Review

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Concurrent Validity and Reliability of Inertial Sensor-Based Wearables for Quantifying Spatial-Temporal Gait Parameters After Stroke: A Systematic Review

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Highlights

What are the main findings?

- Wearable inertial sensors show good-to-excellent validity and reliability for spatial gait parameters in post-stroke populations, but lower performance for temporal outcomes, especially for swing time.
- Paretic-side measurements derived from wearable sensors consistently present lower agreement with the reference system than the non-paretic side, but they show similar test-retest reliability.
- Changes exceeding 0.2 $m \cdot s^{-1}$ in gait speed, 9 $steps \cdot min^{-1}$ in cadence, and 16 cm in step or stride length can be interpreted as true changes in stroke patient gait status.

What are the implications of the main findings?

- Spatial gait parameters derived from wearable sensors can be confidently used for clinical monitoring and patient stratification, while temporal parameters require cautious interpretation.
- Improving gait-event algorithms and standardizing protocols is essential to enhance the accuracy of temporal gait metrics and support broader clinical adoption of wearable-based gait assessment.

Abstract

This systematic review examined the validity and reliability of wearable inertial sensor systems to quantify spatiotemporal gait parameters in post-stroke adults, a population in which gait asymmetry, altered motor control, and compensatory strategies challenge accurate measurements. Four databases were searched up to December 2025, and studies were included when they assessed concurrent validity or test–retest reliability of wearable derived spatiotemporal parameters against laboratory-based reference systems. Fifteen studies involving a total of 286 participants were analyzed. Spatial parameters as gait speed, cadence, and step and stride length showed consistent good-to-excellent agreement with reference instruments and high test–retest reliability. Temporal parameters demonstrated greater heterogeneity, with larger absolute errors, wider limits of agreement, and lower relative agreement, particularly for swing time. Paretic-side measurements showed reduced between instrument agreement compared to the non-paretic side, although within-subject reliability remained moderate to high. No consistent influence of sensor number on measurement accuracy. Overall, wearable inertial sensors provide robust estimates of spatial gait parameters in post-stroke populations, while temporal outcomes remain limited, likely due to the challenge to detect gait events that arise from stroke-related alterations in gait biomechanics. Taking these findings as a whole suggests that deviations from regular gait biomechanics, whether due to reduced speed particularly at low walking speeds of 0.4 m/s, asymmetry, or to the use of assistive devices, compromise the ability of wearable-based algorithms to accurately identify gait events.

Keywords: post-stroke gait; spatiotemporal gait parameters; inertial measurement units; wearable sensors

1. Introduction

Strokes are the second leading cause of mortality and the primary cause of disability worldwide [1,2]. According to recent estimates from the Global Burden of Disease study, approximately 11.9 million new stroke cases occur annually, while 93.8 million people live with functional sequelae from stroke events [3]. Gait disturbances are among the most disabling post-stroke consequences, limiting autonomy [4], restricting participation in the activities of daily living [5] and increasing the risk of falls [6] even in patients with relatively high levels of independence. Only around 50% of whom achieve fully autonomous ambulation after stroke [7–9]. Gait impairments, which are closely associated with hemiparesis, are characterized by reduced walking speed, decreased step length and cadence, prolonged swing phase, reduced knee and hip flexion, increased variability and asymmetry of gait patterns as well as abnormalities in the kinematics and kinetics of the lower limbs [10–13]. Insufficient weight transfer towards the affected limb, delays in postural responses and a compensatory shift of the center of mass towards the unaffected side further compromise gait efficiency [14,15]. Gait deficits arise from a complex interplay of symptoms present in people with stroke such as spasticity, muscle weakness, impaired intermuscular coordination, postural control deficits, and reduced somatosensory sensitivity. Ultimately, this cluster of symptoms affects the efficiency, stability and safety of walking [16–18].

Consequently, an accurate and comprehensive gait assessment is essential to guide clinical intervention to promote a greater independence in activities of daily living in this population. Gait is commonly assessed in clinical setting through the use of conventional clinical tools such as timed walking tests [19] and distance-based assessments [20], observational standardized scales [21] or patient-reported outcome measures [22]. Although these approaches are widely used because they are low cost and easy to use, they lack the kinematic and spatiotemporal resolution required to accurately characterize gait impairments, capture subtle motor deficits or describe inter-individual variability in post-stroke walking patterns [23,24]. Instrumented laboratory methods allow for a detailed analysis; however, their high cost, specialized infrastructure requirements and extensive training and data processing time restrict routine clinical use [25,26]. Therefore, quantitative and integrative approaches are needed to enable a comprehensive gait evaluation, optimize clinical interpretation and support evidence-based therapeutic decisions. Recent technological advances have facilitated the development of portable inertial sensors that can measure spatiotemporal gait parameters previously accessible only in specialized laboratories [27]. These devices offer clear advantages, including lower cost, low energy consumption, ease of use and light weight, therefore allowing for their application in both clinical settings and patients' daily environments [28]. However, clinical implementation in post-stroke populations remains limited, primarily due to the scarcity of studies supporting their reliability, validity and sensitivity. Previous reviews on wearable

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technologies for post-stroke gait have mainly focused on the reliability and validity of basic outcomes, such as gait speed or step count [29,30]. However, a comprehensive and clinically interpretable systematic evaluation of the measurement error of these devices in relation to gold standards (i.e., concurrent validity) and the consistency across measures (i.e., reliability) of spatiotemporal gait parameters is still necessary. Moreover, existing evidence has not yet been examined in relation to key sources of methodological heterogeneity, including number of sensors and participants' level of disability of the most affected limb [28,30–34], which limit the comparability across studies and hindering the transfer of wearable-based gait assessment into clinical practice. Consequently, the aim of this systematic review is to examine how key methodological decisions and participants' disability influence the reliability and validity of spatiotemporal gait parameters derived from wearable inertial sensors in post-stroke populations.

2. Materials and Methods

This systematic review was conducted in accordance with the PRISMA 2020 guidelines and previously registered in PROSPERO (CRD420251155668; September 29, 2025). The review framework considered the construct of interest, spatiotemporal gait parameters in post-stroke adults, the measurement instruments which consisted of wearable devices incorporating inertial sensors and the psychometric properties under evaluation, which included reliability, validity and measurement error.

2.1. Protocol Clarification

Three deviations from the originally registered PROSPERO protocol were made to better align the review with its objectives. First, randomized controlled trials (RCTs) were initially included; however, during the screening phase it became clear that RCTs did not report the level of methodological detail required to evaluate measurement properties of wearable devices. For this reason, no RCTs were included. Second, although AMSTAR-2, Cochrane RoB-2 and ROBINS-I were noted in the PROSPERO record for risk of bias assessment, these tools were not applied as they are not appropriate for evaluating measurement properties. Instead, the COSMIN checklist was used and the certainty of evidence was assessed using the GRADE approach, as originally intended. Third, the inclusion criteria were refined: only studies measuring at least two spatiotemporal gait parameters were considered.

2.2. Eligibility Criteria

Studies were eligible when they examined adults aged 18 years or older with a clinical stroke diagnosis, regardless of their post-stroke phase and who were capable of walking independently or with assistive devices. Concurrent validity and test–retest reliability studies were included if they reported psychometric properties of wearable devices based on inertial sensors during gait assessment and they assessed at least one spatiotemporal gait parameter other than gait speed or cadence. Specifically, concurrent validity studies had to include at least a concordance or agreement index between the wearable device and the gold standard instrument (optical motion capture systems, instrumented walkways or video cameras). Validity studies were excluded if they only presented mean error differences or statistical comparisons between instruments. Within- and between-session test–retest reliability studies were included if they reported at least one absolute or relative reliability index. In addition, studies were excluded if they involved additional neurological, psychiatric, musculoskeletal, or rheumatological conditions, or any contraindication to gait evaluation or physical activity. Studies focusing on insole- or sock-based sensor systems were also excluded. Trials that used additional reference systems, such as motion capture or pressure walkways, were included if wearable-derived outcomes were reported independently. Articles published in English were considered.

2.3. Information Sources and Search Strategy

A systematic search was conducted independently by two reviewers (V.M.-P. and D.S.-G.) in the following electronic databases: CENTRAL, PubMed, Embase, and Scopus. Search terms combined keywords and MeSH terms related to stroke, wearable devices, gait, and psychometric properties, adapted for each database (Supplementary material 1). The reference lists of the included studies were manually screened to identify additional relevant publications. Searches included all articles published up to December 23rd, 2025.

2.4. Study Selection

Titles and abstracts were independently screened by two reviewers (V.M.-P. and D.S.-G.), and potentially eligible articles were assessed in full text. Any discrepancies between the reviewers were resolved through discussion or consultation with a third reviewer (D.B.) Duplicate records were removed prior to screening. The selection process is illustrated in a PRISMA flow diagram (Figure 1).

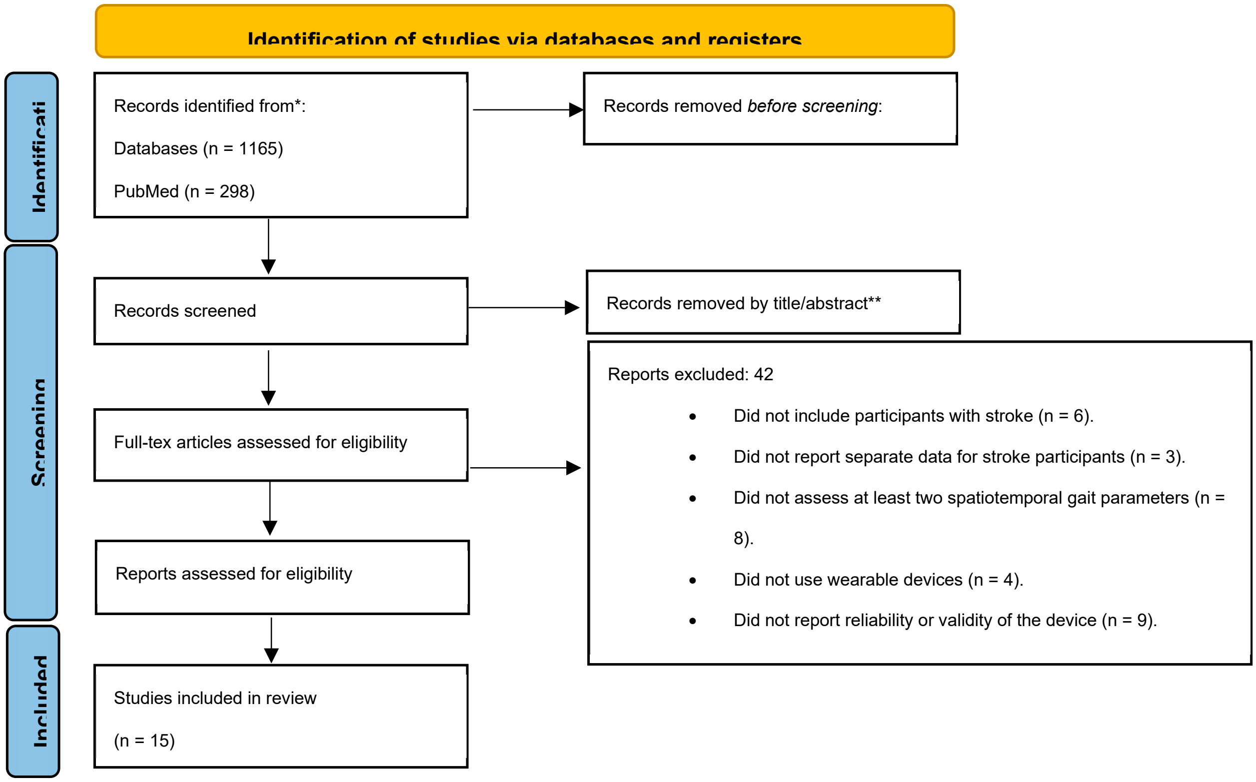

Figure 1. Flow chart outlining the study selection process following the PRISMA 2020 guidelines.

2.5. Data Extraction

Data extraction was independently performed by two reviewers (V.M.-P. and D.S.-G.). Any discrepancies were resolved through discussion or consultation with a third reviewer (D.B.). The extracted information included study characteristics (age, number of participants, sex, post stroke phase (time since stroke), gait speed, functional ambulation categories, paretic side, assistive device used), device characteristics (type of wearable, brand/model, number and placement of sensors, sampling frequency, software used), measurement conditions, reference standards employed (type, brand/model, placement, protocol) and spatiotemporal gait parameters assessed (minimum two per study, including walking speed, cadence, step and stride length, step and stride time, stance and swing time, double support, variability, asymmetry, and any additional parameters). For validity outcomes, extracted metrics included concurrent validity indexes related to the degree of relative

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[Intraclass correlation, coefficient (ICC), Pearson's r, etc.] or absolute agreement [Bland–Altman limits of agreements (LoA), standard deviation (SD), root mean square error (RMSE), mean absolute error (MAE), etc.] between instruments. For reliability studies, extracted outcomes included test–retest absolute [standard error of measurement (SEM), SD, coefficient of variation (CV), minimal detectable change (MDC), etc.] or relative indexes [ICC, Pearson's r, etc.].

2.6. Risk of Bias/Quality Assessment

The methodological quality and risk of bias of the included studies were independently assessed by two reviewers (V.M.-P. and D.S.-G.) using a modified version [35] of the Consensus-based Standards for the Selection of Health Measurement Instruments (COSMIN) risk-of-bias tool for observational studies [36]. Any disagreements were resolved through discussion or consultation with a third reviewer (D.B). For this review, the quality assessment comprised seven domains for concurrent validity studies and five domains for reliability studies. Each dimension was rated as excellent, good, fair, or poor quality; then, the overall methodological quality of each study was determined using the "worst-score-counts" principle, by which the lowest domain rating defined the final quality classification.

2.7. Data Synthesis

A narrative synthesis was conducted to summarize the psychometric properties of wearable devices for gait assessment. Validity and reliability outcomes were grouped by device type, number and placement of sensors, assessed spatiotemporal gait parameters and context of application.

To enhance comparability across studies assessing agreement between instruments in the concurrent validity, ± LoA at 95% was used as the primary common metric. When LoA were not explicitly reported, they were estimated from related agreement indices, including the RMSE and the MAE. Specifically, 95% LoA was calculated as ±1.96 × RMSE. When only MAE was available, a normal error distribution was assumed, such that MAE ≈ 0.8 × SD; consequently, 95% LoA was estimated as ±1.96 × (MAE / 0.8). ICC was considered as the primary metric for assessing concordance between instruments.

To enhance comparability across studies assessing absolute reliability, the MDC at the 95% confidence level (MDC_{95}) was used as the primary metric. The MDC is equivalent to the smallest detectable change (SDC) or the smallest detectable difference (SDD). When MDC values were not explicitly reported, they were derived from related agreement indices, specifically the SEM, using the formula $MDC_{95} = 1.96 \times \sqrt{2} \times SEM$. We chose to register and compute MDC from related outcomes as it accepted by researchers and clinicians to be a benchmark to distinguish between clinically relevant and irrelevant changes following therapeutic interventions or disease worsening [37]. ICC were used as the primary metric for assessing relative reliability. Predefined qualitative categorization for ICC was set at excellent (≥0.90), good (0.750–0.899), moderate (0.500–0.749) and poor (<0.500) [38].

3. Results

The full database created for the present systematic review is available in Supplementary material 2. The 15 studies included in this systematic review on spatiotemporal gait parameters measured with wearable inertial sensors comprised a total of 286 post-stroke participants, predominantly in the chronic phase. The mean age across studies ranged from 51.6 to 69.0 years. Participants' gait impairment showed marked heterogeneity, with reported gait speeds ranging from below 0.4 m/s to above 1.0 m/s. Hemiparesis distribution was reported in ten studies, with 92 participants presenting left-sided and 88 right-sided involvement. The use of assistive devices was documented in seven studies, with prevalence ranging from 13% to 83%.

Table 1. Characteristics of the participants included in the selected studies.

Authors (Year)	Age (years)	n	Sex	Post-stroke phase (time since stroke)	Gait speed (m/s)	FAC	Paretic side	Assistive device use (%)
Contreras et al., (2024)	52.3 ± 26.7	15	2 F 13 M	N/A	0.86 ± 0.17 m/s (without AD) 0.49 ± 0.18 m/s (with AD)	N/A	N/A	N/A
De Miguel-Fernández et al., (2023)	58.5 ± 10.9	6	2 F 4 M	Chronic (10.2 ± 11 years)	0.34–1.14 m/s	2–4	6 L	83.3% (Cane: 4, AFO: 3)
Desai et al., (2023)	51.6 ± 12.7	23	10 F 13 M	Chronic (97 ± 66 months)	0.40 ± 0.20 m/s	3–5	11 L 12 R	N/A
Ensink et al., (2023)	61 ± 11	10	3 F 7 M	N/A	Median 0.62 m/s (0.14–1.73 m/s)	3–5	4 L 6 R	N/A
Hendriks et al., (2022)	69 ± 9	11	5 F 6 M	N/A	0.73 ± 0.30 m/s (10MWT) 0.51 ± 0.16 m/s (spontaneous)	2–5	5 L 6 R	N/A
Huber et al., (2022)	63.1 ± 12.4	20	7 F 13 M	Chronic (76 months)	Median 1.34 m/s (IQR 0.77–1.47; range 0.38–1.77)	3–5	9 L 11 R	0%
Lefeber et al., (2019)	67	25	12 F 13 M	Subacute 84.4 ± 41.7 days	0.70 ± 0.22 m/s (paretic) 0.76 ± 0.23 m/s (non-paretic)	3-4	N/A	AD: 56% (Cane: 12%, Crutches: 16%, AFO: 4%, Rollator: 20%, Walker: 4%)
Lanotte et al., (2024)	62.3 ± 14.3	39	17 F 22 M	Acute-Subacute (17 ± 11.9 days)	0.03–2.00 m/s	N/A	16 L 23 R	N/A
Moore et al., (2017)	63 ± 11	23	4 F 19 M	Chronic (66 ± 48 months)	0.90 ± 0.40 m/s	N/A	N/A	Cane/other: 3 (13%), AFO Push Aequi: 4 (17%)
Naef et al., (2025)	63.9 ± 15.5	21	10 F 11 M	Subacute (5.19 ± 10.73 months)	>0.8 m/s (76.1%) 0.4–0.8 m/s (19.1%) <0.4 m/s (4.8%)	N/A	16 L 5 R	Rollator: 1 (4.76%), Dropped foot stimulator: 1 (4.76%), Foot orthoses: 3 (14.29%)
Punt et al., (2014)	61.8 ± 8.8	33	16 F 17 M	Chronic (5.6 ± 3.8 years)	0.88 m/s (mean 6MWT)	3–5	N/A	N/A
Revi et al., (2024)	61±12	8	8 M	Chronic (5.4 ± 2.5 years)	0.93 ± 0.33 m/s	N/A	4 L 4 R	N/A
Schwarz et al., (2023)	62	28	9 F 19 M	Chronic (63.71 months)	1.03 m/s (mean 10MWT)	N/A	15 L 13 R	AD: 9 (32%) AFO: 4 (14%)
Trojaniello et al., (2015)	58.6 ± 12.1	10	2 F 8 M	N/A	0.61 ± 0.24 m/s	2-5	N/A	6 (60%)
Wüest et al., (2016)	64.7 ± 9.2	14	2 F 12 M	N/A	0.57 ± 0.17 m/s	N/A	6 L 8 R	5 (35.7%)

Post stroke phases = Acute (1–7 days), Subacute (7 days–6 months), Chronic (>6 months); Age, time since stroke and gait speed data are presented as Mean ± SD (standard deviation); n = sample size; R = right hemisphere; L = left hemisphere; AD = assistive device; CVA = cerebrovascular accident (stroke); CA = community ambulators; HA = Household ambulators; AFO = ankle-foot orthosis; Rollator = four-wheeled walking aid; Walker = standard walking frame; FAC = Functional Ambulation Classification.

Table 2. Wearable characteristics and protocol design of the selected studies.

					Test-retest reliability			**Concurrent validity**		
Author (Year)	**Wearable**	**Sensor number and placement**	**Outcomes**	**Gait protocol**	**Time interval**	**Absolute indexes**	**Relative indexes**	**Reference instrument**	**Absolute indexes**	**Relative indexes**
Contreras et al., (2024)	One Stop	2 smartphones Anterolateral thighs.	Speed, cadence, step length, stride length, single stance time, swing time, double support	SGS 2MWT Treadmill				Optical motion system (Vicon Systems)	LoA	ICC
De Miguel-Fernández et al., (2023)	BNO055, Bosch	2 IMUs Shanks, near the ankle	Speed, stride time, stance time, swing time	SGS 5MWT Treadmill				Optical motion system	MAE,	$ICC_{A,1}$ $ICC_{C,1}$
Desai et al., (2023)	APDM Opal IMUs	3 sensors Secured at L3 and dorsal feet (bilateral, around each shoe)	Speed, stride length, stance time, double support	SGS 5MWT Treadmill	1 week	SEM MDC	ICC	Optical motion system (Vicon Systems)	LoA	CCC
Ensink et al., (2023)	MTw Awinda, Xsens	4 IMUs Dorsal feet, sternum, lower back (L4/5)	Speed, stride length, stride time	SGS 2MWT Treadmill				Optical motion system (Vicon Systems)	SD	
Hendriks et al., (2022)	Shimmer®3 IMUs	2 Sensors Bilateral lateral malleolus (ankles)	Cadence, stride length	SGS 4 trials 10-m walkway				Video camera		Pearson's r
Huber et al., (2022)	Garmin Forerunner 35	1 sensor Non-dominant wrist; ankle (sensor placement ambiguous)	Cadence, step length	SGS Outdoor test 1-km track	Within-Session 2 trials	SDC	$ICC_{3,k}$			
Lanotte et al., (2024)	Bionic Pro and SageMotion	2 IMUs on left and right lower legs (shanks)	Step time, single stance time, swing time, double support	SGS, FGS 6 trials 10-m walkway				Electronic walkway (GaitRite)	LoA	ICC
Lefeber et al., (2019)	Physilog4 Silver 10D	2 Sensors Dorsal shoe, 1 sensor per foot	Speed, cadence, stride length, stride time, stance time, swing time, double support	SGS 10 trials	Within-session 20 minutes	SEM SDC	$ICC_{3,1}$	Optical motion system (Vicon Systems)	LoA	$ICC_{3,1}$

				12-m walkway						
Moore et al., (2017)	AX3, Axivity	1 Sensor L5	Step length, step time, stance time, swing time	SGS 2MWT 25-m track	1 week	LoA	ICC	Electronic walkway (GaitRite)	LoA	ICC
Naef et al., (2025)	Physilog 5	2 Sensors One sensor per shoe, over the shoelaces	Speed, cadence, stride length	FGS 4 trials 10-m walkway	Within-session Supervised vs non-supervised	SD	$ICC_{A,1}$ $ICC_{C,1}$ $ICC_{2,1}$			
Punt et al., (2014)	FESTA	1 Sensor Around posterior waist, between posterior superior iliac spines	Cadence, step length	3-GS 2MWT Treadmill	2 days - 2 weeks	SEM, MDC95	$ICC_{3,1}$	Video camera	MRRSE (%)	$ICC_{3,1}$
Revi et al., (2021)	MTw Awinda, Xsens	2 IMUs One IMU per thigh.	Speed, stride time, stride length	SGS 6MWT 26.6-m track				Optical motion system (Qualisys system)	MAE RMSE	$ICC_{2,1}$
Schwarz et al., (2023)	Xsens MVN awinda	17 sensors	Speed, step length, swing time, stance time	SGS 6 trials 10-m walkway 6MWT	Within-session 30 minutes	SEM, MDC95	$ICC_{2,1}$			
Trojaniello et al., (2015)	OpalTM, APDM	1 sensor Lumbar, L4–S2.	Step time, stride time, stance time, swing time	SGS 1MWT 12-m walkway				Electronic walkway (GaitRite)	MAE MAE%	
Wüest et al., (2016)	Physilog	8 sensors each wrist, each shank, trunk, each foot, lumbar 3	Speed, cadence, stride length	FGS 3 trials mTUG 7-m distance	Within-session 15 minutes	SEM SDD, LoA	$ICC_{1,k}$			

1MWT: 1-minute walking test; 2MWT: 2-minute walking test; 5MWT: 5-minute walking test; 6MWT: 6-minute walking test; mTUG: modified timed up & go test; CV: Coefficient of variation; MD: Mean difference; MAE: Mean absolute error; MRRSE: Mean relative root square error; RMSE: Root Mean Square Error; ICC: Intraclass correlation coefficient; CCC: Lin's concordance correlation coefficients; SGS: Self-selected gait speed; FGS: Fast gait speed; 3-GS: three gait speeds; SEM: Standard Error of Measurement; SDC: smallest detectable change; MDC: minimal detectable change; SDD: smallest detectable difference; LoA: limits of agreement

Across the 15 included studies, 11 assessed validity [26,38–47], 8 of them evaluated reliability [32,38,39,42,47–50]. Out of these, there were 4 examined that examined both measurement properties [38,39,42,47]. The most frequently reported spatiotemporal parameters were spatial variables [i.e., walking speed (9), stride length (9), cadence (7) and step length (5)] followed by temporal parameters [i.e., stance time (7), swing time (6), stride time (5) and step time (3)) and support-related metrics, particularly double support time (4)].

Most studies compared wearable-derived outcomes against reference instruments, primarily optical motion capture systems or instrumented walkways, while a smaller number employed video-based analyses. Walking protocols varied and included the 10-meter, 1-minute, 2-minute, 5-minute, and 6-minute walking tests and walkway and treadmill walking. One study calculated the spatial-temporal gait parameters from the modified Timed Up and Go tests. Assessments were conducted under self-selected gait speed in most of the cases (n=13). Sensor placement depended on the number of units used. There were single-sensor configurations located at the waist or L4-L5 (n=4), 2-sensor configurations placed on the lower limb (n=6) and multi-sensor systems (3 to 17 sensors) distributed across the feet, shanks, thighs, trunk, and lumbar region.

Validity

Overall, several studies were classified as having fair or poor overall quality as a result of applying the worst-score-counts principle, despite reporting acceptable validity outcomes. Most studies obtained good to excellent ratings in domains related to the description of the gold standard and the statistical indices used for the validation analysis. Conversely, sample size adequacy and handling of missing data were the most frequent methodological shortcomings, often rated as fair or poor. A full risk of bias analysis can be found in supplementary material 3.

Absolute (Table 3) and relative (Table 4) agreement analyses demonstrated good to excellent agreement between wearable sensor–based systems and reference instruments for gait speed, cadence, step length and stride length. When comfortable speed was assessed, LoA% values below 20% were observed in 88.0% of cases (22/25), while ICC values exceeded 0.75 in 91.1% (31/34) and 0.90 in 76.5% (26/34) of the reported outcomes. LoA range from 0.05–0.15 $m \cdot s^{-1}$ for gait speed, 1–3 $steps \cdot min^{-1}$ for cadence, and 0.05–0.08 m for stride length. Lower agreement scores were observed in the study by Punt et al. [39], who showed that error between instruments increased (LoA%: 11.4-17.8%) when participants walked at a slower pace than the regular and faster speed (LoA%: 6.7-21.1%) for cadence and step length while ICC was similar. The study by Contreras et al. [40] also showed that walking with an assistive device reduced relative agreement (ICC: 0.64–0.76) and increased measurement error (LoA%: 20.7–40.3%) compared with walking without an assistive device (ICC: 0.88–0.92; LoA%: 14.4–23.0%) for gait speed, step length and stride length, swing time and double support duration percentage.

Temporal gait parameters showed lower agreement. Only 20% of cases (4/20) showed absolute errors below 100 ms, while LoA% values exceeded 20% in 60.9% of cases (14/23). Relative validity was also reduced, with ICC values below 0.75 in 47.8% of cases (11/23).

When validity outcomes were stratified by limb side, spatiotemporal parameters derived from the paretic limb showed larger measurement error than those obtained from the non-paretic side. Across four studies, LoA for stride length on the paretic limb ranged from 9–17 cm, whereas values for the non-paretic limb were consistently lower, typically ranging from 4–9 cm. For temporal parameters, absolute errors on the paretic side ranged between 80 and 330 ms, compared with 40–230 ms on the non-paretic side. In terms of relative agreement, all spatiotemporal parameters derived from the non-paretic limb showed good to excellent agreement with reference instruments except in Lefeber et al. [42] for swing and stance time (ICC=0.63). In contrast, paretic-side measures showed greater variability, reaching ICC values above 0.75 in 69.2% of outcomes (9/13).

Regarding the number of sensors, no clear differences were observed between the LoA shown by single sensors placed on the lower back and sensor-based systems placed on the lower limb.

Table 3. Limits of agreement between the inertial sensor device and the gold standard instrument in raw (original units) and relative to the mean (%) units.

Authors (Year)	Conditions	Speed (m/s)	Cadence (step/min)	Step Length (m)	Stride Length (m)	Step Time (s)	Stride Time (s)	Stance Time (s)	Swing Time (s)	Double Support (%)
1 SENSOR										
Punt et al. (2014) – 2MWT (Treadmill)										
FESTA	*CS-15%*		10.23 (11.4%)	0.08 (17.8%)						
	CS		6.45 (6.9%)	0.06 (12.1%)						
	CS+15%		6.49 (6.7%)	0.05 (10.4%)						
Moore et al., (2017) – 2MWT (25-m track)										
AX3		0.05 (-----)		0.30 (-----)		0.21 (-----)		0.06 (-----)	0.21 (-----)	
Trojaniello et al., (2015) – 1MWT (12-m walkway)										
OpalTM, APDM	*Paretic side*				0.17 (12.52%)	0.22 (32.91%)		0.33 (34.66%)	0.32 (78.88%)	
	Non-paretic side				0.06 (4.72%)	0.22 (32.54%)		0.23 (24.50%)	0.23 (56.35%)	
2 SENSORS										
Contreras et al. (2024) – 2MWT (Treadmill)										
One Stop	*with AD*	0.23 (40.3%)	1.56 (1.9%)	0.19 (46.4%)	0.31 (37.3%)				----- (20.7%)	11.2 (30.2%)
	without AD	0.15 (16.3%)	1.89 (1.8%)	0.10 (23.6%)	0.15 (14.4%)				----- (12.2%)	6.9 (23.0%)
De Miguel-Fernández et al., (2023) – 5MWT (Treadmill)										
BNO055, Bosch	*Paretic side*	0.17 (6.7%)			0.09 (19.0%)		0.10 (5.9%)	----- (9.2%)	----- (20.7%)	
	Non-paretic side				0.09 (18.3%)		0.04 (2.3%)	----- (9.2%)	----- (27.9%)	
Lefeber et al. (2019) – 10 trials (12-m walkway)										
Physilog4, S. 10D	*Paretic side*	0.10 (14.0%)	3.21 (3.4%)		0.12 (12.3%)			0.08 (9.1%)	0.08 (15.1%)	10.5 (32.7%)
	Non-paretic side	0.05 (6.7%)	2.82 (3.0%)		0.04 (4.8%)			0.19 (19.8%)	0.19 (42.2%)	15.4 (47.3%)
Lanotte et al., (2024) – 6 trials (10-m walkway)										
Bionic Pro						0.36 (------)	0.40 (------)	0.52 (------)	0.45 (------)	0.70 (-----)*
Revi et al. (2021) – 6MWT (26.6-m track)										
MTw Awinda	*Paretic side*	0.08 (-----)			0.10 (-----)					
	Non-paretic side	0.06 (-----)			0.07 (-----)					
≥ 3 SENSORS										
Ensink et al., (2023) – 2MWT (Treadmill)										
MTw Awinda (4 sen.)		0.06 (9.5%)			0.12 (15.1%)		0.08 (5.5%)			

ICC decimal digits have been rounded to two digits. For temporal parameters, ICC values are presented in non-italics or italics when the original units were raw (s) or standardized to the stride time (%).
*LoA calculated the absolute time (s); CS = *Comfortable Speed; AD = Assistive device*; 1MWT: 1-minute walking test; 2MWT: 2-minute walking test; 5MWT: 5-minute walking test; 6MWT: 6-minute walking test.

Table 4. Relative agreement between the inertial sensor device and the gold standard instrument assessed through the Intraclass Correlation Coefficient (ICC).

Authors (Year)	**Conditions**	**Speed (m/s)**	**Cadence (step/min)**	**Step Length (m)**	**Stride Length (m)**	**Step Time (s)**	**Stride Time (s)**	**Stance Time (s)**	**Swing Time (s)**	**Double Support (%)**
1 SENSOR										
Punt et al. (2014) – 2MWT (Treadmill)										
FESTA	*CS-15%*		0.84	0.96						
	CS		0.91	0.96						
	CS+15%		0.96	0.97						
Moore et al., (2017) – 2MWT (25-m track)										
AX3		0.74		-0.41		0.80		0.76	0.43	
2 SENSORS										
Contreras et al. (2024) – 2MWT (Treadmill)										
One Stop	*with AD*	0.76	0.99	0.64	0.69				$0.84^{\$}$	0.44
	without AD	0.91	0.99	0.88	0.92				$0.62^{\$}$	0.68
De Miguel-Fernández et al., (2023) – 5MWT (Treadmill)										
BNO055, Bosch	*Paretic side*	0.94			0.98		0.95	$0.64^{\$}$	$0.67^{\$}$	
	Non-paretic side				0.99		0.99	$0.80^{\$}$	$0.80^{\$}$	
Hendriks et al. (2022) – 4 trials (10-m walkway)										
Shimmer®3		0.93*			0.81*					
Lefeber et al. (2019) – 10 trials (12-m walkway)										
Physilog4, S. 10D	*Paretic side*		0.99		0.96			0.67	0.97	0.88
	Non-paretic side		0.99		0.99			0.63	0.63	0.77
Lanotte et al., (2024) – 6 trials (10-m walkway)										
Bionic Pro						0.95	0.98	0.96	0.41	0.90***
Revi et al. (2021) – 6MWT (26.6-m track)										
MTw Awinda	*Paretic side*	0.99			0.99					

	Non-paretic side	0.99	0.99		
			≥ 3 SENSORS		
Desai et al. (2023) – 5MWT (Treadmill)					
APDM Opal	*Paretic side*	0.96**	0.93**	0.56$^{\$**}$	0.66**
	Non-paretic side		0.96**	0.75$^{\$**}$	

ICC decimal digits have been rounded to two digits.

For temporal parameters, ICC values are presented in non-italics or italics when the original units were raw (s) or standardized to the stride time (%).

*Pearson's correlation; **Lin's concordance correlation coefficients; *ICC calculated the absolute time (s); $^{\$}$Agreement indexes were calculated from the gait temporal outcomes in percentage of the gait cycle; 2MWT: 2-minute walking test; 5MWT: 5-minute walking test; 6MWT: 6-minute walking test; TUG: Timed up & go.

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Reliability

Overall, applying the worst-score-counts principle led several studies to be classified as having fair or poor overall quality due to the low sample sizes and poor handling of the missing data. All studies correctly calculated the ICC as the main reliability index. The full risk of bias analysis can be found in the supplementary material 3.

Absolute (Table 5) and relative reliability (Table 6) analyses showed good to excellent test–retest reliability for gait speed, cadence, step length and stride length across most of the wearable sensor–based systems. For these parameters, absolute measurement error, MDC% values fell below 20% in 73.3% of the cases (22/30), while ICC values exceeded 0.75 in 93.9% (31/33) and 0.90 in 81.8% (27/33) of the reported outcomes. Multi-sensor systems (≥ 3 sensors) showed good absolute reliability scores with MDC ranging from 0.01–0.08 $m \cdot s^{-1}$ for gait speed, and from 0.01–0.06 m for step/stride length, apart from the study by Schwarz et al. [32] conducted in short walking trials. Single or two sensor systems showed higher MDC ranging from 0.13–0.32 $m \cdot s^{-1}$ for gait speed, and from 0.02–0.31 m for step/stride length. Relative reliability analyses showed that ICC scores were similar independently of the number of sensors.

Temporal gait parameters showed poorer reliability values. Only 40.0% of cases (6/15) showed absolute errors below 100 ms, while LoA% exceeded 20% in 52.4% of cases (11/21). Conversely, relative reliability was good to excellent, with ICC values above 0.75 in 76.9% of cases (20/26).

When reliability outcomes were stratified by limb side, the studies that performed side-specific analyses did not report consistent differences between the paretic (ICC: 0.55-0.99; LoA%: 5.7-42.0%) and non-paretic limbs (ICC: 0.55-0.99; LoA%: 5.6-50.8%).

Table 5. Absolute test-retest reliability assessed through the minimal detectable change in original units and relative to the mean (%).

Author (Year)	Conditions	Speed (m/s)	Cadence (step/min)	Step Length (m)	Stride Length (m)	Step Time (s)	Stride Time (s)	Stance Time (s)	Swing Time (s)	Double Support (%)
1 SENSOR										
Huber et al. (2022) – Outdoor test (1-km track)										
Garmin Fore. 35	*All participants*		2.0 (1.7%)	0.05 (12.6%)						
	Walking ≥ 1 m/s		2.6 (2.2%)	0.02 (5.2%)						
Moore et al. (2017) – 2MWT (25-m track)										
AX3		0.32 (29.6%)		0.31 (48.5%)		0.28 (48.3%)		0.33 (44.5%)	0.26 (53.5%)	
Punt et al. (2014) – 2MWT (Treadmill)										
FESTA	*CS -15%*		9.53 (10.5%)	0.14 (33.3%)						
	CS		9.40 (10.0%)	0.10 (20.8%)						
	CS+15%		7.60 (7.9%)	0.10 (19.2%)						
2 SENSORS										
Lefeber et al. (2019) – 10 trials (12-m walkway)										
Physilog4 S. 10D	*Paretic side*	0.168 (21.9%)	9.82 (10.5%)		0.16 (17.2%)			0.11 (13.4%)	0.11 (21.8%)	12.04 (41.0%)
	Non-paretic side	0.130 (18.3%)	9.39 (10.2%)		0.10 (11.6%)			0.09 (9.3%)	0.09 (19.0%)	10.66 (34.9%)
Naef et al. (2025) () – 4 trials (10-m walkway) *										
Physilog 5		0.27 (-----)	16.62 (-----)		0.24 (-----)					
≥ 3 SENSORS										
Desai et al. (2023) – 5MWT (Treadmill)										
APDM Opal	*Paretic side*	<0.01 (0.8%)			0.03 (4.9%)			---- (1.8%)		1.33 (3.6%)
(3 sen.)	*Non-paretic*				0.02 (3.8%)			---- (0.8%)		
Schwarz et al. (2023) – 6 trials (10-m walkway)										
MTw Awinda	*Paretic side*	0.58 (48.9%)		0.19 (29.5%)				0.28 (42.0%)	0.17 (34.6%)	
(17 sen.)	*Non-paretic side*			0.22 (34.9%)				0.36 (50.8%)	0.14 (32.2%)	

Schwarz et al. (2023) – 6MWT (predefined walkway)										
MTw Awinda (17 sen.)	*Paretic side*	0.08 (7.5%)		0.06 (10.0%)				0.05 (5.7%)	0.03 (5.7%)	
	Non-paretic side			0.04 (6.9%)				0.05 (5.6%)	0.03 (6.3%)	
Wüest et al. (2016) – 3 trials TUG (7-m walking distance)										
Physilog (8 sen.)		0.02 (2.13%)	1.34 (1.42%)		0.01 (1.29%)			---- (1.44%)		

CS: Comfortable Speed; -----: MDC values could not be calculated from the original data for Stance Time.

*Naef et al.'s reliability analyses were carried out comparing Supervised Versus Unsupervised Tests; 2MWT: 2-minute walking test; 5MWT: 5-minute walking test; 6MWT: 6-minute walking test; TUG: Timed up & go.

Table 6. Relative test-retest reliability measured through the Intraclass Correlation Coefficient (ICC).

Author (Year)	**Conditions**	**Speed (m/s)**	**Cadence (step/min)**	**Step Length (m)**	**Stride Length (m)**	**Step Time (s)**	**Stride Time (s)**	**Stance Time (s)**	**Swing Time (s)**	**Double Support (%)**
1 SENSOR										
Huber et al. (2022) – Outdoor test (1-km track)										
Garmin Forerunner 35	*All participants*		0.98	0.98						
	Walking ≥ 1 m/s		0.97	0.95						
Moore et al. (2017) – 2MWT (25-m track)										
	AX3	0.53		0.42		0.84		0.82	0.86	
Punt et al. (2014) – 2 MWT (Treadmill)										
FESTA	*CS-15%*		0.94	0.88						
	CS		0.95	0.94						
	CS+15%		0.97	0.94						
2 SENSORS										
Lefeber et al. (2019) – 10 trials (12-m walkway)										
Physilog4 Silver 10D 35	*Paretic side*	0.95	0.96		0.94		0.98	0.55	0.55	0.82
	Non-paretic side	0.97	0.97		0.98		0.98	0.93	0.93	0.92
Naef et al. (2025) – 4 trials (10-m walkway) *										
Physilog 5		0.90	0.88		0.88					
≥ 3 SENSORS										
Desai et al. (2023) – 5MWT (Treadmill)										
APDM Opal (3 sensors)	*Paretic side*	0.99			0.99			0.96		0.99
	Non-paretic side				0.99			0.99		
Schwarz et al., (2023) – 6 trials (10-m walkway)										

MTw Awinda, Xsens (17 sensors)	*Paretic side*	0.84		0.88				0.67	0.60	
	Non-paretic side			0.87				0.64	0.46	
Schwarz et al., (2023) – 6MWT (predefined walkway)										
MTw Awinda, Xsens (17 sensors)	*Paretic side*	0.99		0.98				0.98	0.99	
	Non-paretic side			0.99				0.99	0.95	
Wüest et al. (2016) – 3 trials TUG (7-m walking distance)										
Physilog (8 sensors)		0.98	0.98		0.99			0.96		

CS: Comfortable Speed; ICC decimal digits have been rounded to two digits.; *Naef et al.'s reliability analyses compare Supervised Versus Unsupervised Tests; 2MWT: 2-minute walking test; 5MWT: 5-minute walking test; 6MWT: 6-minute walking test; TUG: Timed up & go.

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4. Discussion

The results of this systematic review indicate that the performance of wearable inertial sensor systems for quantifying spatiotemporal gait parameters in the post-stroke population is heterogeneous and clearly depends on the type of parameter analyzed. Overall, spatial parameters showed generally good validity and reliability, whereas temporal parameters exhibited a more limited performance. Gait disturbance caused by the affected side (i.e., paretic side) also limited the ability of the wearable system to accurately determine spatiotemporal gait parameters compared to the reference systems but not the reliability of the results. The number of sensors didn't seem to determine the accuracy of the wearable system compared to the reference system, but it limited the test-retest reliability.

Our main results showed that gait speed, cadence, and step and stride lengths consistently emerged as the most robust indicator, showing the lowest absolute errors and the highest levels of agreement with the reference systems [26,38–47] as well as the best reliability scores [32,38,39,42,47–50]. In contrast, temporal parameters showed larger error discrepancies and test-retest variability. Although this pattern observed in the post-stroke population was largely consistent with findings reported in meta-analyses of healthy adults [33] and older adults [51], our results showed slightly poorer relative agreement and relative reliability in the temporal parameters. Based on ICC/r comparison, gait speed, cadence and step and stride length were the most robustly estimated parameters, showing a relative agreement and reliability in post-stroke populations (ICC/r ≈ 0.75–0.95) comparable with the agreement observed in older adults (ICC/r ≈ 0.80–0.95) and in healthy adults (ICC/r ≈ 0.85–0.99). The strength of the association between wearable-based measures and reference systems, together with their high test–retest consistency, supports the use of the wearable systems included in this review as valid tools to rank/classify stroke patients according to their level of impairment in these gait parameters [52]. Furthermore, the absolute reliability analyses based on the MDC estimates indicate that changes exceeding approximately 0.2 $m \cdot s^{-1}$ in gait speed, 9 $steps \cdot min^{-1}$ in cadence and 16 cm in step or stride length, as detected by most wearable systems, can be interpreted at the individual level as true changes in patient status, rather than as consequences of measurement error or normal biological variability [52,53].

Temporal parameters exhibited a more heterogeneous behavior compared to spatial parameters. Discrepancies between wearable-based and reference systems, as well as absolute test–retest reliability, frequently exceeded the LoA and MDC values of 100 ms, or 20%, particularly for stance and swing time. The fact that stride and step time showed better validity and reliability scores may be related to fact that they only require detecting the initial contact for their calculations, while it is necessary to detect the final contact for stance and swing time [42]. Although the estimation of temporal parameters by wearable devices in stroke patients seems compromised, relative reliability showed good to excellent ICC scores (ICC/r ≈ 0.80–0.99) for stride and step time, and moderate to excellent ICC scores (ICC/r ≈ 0.80–0.99) for most stance time and most of the swing time estimations (ICC/r ≈ 0.56–0.99). These results are comparable with those observed in both healthy adults and older adults [33,51] for stride, step, stance time and swing time (ICC/r ≈ 0.81–0.99). From the authors' perspective, the observation of high relative reliability (i.e., high ICC values), despite the large absolute test–retest error (i.e., high MDC), may be explained by the fact that ICC estimates depend on the ratio between-subject and within-subject variability [54]. In this context, stroke patients may exhibit a marked heterogeneity in gait performance across individuals (high between-subject variability), which can yield high ICC values even when the test-retest consistency within individuals is relatively low. These findings suggest that, for temporal gait parameters, between-subject variability associated with differing levels of disability outweighs within-subject variability, thereby increasing relative reliability estimates. Consequently, although absolute measurement error remains substantial, wearable-based assessments of temporal parameters may still be considered sufficiently reliable to rank or classify individuals and to monitor group-level trends in post-stroke populations.

Conversely, the high absolute test-rest fluctuations suggest that detecting small individual-level changes in temporal parameters can be challenging.

The lower absolute agreement and reliability observed in our review, particularly for temporal gait parameters, may be partly attributable to limitations of gait event–detection algorithms when applied to individuals with pronounced biomechanical alterations [54], such as those commonly observed after a stroke [55]. Supporting this interpretation, Punt et al. [39] reported that wearable devices exhibited larger measurement errors at slower walking speeds, while Contreras et al. [40] observed increased errors when gait was assessed under assisted walking conditions. Taken together, these findings suggest that deviations from regular gait biomechanics, whether due to reduced speed, especially at low walking speeds of 0.4 m/s [56], to asymmetry [57] or to the use of assistive devices, compromise the ability of wearable-based algorithms to accurately identify gait events. Comparison between paretic and non-paretic limb seem to support this idea. Both spatial and temporal gait parameters showed reduced concurrent validity of the wearable device on the paretic side compared to the non-paretic side. These differences are likely caused by post-stroke biomechanical alterations, including slower, more rigid gait, asymmetric swing-to-stance ratios and reduced dorsiflexion observed mainly in the paretic limb [58]. It must be noted that, despite the lower absolute agreement between the wearable and reference system on the paretic side, test–retest reliability remained similar between limbs. While Lefeber et al. [42] found lower test-retest consistency for the paretic limb, Schwarz et al. [32] found the opposite results.

Finally, owing to the limited number of available studies, this review was unable to elucidate the potential influence of sensor numbers on the accuracy of temporal gait parameters in post-stroke populations. In contrast, the larger body of evidence evaluating the reliability of multi-sensor wearable systems (≥ 3 sensors) assessing gait speed and step and stride length suggests that they might present an enhanced ability to detect subtle changes in the stroke patient’s gait status in those parameters. Based on the findings by Desai et al. [47], Schwarz et al. [32] and Wüest et al. [50] findings, small changes in gait speed (>0.08 $m \cdot s^{-1}$) and step or stride length (>6 cm) may be interpreted as clinically relevant when assessed using multi-sensor wearable configurations. Conversely, based on the single- or dual-sensor system reliability findings [38,48,49], larger changes (ranging from 0.13 to 0.32 $m \cdot s^{-1}$ for gait speed and from 0.02 to 0.31 m for step or stride length depending on the sensor system) would be required to ensure that the observed differences reflect the true change in stroke gait status rather than day-to-day variability.

4.1. Limitations and Future Research

This systematic review has several limitations that should be considered when interpreting its findings. The included studies were characterized by small sample sizes, heterogeneous walking protocols and variability in sensor placement and algorithms, which limit generalizability. Moreover, few of the studies explicitly examined the influence of patient-specific factors, such as motor impairment severity, gait asymmetry and walking speed on wearable system performance. In addition, this review did not address the impact the algorithm selection had on the reliability of the gait event detection (e.g., initial contact, toe-off, etc.) which are precursors to spatiotemporal outcomes. Future research should address all these voids by clarifying their impact on the validity, reliability, and responsiveness of inertial sensor–based gait measures. In addition, longitudinal and real-world studies (including evaluations of responsiveness to clinical interventions and investigations into the minimum sensor configurations required for accurate parameter estimation), are needed to enhance the clinical and translational relevance of wearable gait assessment technologies.

5. Conclusions

Wearable inertial sensor systems provide valid and reliable measurements of post-stroke gait parameters, particularly for spatial metrics. Temporal parameters remain more susceptible to measurement error, especially on the paretic side when compared with reference systems; however,

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test–retest reliability was comparable between limbs. Finally, this review was unable to determine whether sensor quantity alone influences measurement accuracy relative to reference systems, although multi-sensor wearable configurations appear to yield more stable test–retest gait assessments.

Supplementary Materials: The following supporting information can be downloaded at website of this paper posted on Preprints.org.

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Abbreviations

The following abbreviations are used in this manuscript:

ICC	Intraclass correlation coefficient
LoA	Bland–Altman limits of agreement
SD	Standard deviation
RMSE	Root mean square error
MAE	Mean absolute error
SEM	Standard error of measurement
CV	Coefficient of variation
MDC	Minimal detectable change

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