that detects fall candidates using reconstruction error of accelerometer signals followed by a hyper-ensemble of balanced random forests trained by acceleration and movement features. Hildebrand et al. compared three methods for detecting falls in pwMS: traditional paper fall calendars, real-time self-reporting using a body-worn device, and automated fall detection using the same device. The results showed that paper calendars had a sensitivity of 61.4% and a false discovery rate of 6.7%, indicating that they likely underestimate the number of falls. In contrast, the automated detection system had a high sensitivity of 92.1% but also a high false discovery rate of 91.9%, which likely overestimated fall occurrences. This study highlighted the challenges of balancing high sensitivity with minimizing false positives in real-world applications. Kushner et al. focused on extracting movement complexity metrics from wearable sensors. This study used a k-nearest neighbors machine learning algorithm for room detection and complex statistical methods to estimate movement-based fall risk. The findings indicated that movement complexity, measured by the entropy of room transitions, was notably higher in the periods leading up to falls, suggesting that increased movement complexity is a strong predictor of fall risk. Arpan et al. used a different set of wearable technologies to passively monitor gait and turning behaviors in daily life to predict falls in pwMS. This setup involved triaxial accelerometers, gyroscopes, and magnetometers (Opal sensors) placed on the top of the foot and integrated into instrumented socks, along with a sensor worn on the lower lumbar region. The data collected from these sensors were processed using an unscented Kalman filter technique to fuse accelerometer and gyroscope data and identify walking bouts and turning behaviors. The raw data were further processed using commercial gait analysis algorithms in Mobility Lab to derive spatial and temporal measures of gait and turning. The study found that reduced plantarflexion during toe-off, reflected by the pitch angle of the foot during the push-off phase of walking, was the most significant predictor of falls, achieving an AUC of 0.86, indicating strong predictive power [25].

Seven studies [26,28–30,35–37] focused on integrating advanced wearable sensor technologies and complex data analysis methods to monitor and predict fall risks in Parkinson's disease (PD) patients. Silva de Lima et al. used a wearable sensor worn as a necklace (Philips Lifeline FD100) to monitor falls in PD patients within their home environments. Although the study did not predict falls, it revealed a significantly higher incidence of falls in PD patients compared to controls, demonstrating the pronounced fall risk in this population [35].

Three studies used compact gait analysis systems to collect comprehensive kinematic data. Ma et al. and Sturchio et al. used the Mobility Lab (APDM, Portland, OR, United States) consisting of six wearable sensors (accelerometers, gyroscopes, and magnetometers) placed on the feet, wrists, sternum, and lumbar region. Ulrich et al. used Mobile GaitLab (Portabiles HealthCare Technologies GmbH. Erlangen, Germany) with sensors positioned on the instep of both the left and right shoes. Ma et al. focused on the variability in gait as a predictive marker for falls in PD patients, capturing metrics such as stride length, gait cycle time, and range of motion of the trunk in the sagittal plane. The authors found that variability in trunk range of motion during walking was a significant independent risk factor for falls in PD patients, with a prediction accuracy of AUC of 0.75. The overall logistic regression model, which included multiple gait parameters, predicted falls with a higher accuracy, with an AUC of 0.84 [37]. Sturchio et al. focused on fall risk in PD patients with orthostatic hypotension and found that waist sway, jerkiness, and postural sway were more predictive of falls than traditional clinical assessments, achieving an AUC ≥ 0.81 for predicting fall risk. [26]. Ullrich et al. focused on fall risk prediction in PD patients, by analyzing real-world gait data. The study employs machine learning algorithms, notably Random Forest classifiers, to analyze the aggregated gait data for fall risk prediction. The highest predictive performance was achieved using participant-wise aggregated data, resulting in a balanced accuracy of 74%, with a sensitivity of 60% and specificity of 88% [30].

Greene et al., explored the utility of wearable sensors during the TUG test to develop a digital biomarker for predicting fall counts (QTUG™, Kinesis Health Technologies, Dublin, Ireland). The study applied two statistical approaches to predict fall counts: a falls risk assessment algorithm reported in previous studies by the same team [39,40], and an ensemble model combining elastic net and regression models using Poisson regression. The research findings suggest a strong association between the fall's counts predicted from the inertial sensor data and actual falls [28]. Nouriani et al. validated an activity recognition algorithm and developed novel behavioral biomarkers to assess fall risk in patients with movement disorders, focusing on PD and Normal Pressure Hydrocephalus (NPH). The study used five IMUs (SparkFun, Inc. Boulder, CO, United States) strategically placed on the chest, upper legs, and lower legs of the subjects, capable of measuring acceleration, angular rates, and orientation. The core of the study's methodology involves a deep learning-based activity recognition architecture using a convolutional neural network combined with long short-term memory (CNN-LSTM) cells. This advanced machine learning approach allows for the accurate detection of complex activities and postural transitions that are critical indicators of fall risk. The algorithm's performance was validated against video [36].achieving high sensitivity (>95%) in detecting activities and an 80% sensitivity for near falls

Lastly, Pallavi et al. used a novel WS (SmartWalk) to evaluate knee flexion and gait indices during walking tasks under different cognitive load conditions. The study found that variability in knee flexion increased significantly under dual-task conditions, which were closely associated with a fear of falling. The findings indicate significant increases in variability of knee flexion during walking tasks, particularly under dual and multiple task conditions, which pose higher cognitive demands and thus exacerbate gait and postural disturbances in PD patients. A strong relationship between measured indices and clinical assessments of fear of falling was found using statistical analyses including k-means clustering and correlation assessments [29].

Two studies [31,32] focused on fall assessment in stroke survivors. Botonis et al. investigated the efficacy of wearable airbag technology (Wolk De Heupairbag, Wolk Company, Netherlands) paired with machine learning models to prevent falls. The device included three IMU sensors (on the hips and lower back) and used adaptive boosting (AdaBoost) classifiers to differentiate falls from non-falls. Two models were developed: one trained on stroke survivors and the other on control data. The stroke-specific model

significantly outperformed the control model in detecting true falls, especially in classifying complex fall movements in anterior-posterior directions. Additionally, training the model with daily activity data enhanced its accuracy in fall classification [32]. Taylor-Piliae et al. explored the feasibility of using a wearable sensor technology PAMSys (Biosensics LLC, MA, USA), for objective fall risk and gait monitoring in community-dwelling stroke survivors. The tri-axial accelerometer was worn in a mid-sternal pocket of a custom t-shirt, continuously recording movement data focused on postural transitions such as sit-to-stand. Data on steps, speed, and movement transitions were recorded over 48 hours and compared with controls. The analysis showed that stroke survivors exhibited worse fall risk indicators, taking longer to change posture and having more failed sit-to-stand attempts compared to controls [31].
The distribution of sensors reveals a concentration on the lower limbs and trunk, with fewer studies utilizing sensors on the hips and wrists (Figure 3).

Discussion

As far as we know, this is the first systematic review analysing the biomechanical features detected from WS for fall risk assessment, in patients with PD, MS, and stroke. Other authors [11] have investigated the role of inertial sensor-based and insole-based wearable devices to evaluate risk of falls in older adults. In line with our results, these authors identified several biomechanical gait parameters, including spatial-temporal parameters, balance features (COP trajectory) as well as ADLs that were registered to detect risk of falls. However, in our systematic review we found some differences in the assessment of the risk of falling related mainly to the characteristics of the neurological disorders considered. Furthermore, we noticed differences between the studies concerning technological equipment.

Pathological and biomechanical gait characteristics leading to falls

Falls in neurological disorders are very common and they can depend on different aspects and features of gait. According to Zhou et al. [41], gait variables related to pace (stride, velocity), rhythm (stride duration, stance/swing time), variability (standard deviation of ankle dorsiflexion at heel strike), and spatial gait variables (stride length, plantar flexion at toe-off, ankle dorsiflexion at heel strike), can help to classify neurological patients as fallers. However, neurological disorders are heterogeneous and each of them has specific features of gait that could lead to an increased risk of falls. For instance, in patients with MS, despite the location, number, and size of MS lesions differ among individuals, there are some common characteristics in gait deficits associated with MS. Patients with MS [42] have can manifest shorter steps, reduced cadence, increased double support time, and increased swing phase time. Moreover, some authors emphasized that MS patients have a reduced joint motion at the hip and ankle and increased joint motion at the knee with a hyperextension that is more pronounced during midstance. Falls in this patient's population can occur early after the onset of the disease, and some factors increase the risk, such as: poor visual acuity, impaired postural control, and altered proprioception. However, the studies included in this systematic review analysed only specific biomechanical metrics related to clinical test (30-CST) [13,34] or analysed spatial-temporal features of gait, and turning angle [23,25,27]. According to Tulipani et al. [34], 30CST could be a useful test to discriminate “fallers” and “non-fallers” in PwMS, since it can detect balance impairments and muscle fatigue, which are associated with falls. Another important aspect is that the fall risk remote monitoring through WS has the potential advantage of augmenting clinical visits to gain a broader perspective of patient function, symptom fluctuation and fall risk. In patients affected by PD, a critical factor that is associated with falls is freezing of gait. However, it is not the only risk factor involved in falls. People with PD can experience bradykinesia as well as weakness and body rigidity that leads to an increase in slowness during gait, closely influencing the rate of falls [43]. According to Pelicioni et al. [44], the reduced strength in quadriceps, poor balance and postural stability as well as reduced mobility (slower TUG test performance) could explain the increased prevalence of balance-related falls. These results are in line with those reported in the included studies. For example, Greene et al., found strong associations between fall counts and several individual gait and mobility parameters, including gait variability, during the TUG test. In particular, gait variability consists of a certain degree of gait variation that in PD patients means a loss of consistency in the ability to produce a steady gait rhythm, thus presenting a likelihood of a fall. In addition, Ma et al., found that PD fallers had a larger RoM in trunk sagittal plane than non-fallers. This aspect was identified by the authors as an independent risk factor for falls in PD patients, and it could be used to predict falls, especially when it is combined with age, gender, and other gait parameters. From these results, it seems that kinematic gait parameters are accurate in detecting the risk of falls, as also confirmed by Sturchio et al. [26]. These authors found that kinematic data extracted from WS showed higher accuracy in the prediction of falls than H&Y, which is considered the most robust clinical predictor of falls in PD. Differently from MS and PD, in post-stroke patients, both balance and gait deficits related to falls were found. According to Weerdesteyne et al. [45], stroke-related balance deficits include postural instability and lack of coordination to both self-induced and external balance perturbations. Gait deficits related to fall risk comprise reduced propulsion at push-off, decreased hip and knee flexion during the swing phase, and reduced stability during the stance phase. However, the selected studies [31,32] have not reported specific biomechanics features related to falls in post-stroke patients. In future studies, it could be essential to select and extract specific features that lead to falls in this patient population.

Technological equipment: considerations and limitations

Fall risk assessment and fall detection have been investigated using wearable technologies. Among these, accelerometers, IMUs and insole-based systems were mostly used in the clinical context. For instance, tri-axial accelerometers and inertial sensors were widely used by the included studies [14]. They measure body movements by detecting speed changes and calculating the resultant acceleration from the displacement of the mass element. In rehabilitation research, the most commonly used types of accelerometers are strain gauge, capacitive, piezoresistive, and piezoelectric. These accelerometers typically have one to three sensing axes, enabling motion detection in one, two, or three dimensions. From our literature analysis [13,23,25,27,33,34], it emerges that triaxial accelerometers were combined with gyroscopes, and EMG sensors, that can capture a wide range of motion data. In particular, gyroscopes calculate changes in angular motion by detecting the Coriolis forces, which are proportional to the rate of angular rotation of the limb. Coupling the accelerometer with EMG data from the lower limb provides more insightful findings, especially in the context of neurorehabilitation. For example, Meyer et al. [24], collected EMG signals plus accelerometer and gyroscope data that allowed the investigation of foot drop. This latter is identified as one of the most frequent causes of falls in pwMS. Interestingly, Tulipani et al. [34], revealed significant associations between accelerometer-derived metrics and clinical assessments, notably in balance confidence and fatigue. These findings indicate that wearable sensors can offer a real-time, objective measure of fall risk that aligns well with traditional clinical evaluations. Moreover, we found that articles on fall risk assessment in PD primarily focused on integrating advanced sensor technologies and complex data analysis methods to monitor, predict, and manage fall risks in PD patients. Some authors used a full-body wearable motion sensor system consisting of six sensors (each one including a tri-axis accelerometer, gyroscope, and magnetometer) to detect kinematic gait data. Contrary to Silva de Lima [46] who developed a tri-axial accelerometer combined with a barometer, which automatically detected falls and allowed users to manually report falls via a button press. This dual functionality enabled the collection of accurate real-time data on fall incidents. According to a previous review by Ferreira et al [47], studies involving WS for fall risk assessment mainly used one accelerometer, which underlines the importance of the use of acceleration data to characterize the score results from clinical standard scales. Data from WS were utilized to detect pre-fall and unbalanced situations, enabling the identification of fall risk events. This approach aims to reduce short-term fall risk by allowing real-time daily monitoring of subjects and providing immediate feedback when a fall risk event occurs.

To this aim, some authors performed the fall risk assessment in an unsupervised setting. Contrary to laboratory settings, real-time fall risk prediction in ADL, detecting fall risk events is more suitable. This approach allows continuous monitoring and alerts subjects when fall-risk events are detected. However, Meyer et al. [24] found that the best performance of the ML model to predict the risk of falls using feature-based models was achieved with laboratory data, indicating that controlled environments yield more reliable data for assessing fall risk. Given that, some authors found that specific biomechanical features of gait (i.e., speed) can be sensible to change when analysed at home or in the laboratory setting. For instance, Carcreff et al. [48] found that children with cerebral palsy exhibited lower gait speeds in daily life compared to lab settings, potentially due to walking barefoot during lab assessments. Other studies have also observed discrepancies between supervised and unsupervised gait speeds in the elderly. Takayanagi et al. [49] identified a weak correlation between daily life and lab gait speeds, with daily speeds being significantly lower. De la Camara et al. [50] noted that clinical gait speed measurements might not accurately reflect habitual speeds and are influenced by physical, mental, and cognitive health. These studies, using IMUs, faced limitations such as short walking distances in labs (2.44 to 10 meters), which are not comparable to daily gait speeds. Even in PD, lab assessments do not always mirror daily activity accurately. Toosizadeh et al. [51] found no significant correlation between lab and home gait parameters, possibly due to small sample sizes and methodological differences. According to Corrà et al. [52], found that specific laboratory tests can better represent gait speed at home. However, the ability to remotely monitor patients at home is beneficial for clinicians as it allows them to assess patients' motor capacity in their

domestic environment. In this sense, both in-lab and daily living assessments using WS can provide complementary insights into PD, enhancing clinical evaluations and patient management.
The sensitivity of supervised versus unsupervised assessments in detecting motor fluctuations in PD remains unclear. Therefore, enhancing clinical care and designing personalized interventions necessitates a better understanding of gait disabilities through comprehensive daily-life performance data from IMUs.

Machine learning algorithms and data analysis processing

In the studies included in this systematic review, a range of AI techniques were applied to analyse data collected via wearable sensors for assessing fall risk in neurological patients. Deep learning models were prominently featured [24,27,36]. These models are particularly proficient at processing sequential data, capturing temporal dependencies essential for interpreting complex gait patterns over time. This choice reflects a growing trend of using advanced AI to detect the complex patterns of movement disorders that are often overlooked by standard clinical assessments. Besides deep learning, traditional machine learning techniques also played a significant role. For instance, feature-based models like support vector machines (SVM) or random forests were used to classify patients based on extracted biomechanical features, such as stride length and turning behaviour [23,30,33]. The preprocessing of sensor data through advanced data fusion and signal processing techniques was another crucial aspect that has emerged from the included studies. These methods prepare the raw data for more effective AI analysis by enhancing data quality and extracting meaningful features. Arpan et al. used unscented Kalman filter techniques to integrate data from multiple sensors, facilitating a more accurate AI-based prediction of fall events [25]. Some studies explored the implementation of AI models that operate in real-time to provide immediate insights or predictive analytics. This approach is particularly useful in a home monitoring context where immediate feedback can prevent falls [46].
Looking ahead, the integration of AI in fall risk assessment could expand in several directions. Tailoring AI models to individual patients' data over time to adapt to changes in their condition or progression of their neurological disease could improve ongoing monitoring and therapeutic accuracy. By incorporating methodologies that adjust to patient-specific needs and conditions, AI can facilitate more dynamic interventions tailored to the evolving profiles of patients. In a recent study, Espinoza Bernal et al. used personalized machine-learning algorithms to monitor and adjust individual rehabilitation strategies for stroke patients. Using data from wearable sensors during a rehabilitation camp, these algorithms provided high classification accuracy and insights into changes in patient mobility. This capability not only demonstrates the potential of AI to adapt to and predict the needs of patients based on real-time data but also highlights its value in managing conditions that affect mobility and stability, enhancing the precision of therapy and potentially improving patient outcomes [53]. Furthermore, another recent study described neural network models specifically designed to capture the dynamic properties of gait, considering both short-term and long-term dependencies in gait cycles. This approach allowed for the identification of individual-specific gait signatures, which are particularly useful in understanding and accommodating the unique gait dynamics of stroke survivors, who often exhibit significant variability in their walking patterns due to

neurological impairments [54].The personalization of AI models to adapt to individual patient profiles over time promises to enhance the precision of interventions, although as AI models evolve, there's also a growing need for explainable AI (XAI) that can make AI decisions more transparent and understandable to clinicians. This will be crucial for building trust and facilitating the integration of AI tools into everyday clinical practice. Future advancements should aim to not only refine the predictive accuracy of fall risk but also ensure that the outcome data are accessible and interpretable for all users involved in the care process. A recent study demonstrated the use of wearable sensors coupled with XAI techniques to provide detailed insights into muscle activity changes, aiding clinicians in understanding the predictive outcomes of AI models [55].

Clinical considerations and future perspectives

Detecting risk of falls in neurological patients' populations has a primary role in the rehabilitation context. In this review, we found several biomechanical parameters related to fall risk, identified through WS. Data extracted from sensors can provide valuable insights into motor deficits associated with fall risk and guide the development of personalised fall prevention programs. In this vein, conventional clinical scale may be not able to capture specific fall-related movements detected by sensors. This discrepancy suggests the importance of body-worn sensors, combining daily-life sensor data with clinical assessment outcomes to enhance fall prediction accuracy. Therefore, daily-life data recording should be preferred over in-lab data collection, as individuals with neurological disorders are more susceptible to the effects of test instructions or external distractions. However, lower activity levels in individuals with neurological disorders may affect the quality of the data collected. Moreover, both the location and method of sensor attachment are crucial when collecting sensor-based data from individuals with neurological disorders. Using multiple sensors might provide more detailed information but is less practical for this patient group. Additionally, researchers or trained staff need to be present to ensure the correct placement and wearing of the sensors. From a practical point, the sensor's location should be chosen carefully to avoid disturbing the participants during the assessment, to replicate the patients' movements in a more realistic and natural way. Technical considerations, such as battery life, data transmission, and storage capacity, must also be factored in when selecting an appropriate sensor for research or clinical practice.

Future studies should incorporate additional information on other fall-risk factors (i.e., cognitive status, comorbidities, sensory functions) that could improve fall prediction accuracy. In addition, future studies should include more than one sensor that may provide more detailed information. In the future, innovative technologies like WS hold promise for enhancing motion analysis and fall risk prediction due to their increasing simplicity, speed, and ease of interpretation compared to traditional methods. However, currently, there is a scarcity of studies with practical clinical applications for gait analysis in neurological populations, particularly in patients with stroke. This gap may be attributed to practical challenges, such as the lack of widely available specialized devices in hospital settings, and economic constraints. Additionally, the absence of direct collaboration between clinicians and bioengineering professionals contributes to this issue. Technological advancements could address these challenges by promoting the use of smart tools, such as smartphones, which are becoming more prevalent in clinical settings, as supported by some studies. Furthermore, increased collaboration between physiotherapists, kinesiologists, and bioengineers is essential for sharing practical insights that inform the development of specific motor training programs based on functional assessments.

Limitations

This systematic review has some limitations that need to be acknowledged. One limitation is the absence of quantitative analysis. In particular, we found considerable heterogeneity among the included studies in terms of sensors used, sensor placement, and biomechanical features extracted, thus conducting a quantitative analysis was not feasible. This limitation underscores the need for caution in generalizing the findings and emphasizes the importance of interpreting the results within the context of individual study characteristics. The selected studies also presented other limitations too, including small sample sizes, lack of control group or normative data and lack of long-term follow-up evaluations. Despite these limitations, our review relies primarily on qualitative synthesis, based on which involved systematically summarizing and interpreting the findings of individual studies to elucidate common themes, patterns, and discrepancies across the literature. As a result, our review provided a comprehensive qualitative synthesis of the available evidence, offering valuable insights into the biomechanical features and WS used to perform fall risk assessment, identifying key implications for clinical practice and considerations for future investigation.

Conclusions

In this systematic review, we highlighted the critical role of wearable technologies in providing an objective and quantitative assessment of fall risk in patients with neurological disorders. Although the included studies were well-executed, we identified significant heterogeneity in sensor placement, types of wearable systems, motor tasks, and evaluation methods. Additionally, we observed that many studies primarily focused on the technological and engineering aspects, often at the expense of the clinical context. However, the absence of a standardized fall risk assessment using wearable systems is likely attributable to ongoing technological advancements, which can also be considered a strength.

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Conflicts of Interest

None declared.

Abbreviations

AUC: Area Under Curve
CoM: Center of Mass
CoP: Center of Pressure
DL: Deep Learning
EDSS: Expanded Disability Status Scale
EMG: Electromyography
H&Y: Hoehn and Yahr Scale
IMU: Inertial Measurement Unit
IQR: Interquartile Range
LSTM: Long Short-Term Memory
ML: Machine Learning
MS: Multiple Sclerosis
NPH: Normal Pressure Hydrocephalus
PAMSys: Physical Activity Monitoring System
PD: Parkinson's Disease
PECO: Population Exposure Comparison Outcome
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PwMS: People with Multiple Sclerosis
ROC: Receiver Operating Characteristic
SP: Secondary Progressive
TUG: Timed Up and Go
UPDRS: Unified Parkinson’s Disease Rating Scale
WD: Wearable Devices
WS: Wearable Sensors

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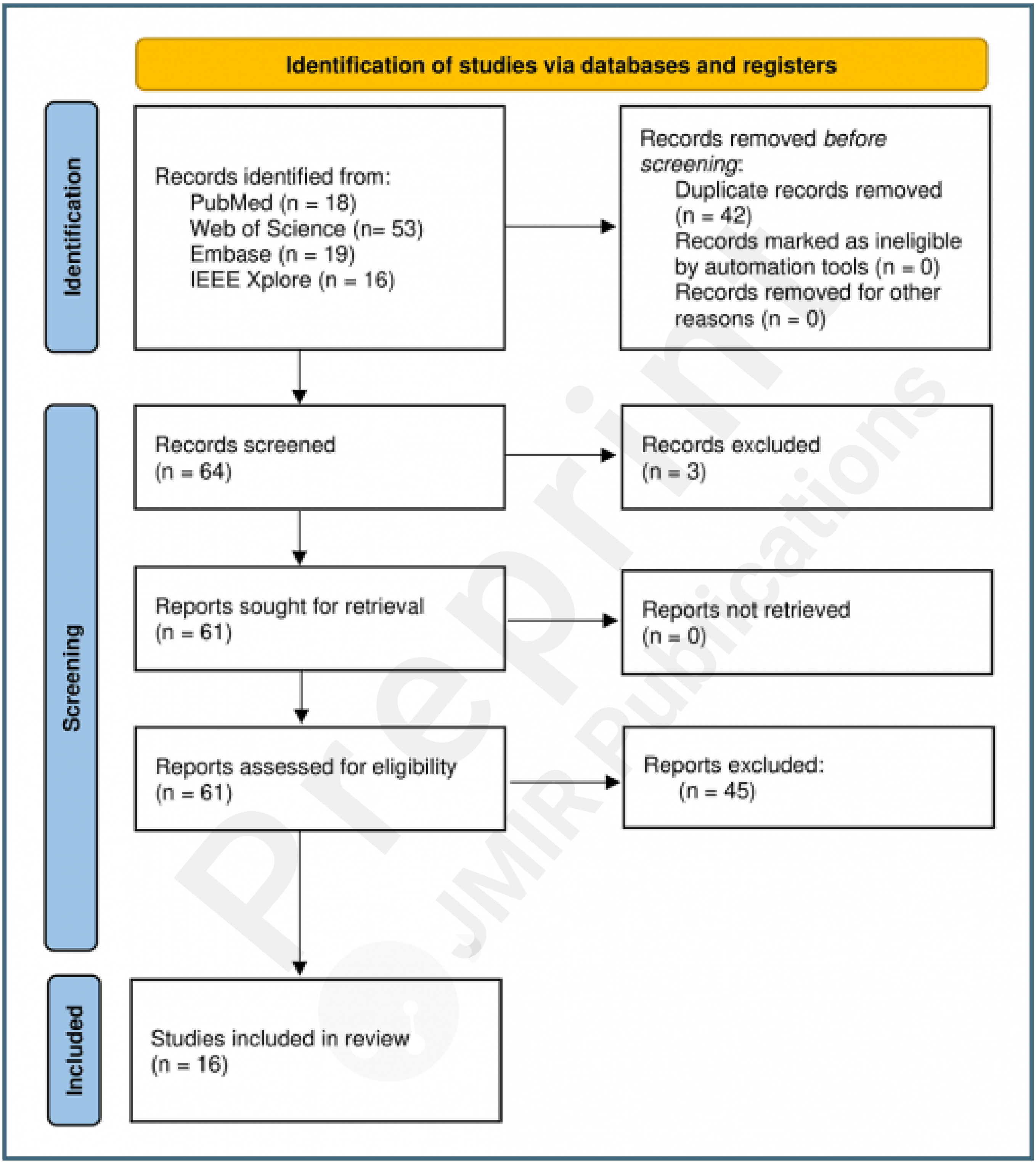
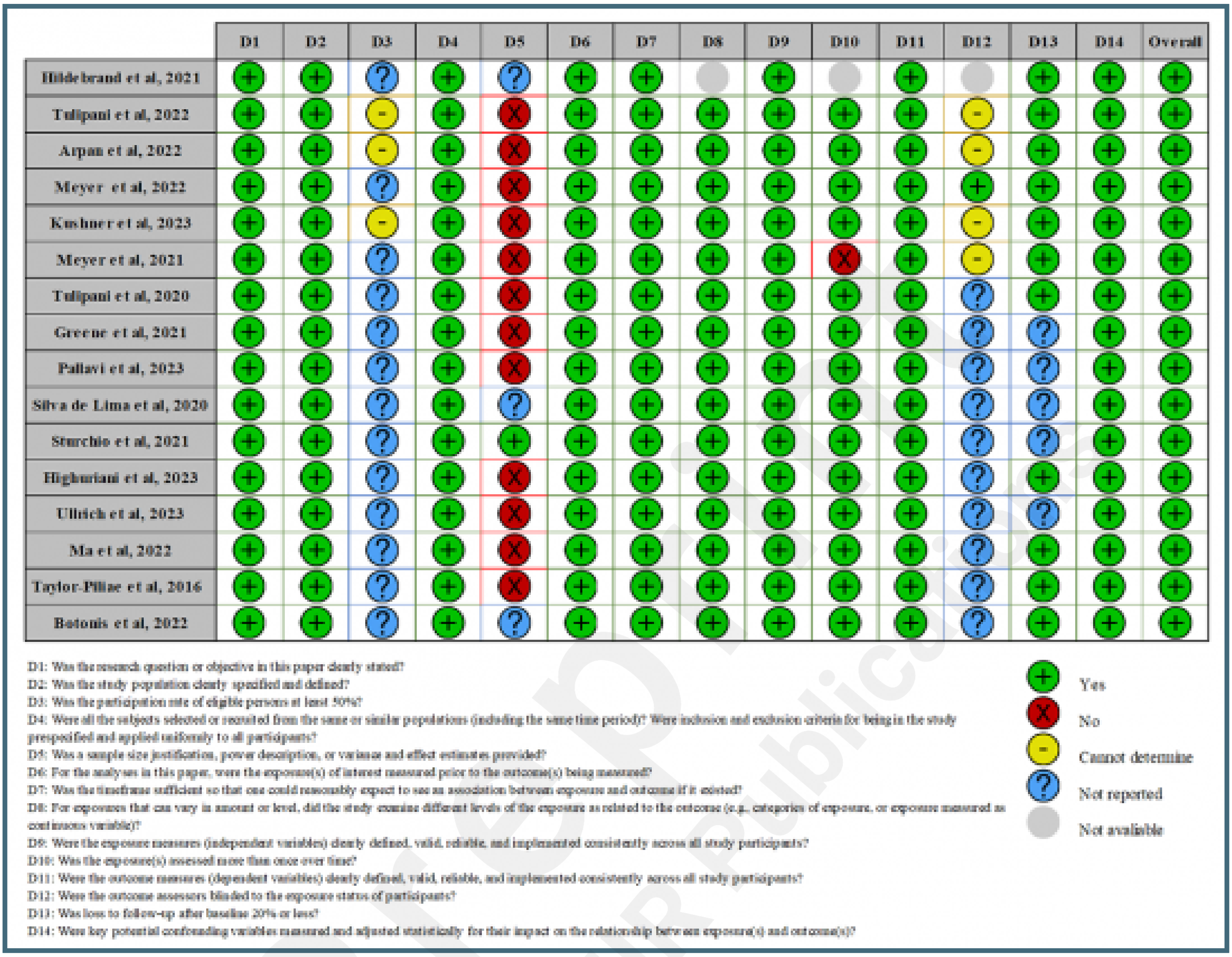
Supplementary Files

Figures

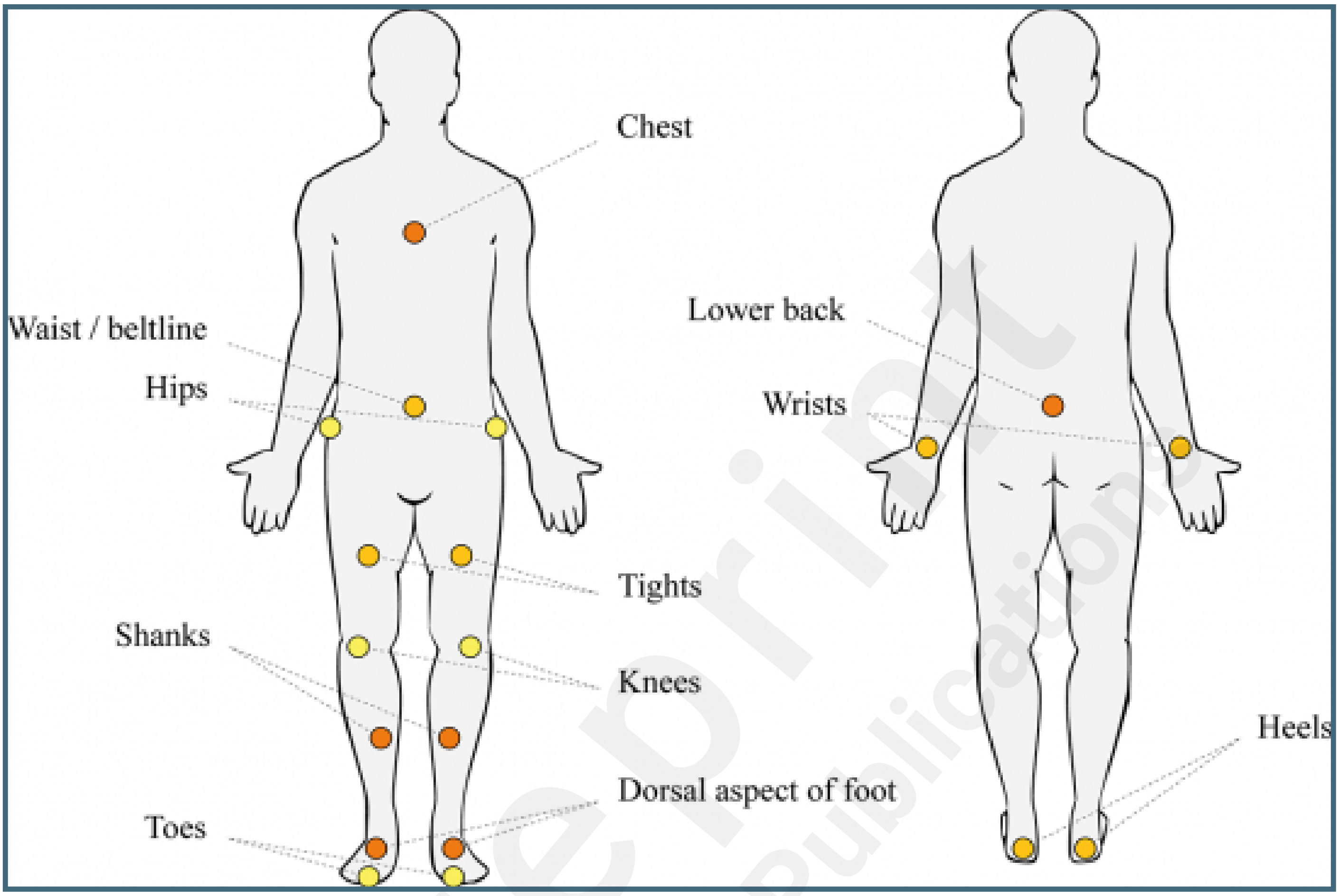
PRISMA flow-diagram.



Risk of bias assessment.



Sensors location adopted across the included studies. Yellow: n?2; light orange: 3?n?5; dark orange: n?6.



Multimedia Appendixes

Search queries.
URL: http://asset.jmir.pub/assets/59e49ba7d05121b0dde13b0c07e70d1a.docx

Prisma checklist.
URL: http://asset.jmir.pub/assets/eea28f4e9031a6a75f6afdcf590461d3.docx