Review Article

Gait metrics analysis utilizing single-point inertial measurement units: a systematic review

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Background: Wearable sensors, particularly accelerometers alone or combined with gyroscopes and magnetometers in an inertial measurement unit (IMU), are a logical alternative for gait analysis. While issues with intrusive and complex sensor placement limit practicality of multi-point IMU systems, single-point IMUs could potentially maximize patient compliance and allow inconspicuous monitoring in daily-living. Therefore, this review aimed to examine the validity of single-point IMUs for gait metrics analysis and identify studies employing them for clinical applications.

Methods: The Preferred Reporting Items for Systematic Reviews and Meta-Analyses Guidelines (PRISMA) were followed utilizing the following databases: PubMed; MEDLINE; EMBASE and Cochrane. Four databases were systematically searched to obtain relevant journal articles focusing on the measurement of gait metrics using single-point IMU sensors.

Results: A total of 90 articles were selected for inclusion. Critical analysis of studies was conducted, and data collected included: sensor type(s); sensor placement; study aim(s); study conclusion(s); gait metrics and methods; and clinical application. Validation research primarily focuses on lower trunk sensors in healthy cohorts. Clinical applications focus on diagnosis and severity assessment, rehabilitation and intervention efficacy and delineating pathological subjects from healthy controls.

Discussion: This review has demonstrated the validity of single-point IMUs for gait metrics analysis and their ability to assist in clinical scenarios. Further validation for continuous monitoring in daily living scenarios and performance in pathological cohorts is required before commercial and clinical uptake can be expected.

Keywords: Accelerometry; gait analysis; wearable electronic devices

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Introduction

Human gait is affected by ageing as well as numerous musculoskeletal and neurological ailments. Consequently, gait analysis has wide-ranging clinical applications from diagnosis and severity assessment as well as evaluation of intervention and rehabilitation efficacy in neurological and

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orthopedic conditions (1-8) to identifying falls risk and frailty status (9,10). Qualitative and subjective measures generally constitute routine clinical gait analysis, with patient self-reporting and clinician observation sometimes integrated with clinical tests such as the Timed-Up-And-Go and 6-minute walking test (6MWT) (11). These approaches impose significant interobserver inaccuracies and deny appreciation of kinematic and kinetic intricacies that can be obtained from quantitative gait assessment (12).

The gold-standard for quantitative gait analysis, optoelectronic stereophotogrammetry, features infrared cameras that capture three-dimensional trajectories of reflective markers placed on the subject that are processed to accurately assess spatio-temporal and kinematic variables of gait (13). Stereophotogrammetry is often combined with force plates that measure ground-reaction forces (GRF) to determine kinetic forces and electromyography (EMG) systems to measure muscle activity during gait. However, these systems are expensive, time-consuming, and require expert operation and equipment. Furthermore, restriction of their performance to dedicated laboratory settings limits portability, access and external validity of measures obtained to free-living gait (11).

In response, wearable sensors (goniometers, EMG systems, sensing fabric etc.), particularly accelerometers alone or combined with gyroscopes and magnetometers in an inertial measurement unit (IMU), are proving to be the logical alternative for gait analysis. Cheap, small and portable, wearables could potentially enable continuous gait metrics analysis in daily living (14-17). Furthermore, fast preparation and processing negate the need for expert operation, enhancing practicality. Multi-point IMU systems have been validated against standards (18-23) and employed clinically for gait metrics analysis (24-28); however, issues with intrusiveness and consistency of complex sensor placement limit real-life adoption (29). Although not as accurate and reliable as multi-point IMU systems (30), single-point IMUs have nonetheless demonstrated enormous potential. They have clinical uses, such as with the assessment of Parkinson's Disease (PD) severity (31,32) and the evaluation of falls risk in preventative health care (33,34), and personal uses, such as with the tallying of daily steps in consumer-grade watches (4,35). Commonly used single-point IMUs and their specifications are detailed for comparison in *Table 1*.

Moreover, presuming validated accuracy is demonstrated, single-point IMUs could potentially maximize patient compliance and comfort and allow inconspicuous monitoring in daily-living. Consequently, any future mass uptake of IMUs in clinical and commercial settings is likely to be dependent upon the validation and applications of single-point IMUs and not of multi-point IMU systems. Therefore, this review will provide a synopsis of inertial sensor principles, practical considerations and gait metrics analysis capabilities before examining the validity and clinical applications of single-point devices for gait analysis. We present the article in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Guidelines (PRISMA) checklist (available at https://dx.doi.org/10.21037/mhealth-21-17).

Inertial sensors: principles and practical considerations

Inertial sensors, accelerometers and gyroscopes, are often fabricated into microelectromechanical systems (MEMS) alone or together as an IMU and employed for gait metrics analysis (78).

Accelerometers measure acceleration along their sensitive axis, ranging from uni-axial to the commonly employed tri-axial sensitivity which allows appreciation of movement along the antero-posterior, horizontal and vertical planes. However, current devices are susceptible to drift errors due to change in mechanical or electrical properties and noise from amplified mechanical motions. Furthermore, the measured acceleration comprises both the inertial acceleration associated with changes in velocity, and gravitational acceleration superimposed along the accelerometer's sensitive axes. Removing this confounding effect of gravity can be difficult (78). To appreciate velocity and distance, numerical integration of acceleration data is required, causing noise and drift errors to accumulate, imposing significant limitations on long-term accelerometer employment. Without compensation for this drift, readings become useless. Compensation requires frequent accelerometer recalibration, achieved through zero-velocity updates (ZUPT), using an external event indicating an instantaneous null in movement such as a footstep (79).

Gyroscopes measure angular velocity, demonstrating greater accuracy than accelerometers as measurement is absolute with no external information considered (80). However, gyroscopes only return rate of change of angular position; to detect relative orientation, integration of the signal is required. This leads to accumulation of drift errors and noise, similar to accelerometers (80). Furthermore, lack of an initial reference compared to accelerometers means gyroscopes cannot be recalibrated, resulting in accumulation of errors and limited long-term

Table 1 Common single-point IMUs and their specifications

References	Sensor	Placement	Gait metrics demonstrated to be captured	Component MEMS sensors	Other known specifications
(31,36-40)	Locometrix	Lower back, L3–4	GV and stride frequency, length, symmetry and regularity	Tri-axial accelerometer	100 Hz frequency of data capture, resolution 0.001 g
(41-45)	MT product line IMUs (Xsens, Enschede, The Netherlands)	Lower back, L4	MTx was able to capture GV, cadence, step regularity, stride regularity, gait symmetry, step time, step time variability, RMS and HR	Tri-axial accelerometer, gyroscope, and magnetometer	According to MTi (newer than MTx) specifications: Output frequency up to 2 kHz. Accelerometer range 16 g. Gyroscope range 2,000 deg/s. 12.1×12.1×2.55 mm^3 (without encasing). 0.6 grams (without encasing)
(46,47)	Pi-node (Philips, The Netherlands)	Lower back, L4	GV, step time, step time variability, cadence, stride length, stride length variability and non-linear measures (gait variability and symmetry)	Tri-axial accelerometer	100 Hz frequency of data capture
(48-59)	DynaPort IMUs (McRoberts, The Hague, The Netherlands)	Lower back	Step count, GV, stride time variability, stride regularity and cadence	Tri-axial accelerometer, and gyroscope	100 Hz frequency of data capture. 106.6×58×11.5 mm^3. 55 grams. 14-day maximum measurement duration
(60-64)	G-walk (BTS Bioengineering Milan, Italy)	Lower back, L5	GV, SL, stride length and cadence. Gait cycle duration, stance duration, swing duration and double support duration	Tri-axial accelerometer, gyroscope, and magnetometer	Accelerometer range 2, 4, 8, or 16 g (configurable). Gyroscope range 250, 500, 1,000, or 2,000 deg/s (configurable). Magnetometer range ±1,200 uT. Accelerometer sampling rate 4–1,000 Hz (configurable). Gyroscope sampling rate 4 to 8,000 Hz (configurable). 37 grams
(65,66)	Physilog product line (Gaitup, Lausanne, Switzerland)	Chest, 5 cm below sternal notch	GV, non-linear measures (gait stability), RMS and walk-ratio	Tri-axial accelerometer and gyroscope	According to Physilog5 specifications: Accelerometer range 16 g. Gyroscope up to 2,000 deg/s. 26.5×10×47.5 mm^3
(67,68)	GENEActiv (Activinsights, Kimbolton, England)	Lower back or wrist	Step count, stride time, stride time variability, step time, step time variability and non-linear measures (gait variability)	Tri-axial accelerometer	100 Hz sampling frequency
(34,69-71)	Axivity AX3 (Axivity, York, England)	Lower back, L5	Step count, mean bout length, step time, swing time, stance time, step time asymmetry, swing time asymmetry, stance time asymmetry, SL asymmetry, step velocity, SL, swing time variability, step time variability, stance time variability, GV and SL variability	Tri-axial accelerometer	Up to 8 g. 100 Hz. Waterproof. 23×32.5×7.6 mm^3, 11 g weight. Accelerometer range 2, 4, 8, or 16 g (configurable). Accelerometer sampling rate 12.5–3,200 Hz (configurable)

Table 1 (*continued*)

Table 1 (*continued*)

References	Sensor	Placement	Gait metrics demonstrated to be captured	Component MEMS sensors	Other known specifications
(72)	MIMAMORI-Gait system (LSI Medience Corp, Tokyo, Japan)	Back of waist	GV, SL, cadence, step time, step time variability and double support time	Tri-axial accelerometer	100 Hz frequency of data capture 75×50×20 mm^3, 120 grams
(73)	activPAL (PAL Technologies, Glasgow, Scotland)	Upper thigh	Step count, cadence	Uni-axial accelerometer	20 Hz frequency of data capture. 53.0×35.0×7.0 mm^3. 20 grams
(74,75)	Actigraph wGT3X-BT activity monitor (Actigraph, Pensacola, FL, USA)	Lateral waist	Cadence, stride regularity and non-linear measures (intensity, dynamic stability)	Tri-axial accelerometer	50 Hz frequency of data capture. Acceleration range 8 g
(76,77)	e-AR sensor	Behind ear	Stride duration and step time asymmetry. Gait asymmetry	Tri-axial accelerometer	
(4)	Apple Watch (Apple, San Francisco, CA, USA)	Wrist	Daily step count, gait velocity, estimated caloric expenditure, distance travelled	Tri-axial accelerometer and gyroscope	

IMU, inertial measurement unit; g, magnitude of acceleration due to gravity, 9.8 m/s^2; MEMS, microelectromechanical systems; GV, gait velocity; SL, step length; RMS, root-mean square; HR, harmonic ratio.

precision (80). This limitation is often minimized by incorporating a magnetometer in the IMU, able to calibrate sensor orientation with reference to the Earth's magnetic field. However, these devices are prone to interference by magnetic fields created by other devices (80).

Inertial sensor-based gait analysis

While single-point inertial sensors are unable to appreciate kinetic and many kinematic variables of gait, they can determine spatio-temporal parameters. Spatio-temporal parameters are of importance clinically, as they objectively characterize key gait events (GE) and common gait abnormalities (81). A plethora of spatio-temporal parameters are employed in the literature, with some [such as gait velocity (GV) and gait regularity in predicting the staging of PD severity] being more relevant than others in different clinical scenarios (31,32). This review focusses on spatio-temporal parameters based on a validated model (82,83) and clinical guidelines from The Biomathics and Canadian Gait Consortiums Initiative (84). These parameters encompass the mean, variability and asymmetry of temporal (cadence, step time, stride time, stance duration, swing duration, single-support duration, double-support duration) and spatial [step length (SL), stride length, GV step width] components of gait.

As acceleration data retains a time-series nature when extracted, by determining GEs such as heel-strike (HS) and toe-off (TO) within the gait cycle, mean temporal parameters can be quantified. Methods for GE detection are based on signal feature extraction of peaks, valleys or zero-crossings from raw accelerometric or gyroscopic data that may indicate a HS or TO (78). This can be complemented by applying hidden Markov models or Gaussian continuous wavelet-transformation (CWT) to increase GE detection accuracy (29). These methods have been implemented for single sensors placed on the trunk (85-87), waist (88,89), shank (90), ear (76) and foot (91,92). A thigh-based single-point IMU, the Activpal (PAL Technologies, Glasgow, Scotland), has also been used to measure mobility (73,93). However, this sensor has, to our knowledge, not analysed gait metrics beyond step identification in a single-point system.

Spatial parameter estimation proves more difficult due to the aforementioned technical limitations of inertial sensors (29). Current methods are based on abstraction models (e.g., machine-learning, linear regressive models), locomotion models [e.g., inverted pendulum (IP), double-

IP] and numerical integration. Those employed for single-point sensors include: direction integration (88), linear regression models (89), IP model with double-integration of antero-posterior (86,87) or vertical acceleration from trunk sensors (85); IP model with double integration of AP-acceleration from a foot sensor (91); double-IP model with integration of angular velocity of the shank (90); and autocorrelation procedures also able to determine temporal parameters, and a measure of regularity and symmetry (94). However, the requirement of numerical integration in these models causes accumulation of drift errors (78). Drift compensation is performed using kinematical reset through ZUPT by assuming foot velocity as zero (91) and shank inclination as vertical during midstance (90); however, these methods only prevent growth of drift error without minimizing the already accumulated error (29). As zero-velocity reset is not possible with trunk sensors due to continuous pelvic motion, drift correction is achieved by applying a high-pass (86) or Kalman filter (88) to retrospectively correct errors, occasionally in combination with direct and inverse integration at every step (88). However, correction efficacy may be limited in pathological gait where vertical trunk acceleration amplitude is lower and variability higher (78).

Linear measures of spatio-temporal variability and asymmetry are subsequently determined from mean spatio-temporal values, commonly expressed as the standard deviation or coefficient of variation and the absolute difference between left and right mean values respectively (95).

In addition to these traditional spatio-temporal parameters, accelerometer-based systems and non-linear calculations introduce new measures (11). Although these complex non-linear, autocorrelation and acceleration-based measures are dimensionless and unable to be validated against a standard, they are employed extensively clinically. Non-linear measures derived from the theory of stochastic dynamics (e.g., phase plot analysis, fractal-scaling index, sample entropy, Lyapunov exponents) allow appreciation of dynamic fluctuations and patterns between gait cycles throughout a walking bout, contrary to traditional linear measures that treat each as independent to the last (11,49,83). These measures represent the smoothness, regularity, stability, variability, complexity and symmetry of gait, showing sensitivity delineating between pathological and healthy subjects (96-98) equal, or superior to the sensitivity of linear measures (99). Similarly, autocorrelation measures of regularity and symmetry represent a clinically relevant (31,44,67), dynamic substitute for spatio-temporal variability and symmetry respectively (36,94). Other measures, including harmonic ratio (HR) based on Fourier analysis and the root-mean square (RMS) of acceleration magnitudes, are clinically relevant indicators of the smoothness, rhythmicity and symmetry of gait (33,100-102).

Methods

Literature Search

The PRISMA guidelines were followed for this systematic review (103) utilizing the following databases: PubMed; MEDLINE; EMBASE; Cochrane. Firstly, key search terms "gait" AND "accelerometer or inertial" were used to locate studies using inertial sensors to monitor gait. Next, "spatiotemporal" or "temporal" or "phase" or "stride" or "length" or "velocity" were used to locate publications that measure clinically relevant gait metrics beyond step-count and activity. Finally, the terms "clinical or valid or validity or test or reference or standard" were included to reflect studies that had tested the validity of these wearable technologies or applied them clinically. Relevant MeSH (Medical Subject Heading) terms, variations and synonyms were adjusted for each database.

Study selection

Studies from the above databases were collated and duplicate studies removed. Primary screening by an independent reviewer (JP) was performed based on the title and abstract of the remaining studies following the developed inclusion and exclusion criteria detailed below. Subsequent eligibility assessment was performed based on the full texts of remaining articles by an independent reviewer (JP) following the inclusion and exclusion criteria.

Inclusion criteria

(I) Articles involving wearable technology/ies.
(II) The wearable technology features an inertial sensor (accelerometer, gyroscope) or is an IMU.
(III) The wearable technology is a single-point sensor.
(IV) Articles written in English.
(V) Journal papers.

Exclusion criteria

(I) Wearable technology/ies only capable of identifying activity or step count.
(II) Wearable technology/ies features multiple sensor points.
(III) Wearable technology/ies classed as robotic or exoskeletons.
(IV) Systematic reviews, books, or conference papers.

Data collection

Following final article selection, results were classified as validation, clinical application or both. Data for validation studies was collected including sensor type(s); sensor placement; study aim(s); conclusions of study; primary gait metrics and methods. Critical analysis of validation studies was also included. Data collected for clinical applications studies included: sensor type(s); sensor placement; primary gait metrics and methods; and clinical application.

Bias analysis

Three different tools were used for risk of bias assessment based on the nature of the studies. Validation and reliability studies were assessed using the Scottish Intercollegiate Guidelines Network (SIGN) methodology checklist for diagnostic tests (104,105). Of the clinical application studies, observational studies were assessed using the Newcastle-Ottawa Scale (106) while randomized-controlled trials (RCTs) were assessed using the SIGN checklist for RCTs (105,107). Case series and case reports were excluded from the use of these bias assessment scales as questions pertaining to comparability no longer apply. Studies were assessed by 3 independent reviewers (WJC), (SMR) and (MM) with at least 2 different reviewers for each study. Discrepancies in assessment were resolved by discussion and reaching a consensus.

Results

From the 1,068 articles retrieved after duplicate removal, 90 articles were selected for inclusion (*Figure 1*). Thirty-two articles assessed the validity of single-point sensors and 48 used single-point sensor gait metrics analysis for clinical applications. Ten articles concurrently assessed validity and employed the device in a clinical application.

Validity of single-point sensors

Among the 42 articles (*Figure 2*), 30 studies utilized trunk-based sensor methods; while 12 studies used alternate locations for the sensor placement which include four studies at the subjects' ear; two at the subjects' shank, two at the subjects' foot, one at the waist; while three other studies utilized smart devices with inertial sensors. The parameters used for validating the sensors include: HS, stride length/duration/regularity, SL/count/duration/length variability/variability/time asymmetry/cycle time/regularity/frequency, GV, cadence, traversed distance, walking time, stance duration, swing duration, single/double support duration, HR, TO and time averaged acceleration.

Validation studies by subject cohort

Among the 42 studies, 59 different cohort of patient population were studied (*Figure 3*). Twenty-five studies involved healthy adults, 11 studies involved elderly subjects, seven studies involved patients with PD, four studies in post-stroke patients with ataxia and three studies in Huntington's Disease (HD). There were two studies each for patients with lower limb amputees and diabetic patients. The remainders were single studies in subjects comprising healthy children, multiple sclerosis (MS) patients, orthopedic patients, muscular dystrophy patients, and patients suffering from motor neuron disease (Table S1).

Clinical application of single-point IMUs

Fifty-eight articles discussed the use of single-point IMUs in clinical setting. Of these, 12 articles discussed the application of sensors in diagnosis and assessing severity of diseases (PD, MS, PN, Alzheimer's disease, age-related changes, frailty and foot & ankle health); 12 studies applied the sensors in monitoring rehabilitation and intervention efficacy (orthopedic, neurosurgical and oncological patients, foot orthoses, medical and physical intervention in neurodegenerative diseases); and 31 studies used sensors to characterize patients with different conditions from healthy subjects. Three articles described both diagnosis and severity of assessment as well as delineating healthy and participants with pathologies (*Table 2*, with more detailed findings of these articles in Tables S1,S2.

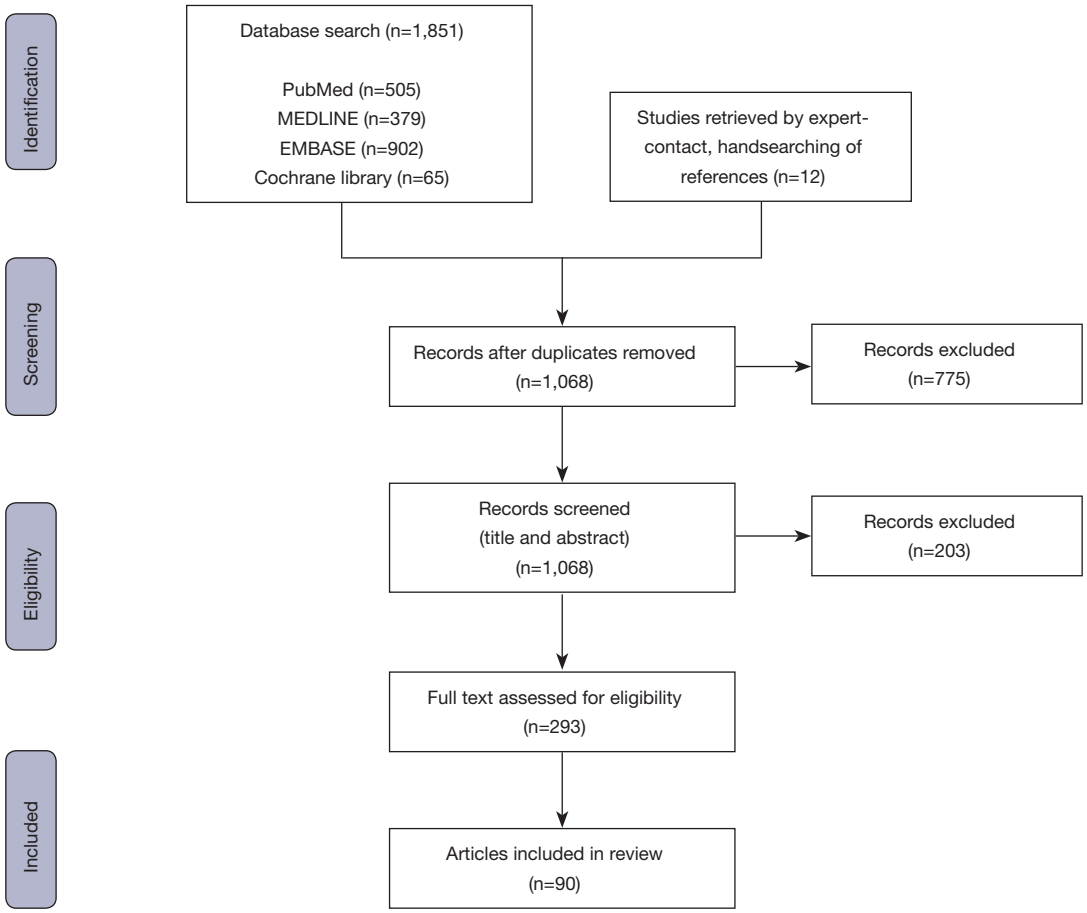

Figure 1 PRISMA methodology.

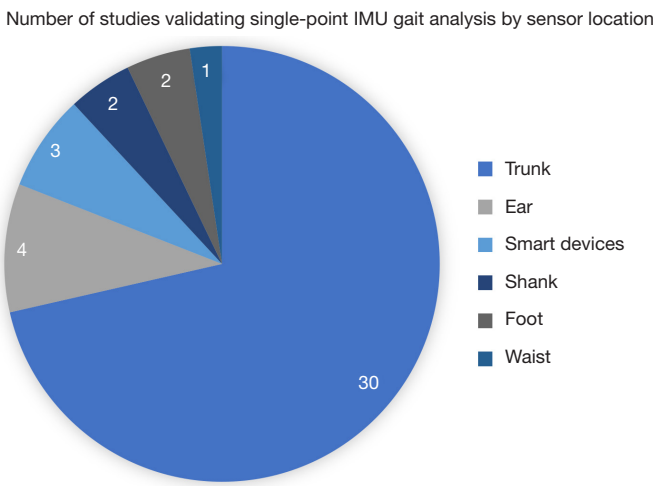

Figure 2 Number of studies validating single-point IMU gait metrics analysis by sensor location. Smart devices have been attached on various locations, some separate to where they were designed to be worn – the iPod touch G4 (iOS 6, Apple Inc.) over L3 (108), the Apple Watch (Apple, San Francisco, CA, USA) on the wrist (4), and the Apple iPhone 5 (iPhone 5, Apple Inc., Cupertino, CA, USA) on the lateral waist (109). IMU, inertial measurement unit.

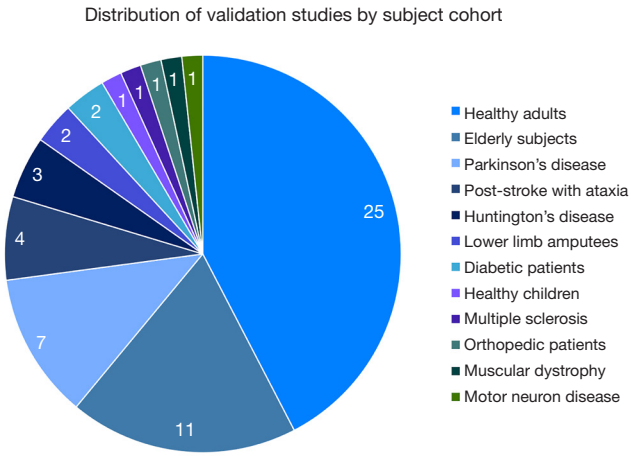

Figure 3 Distribution of validation studies by subject cohort.

Bias assessment

Risk of bias assessment of validity studies did not reveal studies with an unacceptable level of bias. 31 studies were of high quality while nine were of acceptable quality in minimizing bias. The breakdown of the assessment and interpretation is included in Table S3. Areas in which many studies had 'unclear' levels of bias were in the patient selection domain criteria of selecting a consecutive sequence or random selection of participants. Understandably, many of these studies had small sample sizes and recruited volunteers or practiced convenience sampling of patients to achieve this. Many studies were able to reduce bias by conducting simultaneous testing of the IMU and reference standard. Criteria related to the use of a reference standard were not applied to reliability studies that did not use a reference test. The criteria related to pre-specified thresholds of the index test were also largely not applicable.

Of the clinical applicability studies, 30 were scored as "good" quality, eight as "fair" and 12 as "poor". Two RCTs were deemed having acceptable quality and one RCT as high quality in minimizing bias. The breakdown of the bias assessment results and interpretation is included in Appendix 1). Most studies generally missed out a score on ascertainment of outcome using a blind investigation. This may be attributed to a lack of investigators needed to separate carrying out the test and interpreting data. However, this was regarded as not having a large influence on overall bias assessment as measurements using IMUs are automatically recorded to software and not requiring direct human measurement. It would also be difficult to blind assessors to diseased patients with an obvious gait pathology to healthy controls. The RCTs also had unclear blinding of subjects and investigators to treatment groups. The strengths of these studies were the randomization process and standardization of testing and analysis between treatment and control groups.

Discussion

In our review, single-point IMUs have been reasonably validated in the measurement of spatial and temporal gait parameters (85,86,124). However, IMUs have shown difficulty in estimating variability and asymmetry metrics (48,70,118,125-127). Alongside this, whilst IMUs have shown promise in their clinical applications, such as in the diagnosis of disease (31,32,47,53) and the assessment of treatment efficacy (56,113,128), these studies have predominantly relied on straight-line gait metrics. This critically limits external validity to free-living analysis where day-to-day movements typically represent more complex patterns of acceleration and deceleration. Moreover, studies focusing on clinical application have predominantly described obvious gait changes and have not necessarily demonstrated IMUs to be useful in evaluating subtle differences in gait patterns. Therefore, additional studies focusing on validation and clinical application are required before any mass clinical and commercial uptake of single-point wearable sensors can occur.

Table 2 Clinical applications of single-point IMUs

Reference	Application
Diagnosis and severity assessment	
Demonceau *et al.*, 2015 (31)	Determine PD severity
Herman *et al.*, 2014 (57)	Classify PD subtypes
Dalton *et al.*, 2013 Collett *et al.*, 2014 Pau *et al.*, 2016 (47,62,110)	Determine MS severity
Esser *et al.*, 2018 (111)	Detect PN
De Bruin *et al.*, 2012 (53)	Determine PN severity
Gillain *et al.*, 2016 (39)	Predict risk of Alzheimer's development
Kosse *et al.*, 2016 Terrier *et al.*, 2015 (65,108)	Predict age-related gait change
Soangra *et al.*, 2018 Martinez-Ramirez *et al.*, 2015 (43,109)	Predict frailty status/determine severity
Van Schooten *et al.*, 2016 Del Din *et al.*, 2017 (33,34)	Predict falls/determine falls risk
Angthong *et al.*, 2018 (112)	Assessment of foot/ankle conditions
Rehabilitation and intervention efficacy	
Atallah *et al.*, 2014 Rapp *et al.*, 2015 (76,113)	Total hip and knee replacement efficacy and recovery
Jarchi *et al.*, 2016 (77)	Anterior cruciate ligament repair recovery
Mobbs *et al.*, 2018 (4)	Lumbar microdiscectomy recovery
Hojan *et al.*, 2014 (54)	Effect of breast prostheses after mastectomy
Mutoh *et al.*, 2016 Manikowska *et al.*, 2013 (5,56)	Hippotherapy efficacy in cerebral palsy
Henderson *et al.*, 2016 (114)	Rivastigmine efficacy in PD
Terrier *et al.*, 2009 (115)	Prescription footwear efficacy in foot/ankle fractures
Doi *et al.*, 2013 Pau *et al.*, 2014 Perrochon *et al.*, 2015 (38,60,101)	Improvement in gait after physical activity in elderly and cognitive impairment
Delineating pathological subjects from healthy controls	
Barden *et al.*, 2016 Clermont *et al.*, 2016 Bolink *et al.*, 2012 (67,68,116)	Knee osteoarthritis subjects

Table 2 (*continued*)

Table 2 (*continued*)

Reference	Application
Lamoth *et al.*, 2010 Houdijk *et al.*, 2008 (48,49)	Amputee subjects
Terrier *et al.*, 2017 (74)	Chronic lower limb pain subjects
Arvin *et al.*, 2015 (58)	Hip abductor fatigue Subjects
Esser *et al.*, 2011 Mizuike *et al.*, 2009 Meijer *et al.*, 2011 (41,52,102)	Muscular dystrophy/Motor neuron disease/Stroke subjects
Hickey *et al.*, 2016 Matsushima *et al.*, 2015 (70, 117)	Ataxia disorder subjects
Demonceau *et al.*, 2015 Del Din *et al.*, 2016 Esser *et al.*, 2013 Hatanaka *et al.*, 2016 Yang *et al.*, 2011 (31,46,69,72,118)	PD/Progressive supranuclear palsy subjects
Pau *et al.*, 2017 Pau *et al.*, 2018 Storm *et al.*, 2018 (63,119,120)	MS subjects
Dalton *et al.*, 2013 Collett *et al.*, 2014 (47,110)	HD subjects
Manikowska *et al.*, 2013 (55)	Menopausal women
Tanigawa *et al.*, 2018 (121)	Pregnant patients with lumbopelvic pain
Iosa *et al.*, 2013 Saether *et al.*, 2014 (42,78)	Cerebral palsy subjects
Moe-Nilssen *et al.*, 2003 (122)	Dyslexia subjects
Awotidebe *et al.*, 2016 (61)	Type 2 diabetes subjects
Chung *et al.*, 2012 Maquet *et al.*, 2010 Martinez-Ramirez *et al.*, 2016 Lamoth *et al.*, 2011 (37,44,51,123)	Cognitively impaired subjects
Auvinet *et al.*, 2003 Bautmans *et al.*, 2011 (36,50)	Falls risk/fallers

IMU, inertial measurement unit; PD, Parkinson's Disease; MS, multiple sclerosis; PN, peripheral neuropathy; HD, Huntington's Disease. Detailed findings of these articles can be found in Tables S1,S2.

Validating IMU gait metrics analysis

Proposed methods and sensor locations for determination of gait metrics from single-point IMU acceleration data are generally validated against a standard or by test-retest reliability (129). The large portion of validation research employing lower trunk sensors compared with alternative sensor locations is reflected in *Figure 2*.

Trunk-based sensor methods

Association of lower trunk accelerations with HS and TO, and the ability to predict these accelerations with an IP model of the body's center of mass (COM) trajectory, has prompted the proposal of several methods for GE and spatio-temporal parameter estimation from these signals.

Methods by Zijlstra & Hof (86)

Peak detection and IP methods proposed by Zijlstra & Hof (86) utilizing a tri-axial accelerometer over the lower trunk demonstrated accurate detection of GEs and limited mean spatio-temporal parameters when compared to GRF from a treadmill. However, the straight-walking protocol employed limits external validity to daily-living analysis. Similarly, 100% of GEs were detected in only nine subjects of a small sample (n=15) of healthy adults, with 12% of GEs identified falsely in the remaining subjects. Furthermore, SL calculation which requires input of individual leg-length was consistently underestimated before application of a 1.25 correction factor, revealing limitations in the model itself. Further validation in healthy adults has demonstrated accurate estimation of mean spatio-temporal parameters when compared to stereophotogrammetry and dynamometry, however significant differences were found for gait phase durations that rely on determining TO which isn't explicitly detected by the model (124). SL estimation was again detected with less accuracy due to errors implied by double-integration in this method (124). Further model limitations were identified in neurological populations (41) as neither a generic (1.25) or pathology-specific correction factor could be applied for accurate SL estimation, alluding to the need for individual corrections in pathological cohorts. This finding was reflected when validated in child (130) and older cohorts (131). The model has been further validated in small samples of PD subjects against motion capture (132), MS subjects against an instrumented walkway (110) and through test-retest reliability (47) for mean and variability spatio-temporal measures. These studies also assessed reliability of non-linear variability measures (47) and demonstrated feasibility of anterior trunk sensor placement, representing an attenuated version of COM accelerations (110). Methods from Zijlstra and Hof (86) have been incorporated into commercially available IMUs, G-Walk (BTS, Milan, Italy) and DynaPort (McRoberts, The Hague, Netherlands). DynaPort accuracy has been assessed in children (130), lower-limb prosthesis (48), diabetes (53), healthy elderly (125,126) and falls risk subjects (50), while G-walk accuracy has been assessed in healthy adult (133-135), PD (136) and MS (137) subjects. Despite determining mean spatio-temporal parameters accurately in most studies, caution is recommended for interpretation of linear variability and asymmetry parameters (48,125,126). The interpretation of gait phase durations reliant on TO (stance, swing, single, double support time) is also uncertain since this event is not explicitly detected by the algorithm (133,136,137). Furthermore, testing limited to small samples in controlled straight-walking conditions limits power of inference to gait metrics analysis in pathological cohorts or scenarios of daily-living.

Autocorrelation methods utilizing lower trunk accelerations from a tri-axial accelerometer (94) have demonstrated test-retest reliability in a small sample (n=20) of healthy subjects for RMS and mean spatio-temporal parameter assessment (138) in straight-walking protocols. Despite lacking further validation for traditional spatio-temporal parameters, the test-retest reliability of autocorrelation measures of regularity and symmetry have been demonstrated in small samples of elderly, falls-risk and HD subjects in straight-walking protocols (47,50,139).

Methods by McCamley et al. (85)

CWT for GE detection and IP methods for spatial parameter estimation proposed by McCamley *et al.* (85) using a lower trunk IMU have been validated against stereophotogrammetry and force plates. It has also been compared against previous methods from Zijlstra & Hof (86) and González *et al.* (87). Despite limitations of a small sample (n=18) of healthy subjects and a straight-walking protocol of only 3.6 m, the method by McCamley *et al.* (85) provided an improved estimate of SL and GE detection compared to previous methods. Validity for temporal parameter means and variability has been subsequently demonstrated in both controlled and free-living conditions against pressure insoles, despite observed accuracy decreases in free-living conditions (140). Similar protocols in MS patients validated measurement of mean temporal parameters (120). However, variability measures were highly overestimated, with inaccuracies increasing

with length of walking bout, detracting from applicability to continuous monitoring. The lower accuracy for which this method detects TO compared to HS, may account for difficulty estimating variability measures, shown to be highly sensitive to incorrect GE identification compared to mean parameters (120). Method accuracy was also shown to be speed-dependent and decrease with increasing disability, hindering reliability in pathological cohorts (120).

Method by Godfrey et al. (95,141) combining those by Zijlstra & Hof (86) and McCamley et al. (85)

Combining methods by McCamley *et al.* (85) for temporal parameter and Zijlstra & Hof (86) for SL estimation, Godfrey *et al.* (95,141) demonstrated validity against an instrumented walkway and through test-retest reliability in large populations of young and older adults (cumulative n=92) in protocols reflecting daily-living. Despite acceptable agreement for mean spatio-temporal parameters, SL underestimation was again attributed to limitations with generic correction factors, straight-walking dependent IP model and mathematical integration errors. Both methods' measures of spatio-temporal variability and asymmetry were poor, concurring with findings of other studies using an instrumented walkway as a control (70,125-127). In defense of IMUs, Godfrey *et al.* (95) demonstrated that discrepancies in variability and asymmetry were due to inherent differences between IMUs and instrumented walkways used in these studies, rather than IMU inaccuracy. This highlights the importance of caution when choosing a standard for validation purposes. Demonstrated discriminatory power between pathological and healthy cohorts based on IMU asymmetry and variability measures, despite poor agreement with an instrumented walkway, reinforces these conclusions (70).

Other methods of GE and spatio-temporal parameter estimation

Waist-placed sensor and algorithm development has also been validated. Direct integration methods for SL estimation based on a waist placed IMU (88) were validated against stereophotogrammetry. However, limited gait parameters, a small sample (n=9) of healthy patients and accuracy discrepancies between left and right steps due to anatomically asymmetrical sensor placement limit clinical applicability (88).

To combat the plethora of COM methods, a comparison of five methods (85,86,88,89,142) against stereophotogrammetry and force plates for determination of temporal parameters was conducted by Trojaniello *et al.* (143). The different GE identification methods incorporated largely either the zero-crossing or wavelet-based method. Zjilstra & Hof (86) used a zero-crossing method where foot contact was taken as peak forward acceleration preceding the change of sign of acceleration from positive to negative. González *et al.* also used a zero-crossing method to approximate a search window prior to applying certain heuristic rules to determine the peak associated with the contact event (142). In conjunction with the zero-crossing method, Shin *et al.* used a sliding window summing technique to reduce noise (89). The method by McCamley *et al.* involved integrating and differentiating the acceleration signal using Gaussian continuous wavelet transforms prior to identifying initial and final contact events from the minima and maxima of the smoothed signal (85). Köse *et al.* used a wavelet-based method to identify windows of interest prior to decomposition and reconstruction of the original signal based on certain threshold application. Heel strike was then detected as the timepoint between signals of the different local frame axes (88). No statistically significant difference was found between methods for stride and step duration and the standard. However, methods that detect TO in addition to HS to allow determination of gait phase durations (85,87,88) showed a statistically significant difference, due to difficulties detecting the smoother acceleration signals indicating TO (143). Omitting assessment of spatial parameter methods limits completeness of the study. While despite examining a large sample, comparison of methods in healthy controls limits external validity to pathological cohorts. In response, assessment of the three best-performing methods (85,86,89) in 10 hemiparetic, 10 PD and 10 HD subjects against an instrumented walkway was undertaken (144). This revealed a universal decrease in GE detection and temporal parameter accuracy compared to healthy subjects. However, no statistically significant differences were revealed regarding accuracy between IMU methods in any cohort, apart from PD subjects for which methods from Zijlstra & Hof (86) outperformed.

New methods are continuously being formulated for lower trunk IMU analysis of spatial and temporal parameters. Oyake *et al.* (145) recently proposed a new algorithm for SL symmetry determination, validated in stroke subjects, while Sejdić *et al.* (146) validated novel methods against motion capture data in PD and peripheral neuropathy (PN) subjects.

Alternative sensor placements

Despite trunk IMUs maintaining the lion's-share of

research, methods based on alternative sensor positions have also garnered validation attention.

An ear-worn tri-axial accelerometer has been validated in healthy and lower-limb orthopedic subjects against an instrumented treadmill for estimation of mean step time and symmetry (76). A similar sensor has also been validated for the detection of GE's and limited gait parameters in small samples of healthy (147), PD (148) and orthopedic (77) subjects in laboratory conditions.

With placement closer to the ground allowing better GE detection, sensors on the lower limb have also been proposed and validated. GV estimation from a single shank IMU was validated on a treadmill across numerous speeds and slope gradients (90). However, decrease in effectiveness of vertical shank inclination as a ZUPT re-calibration and subsequent GV accuracy with changing incline limits daily-living application. Maqbool *et al.* (149) further validated an algorithm for detection of GEs across walking speeds and slopes in eight healthy and two amputee subjects using a shank gyroscope. Straight-walking protocols and need for the instrumented shank to take the first step limit these studies' clinical applicability. IP methods using one foot IMU have been validated against a treadmill for GV estimation in five healthy subjects (91). However, difficult attachment of the IMU to the shoe, straight-walking protocols and an accuracy decrease with increasing incline limit applicability. Temporal parameter detection has also been validated using a foot IMU in eight healthy adults (92), showing strong correlation with motion capture. Limited validation of comprehensive gait metrics and inability to assess asymmetry and complex trunk-accelerometer measures with lower-limb sensor placement limits clinical applicability (88).

Smart device gait analysis

Smart devices embedded with inertial sensors have become ubiquitous in everyday life, making them an obvious solution for maximizing patient compliance and allowing inconspicuous, portable gait analysis.

Initial proof of concept using an iPhone attached to the lateral malleolus demonstrated test-retest reliability for quantification of time averaged acceleration and step duration (150). However, unrealistic device placement, limited gait parameters and a sample of only one healthy patient limit validity and clinical applicability. Following this, utilizing trunk-based methods for GE detection (85-87) and SL estimation (86), high correlations were found for an iPhone against stereophotogrammetry for the identification of GE and mean spatio-temporal parameters in eleven healthy subjects (151). However, similar unrealistic device placement over the lumbar spine and waist has limited applicability to daily living. Addressing this, the reliability of smartphone locations: body, belt, bag, pocket and hand and validity against an instrumented walkway has been tested (152). Hand positions demonstrated poor reliability and agreement with the standard at slow speeds which only marginally improved at higher velocity, while high validity and excellent reliability were demonstrated in body, bag or belt positions at fast/comfortable speeds, lending traction to their incorporation into everyday gait monitoring. However, universal inaccuracies assessing gait at slow speeds limits application to pathological groups. Furthermore, limited emulation of free-living scenarios was employed with only five to nine steps investigated per trial (152).

Validation status of single-point IMUs

Despite lacking validation for a comprehensive set of gait metrics in alternative positions, current COM systems are a proven alternative for calculation of a range of traditional spatio-temporal measures. However, these algorithms still need development, with caution recommended with interpretation of spatio-temporal variability and symmetry parameters, measures of gait phases and estimation of spatial parameters. Further validation is required in larger samples of pathological groups; Furthermore, their accuracy for continuous monitoring in scenarios of daily living needs to be assessed. Incorporation of these algorithms into commercial devices and smart devices is promising for clinical practicality and uptake.

Clinical applications

Although the vision of single-point IMUs for gait metrics analysis in daily-living is in its infancy (4,34,69,120), these devices have been employed extensively in clinical environments to aid diagnosis and severity assessment, determine rehabilitation and intervention efficacy, and delineate pathological groups from healthy controls (*Table 2*). Of these applications, trunk-based IMUs are uniformly employed with the exception of a limited number of studies utilizing ear (76,77), foot (112,123) and smart-device (4,108,109) analysis.

Diagnosis and severity assessment

Single-point IMU gait metrics analysis has been employed as a method of assessment of ageing, orthopedic and

neurological conditions.

Gait metrics analysis with single-point devices has aided diagnosis and severity assessment in numerous neurological diseases. Lower trunk sensor gait metrics analysis has been used to determine PD severity, demonstrating significantly reduced gait regularity and GV with increasing Hoeh and Yahr stage severity (31,32). Utilizing the commercially available DynaPort, Herman *et al.* (57) have also classified PD subtypes based on increased gait impairment and demonstrated classification superiority based on objective gait measures compared to conventional schemes. In MS, mean spatio-temporal parameter changes have been correlated with increasing disease severity using a G-Walk sensor, while also demonstrating high correlations between gait characteristics and patient-reported outcomes, reinforcing the applicability of gait metrics analysis as a clinical measure (62). Dalton *et al.* (110) also demonstrated significant differences between MS severity groups based on spatio-temporal mean and variability parameters as well as autocorrelation regularity and symmetry. Determining HD severity from trunk-based gait metrics analysis has also shown to correlate with clinical scales using both linear and non-linear measures (47). In diabetes subjects, gait parameters from a trunk IMU have shown good discriminatory power in detecting those with PN in a pilot study with a small sample (111), while De Bruin *et al.* (53) demonstrated the discriminatory power of SL to discern PN severity in type 2 diabetes patients in free-living gait conditions.

Similarly, gait metrics analysis has aided assessment in orthopedic conditions. Using a foot IMU, Angthong & Veljkovic (112) demonstrated significant correlations between obtained spatio-temporal parameters and subjective validated patient-reported outcomes and quality of life scores in patients with foot and ankle conditions such as arthritis, injury and tendinopathy. This is suggestive of the validity of gait assessment in clinical practice as an objective outcome measure.

In cognitive impairment, analysis of mean spatio-temporal and autocorrelation measures using a trunk IMU has been shown to predict risk of decline from mild cognitive impairment (MCI) to Alzheimer's Disease in small sample sizes (n=23) (39). Furthermore, single-point gait quantification has been used to delineate between dementia subtypes (153).

Decline in physical and cognitive capacity with age is associated with frailty and disability, with consequences including falls, hospitalization and death. Numerous studies using single-point sensors and smart-devices have attempted to predict age-related gait changes (65,108), predict frailty status and determine severity (43,109) and predict falls and determine risk (33,34) to allow early-intervention to reduce adverse outcomes.

Rehabilitation and intervention efficacy

Gait metrics analysis using single-point IMUs has been used as an objective measure of rehabilitation and intervention efficacy in a range of conditions.

Single-point IMUs have been employed in the assessment of surgical outcomes and rehabilitation. A range of objective gait measures from trunk IMUs have been obtained to determine operation efficacy and rehabilitation progress after total hip replacement (113) and decompressive laminectomy for lumbar spine stenosis (128). An ear-worn sensor has been used to evaluate recovery from anterior cruciate ligament repair based on gait symmetry (147) as well as total hip and knee replacements based on stride duration and gait symmetry in small samples (76). Similarly, employment of the consumer available Apple Watch (Apple, San Francisco, CA, USA) for detection of GV was claimed invaluable in monitoring recovery through continuous gait monitoring in daily life following lumbar microdiscectomy in a single patient (4).

Assessment of non-operable intervention efficacy has also been determined using trunk IMUs. In cerebral palsy subjects, improvement in spatio-temporal mean and symmetry parameters after one hippotherapy session (56) and increase in mean parameters over a two-year intervention course (5) has been demonstrated. While linear measures of gait variability from trunk accelerations have been used to determine the effectiveness of Rivastigmine in in PD subjects over 32 weeks (114). In orthopedics, the effectiveness of prescription footwear has been assessed through trunk-based autocorrelation gait metrics analysis in severe foot and ankle fractures (115). While in women following single-breast mastectomy, significant influence of external breast prosthesis on spatio-temporal parameters of gait has been demonstrated (54).

Prescribed physical activity programs have been shown to improve physical functioning and reduce risk of falls and adverse outcomes (154). Pau *et al.* (60) utilized a trunk accelerometer to determine the increased effectiveness of vigorous compared to light physical activity on mean spatio-temporal parameters in elderly over 36 weeks. Similarly, the positive effect of PA on a range of spatio-temporal and accelerometer-based measures was demonstrated in MCI (101) and dementia subjects (38) using trunk-based

accelerometry.

The efficacy of neurorehabilitation has also been assessed using trunk-based gait analysis. Santoyo *et al.* (155) demonstrated an increase in mean spatio-temporal parameters following a five-month neurorehabilitation program in 45 MS patients. Furthermore, Zanetta et al. (156) demonstrated similar improvements in cadence and GV after a four-week program, and significant correlation of gait parameters with validated clinical assessments (Berg Balance Scale, 6MWT), validating the usefulness of gait metrics analysis as an objective measure of outcomes.

Delineating pathological and healthy subjects

Most single-point IMU clinical applications focus on delineating between pathological groups with gait impairments and healthy controls. This application enables clinical validation of gait metrics and appreciation of metrics relevant to different pathologies.

Quantification of gait through single-point sensors in musculoskeletal disorders has been assessed. Knee osteoarthritis patients have been delineated from healthy controls based on numerous mean, autocorrelation and accelerometer-based spatio-temporal measures (67,68,116). In amputee gait, measures of stability, regularity and variability (49) as well as mean spatio-temporal parameters (48) have shown significant difference from healthy controls. Hip adductor fatigue has been demonstrated to significantly impact variability and symmetry of gait (58), while patients with chronic lower limb pain have demonstrated significant differences in cadence, variability and symmetry measures compared to controls (74). Using a trunk IMU in pregnant patients, significant differences have also been noted in trunk movement asymmetries between those with and without lumbopelvic pain. (121)

Numerous neurological conditions show altered gait quality using single-point IMUs. In stroke, RMS, autocorrelation measures of regularity and symmetry (102) and GV (52) have shown significant differences compared to controls. The gait impairments of various ataxia disorders have been assessed, demonstrating significant differences in mean, variability and asymmetry of spatio-temporal characteristics as well as autocorrelation and accelerometer-based measures (70,117). In PD, Esser *et al.* (46) demonstrated superior sensitivity of GV and non-linear variability measures compared to mean parameters for delineation from healthy controls in a small sample (n=24). Further works have demonstrated the ability of mean and symmetry spatio-temporal parameters as well as autocorrelation measures in both laboratory and free-living gait to delineate between PD subjects and healthy controls (31,69,72,118). Accelerometer-based measures of gait smoothness (HR) have also been shown to delineate between MS and healthy subjects prior to any measurable changes in mean spatio-temporal parameters (119), while dual-task gait in these patients has shown to result in a significant difference in mean spatio-temporal parameters compared to controls (63). In HD, significant differences have been demonstrated for autocorrelation measures, mean spatio-temporal parameters and both linear and non-linear variability measures against healthy subjects (47,110). Furthermore, in type 2 diabetes (61) and normal pressure hydrocephalus (157), altered spatio-temporal parameters have been demonstrated compared to healthy controls. In child pathological cohorts, differences in gait parameters have also been demonstrated in cerebral palsy (42,78) and dyslexia subjects (122) compared to healthy controls.

The effect of cognitive impairment on gait has also been quantified compared to healthy controls using single-point sensors (37,52,123,153). Gait differences have been quantified in those at risk or with a history of falls, with autocorrelation measures of regularity and symmetry, GV, stride length and step-time asymmetry showing significant discriminative capacity against healthy controls (36,50).

Limitation of single-point IMUs in delineating diseases

Clinical use of IMUs discussed above were mainly describing an obvious gait change (e.g., MS or Parkinson disease) rather than minute structural damages such as a torn hip labrum. Therefore, current use of a single-point IMU has to be considered within the appropriate clinical context. Additionally, the clinical application studies included are largely limited to straight line gait metrics assessment which does not fully reflect real-life movements. Along with the maturation of single-point IMUs in terms of validity, future studies should attempt to assess validity of these sensors in picking up complex movements that reflect real life movements such as falls.

Future prospects

The ability for wearable devices in detecting gait and posture is maturing and undergoing continuous development. Multiple studies have demonstrated the use of wearable technologies in aiding postural analysis as well as serving as a tool for the general population in everyday

postural/activity tracking (158,159). A novel scoring algorithm incorporating gait and postural scores has also been proposed to report patients' outcome in a manner which is simple and conducive to a continuous stream of data that can be remotely monitored by clinicians (160). This ability to remotely measure and record continuous data gives wearable devices an upper hand compared to lab-based instruments which are geographically sparse and perform gait analysis at discrete time points, though validity and standardization remains a drawback currently (4,23,158-160).

Future studies are required before the implementation of IMUs can be recommended to clinicians. In particular, there is an urgent need to validate IMU accuracy in free-living home environments, with most current validation studies instead measuring gait metrics on straight-line pathways. Other parameters such as U-turns, complex acceleration and deceleration that mimics day-to-day movements such as slowing down when approaching a door or chair could be studied. In addition, single-point IMUs have not been consistently shown to have high accuracy when measuring variability and asymmetry metrics. Future studies may assess other models for GE detection, which are continuously being developed, that may more accurately capture these metrics. Moreover, many of the studies focusing on clinical application have described obvious gait changes. While IMUs are still useful in objectively quantifying these changes, more evidence is required to demonstrate the clinical applications of IMUs in the measurement of subtle gait differences. Future studies to compare user acceptability and compliance between single-point IMUs and multi-point IMUs should also be conducted. Studies to determine ideal placement location of single-point IMUs at various body parts could also be conducted. Further developments and validation may one day bridge the gap for incorporating wearable technologies into actual clinical setting in aiding diagnosis and monitoring patient progression.

Conclusions

This review has demonstrated the validity of single-point IMUs as an alternative to current quantitative methods and their ability to assist in clinical scenarios. The accuracy of these systems for detection of traditional metrics as well as the demonstrated clinical relevance of novel, accelerometer-based measures is promising for practicality and efficacy in the clinical context. Further validation for long-term, continuous monitoring in daily living scenarios is required as is performance in larger samples of pathological cohorts before mass commercial and clinical uptake can be expected.

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Footnote

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Supplementary

Table S1 Summary of results and limitations of validation studies

Reference	Sensor(s)/Placement	Aim	Primary Measures and Analysis Methods	Conclusions	Limitations
Trunk					
Zijlstra & Hof, 2003	Tri-axial accelerometer attached over S2.	To validate a proposed algorithm and single-point accelerometer for spatio-temporal gait analysis against a treadmill with force transducers.	Heel strike (HS), stride duration, step length (SL), gait velocity (GV). Methods from Zijlstra, 2003.	GEs and temporal parameters can be obtained from lower trunk accelerations. Reasonable approximations of SL and GV can be obtained by application of an inverted pendulum model and generic correction factor.	Straight-walking in a laboratory limits external validity to daily-living. Healthy subjects limits applicability to pathological cohorts. Spatial parameter calculation required input of individual leg-length and is consistently underestimated before application of a 1.25 correction factor. 100% of GE were detected in only 9 subjects of a small sample size (n=15), 12% of foot contacts identified falsely in the other 6. Limited parameters.
Henrikson *et al.*, 2004	Triaxial accelerometer at L3	To determine the test–retest reliability of trunk accelerometric gait analysis in healthy subjects based on autocorrelation methods.	Stride length, SL and cadence. Methods from Moe-Nilssen, 2004. RMS.	Trunk accelerometric gait analysis using autocorrelation methods in healthy adults is a reliable method.	Straight-walking in a laboratory limits external validity to daily-living. Small sample size (n=20) of healthy subjects limits applicability to pathological cohorts. Limited parameters.
Brandes *et al.*, 2006	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Fitted on lower lumbar spine close to sacrum.	To determine if spatio-temporal parameters can be determined from lower trunk acceleration compared against video footage in healthy children.	Step count, traversed distance, walking time, GV, step duration and SL. Methods from Zijlstra, 2003.	Spatio-temporal gait parameters in children were accurately determined using trunk accelerometry. Inverted pendulum model and individual correction factor provides the possibility to estimate spatial gait parameters in children.	Straight-walking in a laboratory limits external validity to daily-living. Difficulty in children following protocol instructions could impact results. Small sample size (n=20). Healthy child cohort limits applicability to pathological child cohorts. Limited parameters.
Houdijk *et al.*, 2008	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	To evaluate the validity of the DynaPort for the assessment of spatiotemporal parameters of amputee gait against video footage.	Step count, SL, step duration and GV. Methods from Zijlstra, 2003.	DynaPort is a valid tool for determining mean spatiotemporal parameters in prosthetic gait. Although, errors between prosthetic and intact HS detection prevent reliable analysis of symmetry.	Straight-walking in a laboratory limits external validity to daily-living. Despite positive results for mean spatiotemporal parameters, poor assessment of mean step times of intact and prosthetic legs limits analysis of symmetry. Despite good agreement between both methods group means, large differences occur on individual level. Limited parameters.
Hartmann *et al.*, 2009	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over S2	To determine the validity of DynaPort against an instrumented walkway for spatio-temporal gait parameters in older adults and to compare the levels of agreement for averaged step data from different walking distances and individual step data	GV, cadence, step duration and SL, SL variability, step duration and variability. Methods from Zijlstra, 2003.	DynaPort is a valid tool for spatio-temporal gait parameters for averaged step data in elderly at varying speeds. Gait variability measures and individual step data need to be viewed with caution.	Straight-walking in a laboratory limits external validity to daily-living. Small sample size (n=23). Instrumented walkway was not a gold standard for validating the IMU system with respect to gait variability and asymmetry.
Hartmann *et al.*, 2009.	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over S2	To determine the reliability of spatio-temporal gait parameter measurement in older adults on different surfaces	GV, cadence, step duration, SL, SL variability, step duration variability Methods from Zijlstra, 2003.	GV, cadence, step duration and step length under more challenging conditions can be reliably measured in independent living older adults. Gait variability measures need to be viewed with caution.	Small sample size (n=23).
Esser *et al.*, 2011	IMU (MTx, Xsens, The Netherlands) containing a Tri-axial accelerometer, gyroscope and magnetometer attached over L4.	To determine correction factor required for PD, muscular dystrophy, MND, stroke survivors and healthy subjects to estimate step and stride length.	Step time, SL and GV. Methods from Zijlstra, 2003.	Individual correction factors should be determined for patients suffering from a neurological condition.	Straight-walking in a laboratory limits external validity to daily-living. Stopwatch and observation employed as a reference platform. Limited parameters.
Bautmans *et al.*, 2011	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over posterior sacrum.	To investigate reliability of accelerometer gait analysis and correlation with clinical status and fall-risk.	GV, step time asymmetry, methods from {Zijlstra, 2003 #37}. Step regularity., methods from Moe-Nilssen, 2004.	3D-accelerometry based gait speed and regularity showed high reliability when based on two walks of 18 m.	Straight-walking in a laboratory limits external validity to daily-living.
Bugane *et al.*, 2012	F4A (3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. Fitted over L4–L5	To determine the validity of a single trunk accelerometer against stereophotogrammetry and dynamometry for measurement of spatio-temporal parameters in healthy subjects.	SL, stride length, stride duration, step duration, stance duration, swing duration, double support duration, single support duration, GV and cadence. Methods from Zijlstra, 2003.	No statistically significant differences between IMU measurements and standard for most spatio-temporal parameters. Significant differences were found for gait cycle phases.	Subject must stand still for a few seconds before starting and for a few seconds after stopping which may impact results. Straight-walking in a laboratory limits external validity to daily-living. Healthy subjects limits applicability to pathological cohorts.
De Bruin *et al.*, 2012	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over S2.	To investigate the reliability of DynaPort in diabetic patients under single and dual task conditions on a challenging walking course.	SL, GV, step duration, cadence Methods from Zijlstra, 2003.	Spatio-temporal parameters can be reliably measured in adults with diabetes using DynaPort under challenging surfaces.	Limited parameters.
Esser *et al.*, 2012	IMU (Tri-axial accelerometer, gyroscope and magnetometer) placed over L4.	Compare the trunk accelerations in PD subjects measured by an IMU with optical motion capture before deriving spatio-temporal gait measures.	Stride length, GV, step duration. Methods from Zijlstra, 2003.	No difference for trunk accelerations between IMU and OMCS data. No difference found for spatio-temporal parameters.	Small sample-size (n=10). Only recruited patients that could walk independently which may limit applicability to PD patients with increased disability. Limited parameters.
McCamley *et al.*, 2012	IMU (Freesense, Sensorize, srl) containing three accelerometers and three gyroscopes fitted over lumbar spine.	To propose improved methods for determining HS and TO and to assess accuracy of existing algorithms against instrumented mat.	HS, TO and stride duration. Methods from McCamley, 2012.	Newly proposed methods led to improved estimates of GE timing and improved estimate of individual step lengths.	Small sample (n=18) of healthy young adults limits applicability to pathological cohorts. Limited parameters.
Dalton *et al.*, 2013	AD_BRC sensor (triaxial accelerometer) attached to upper sternum.	To investigate the validity of a triaxial accelerometer in detecting gait and balance impairments in pre-manifest and manifest Huntington's disease (HD) subjects compared against a computerized walkway.	SL, stride length, cadence, step time, GV, Step time/SL/stride length variability, methods from Zijlstra, 2003. Step time asymmetry, step/stride regularity calculated. Methods from Moe-Nilssen, 2004.	Sensor showed excellent agreement to a computerized walkway across a range of spatio-temporal parameters and demonstrated significant discriminatory power between healthy, pre-manifest HD and manifest HD subjects.	Accelerometry patterns at level of the thorax are an attenuated version of those closer to the COM which could be a limitation. Instrumented walkway was not a gold standard for validating the IMU system with respect to gait variability.
Zijlstra *et al.*, 2013	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over L2-4.	To compare reliability and validity of four different Inverted Pendulum estimations of step length in elderly subjects.	SL.	Evidence for reliable estimations of mean step length with good to high agreement to reference. No meaningful differences in results between models. Individual correction factors favoured over generic correction.	Limited parameters.
Godfrey *et al.*, 2014	Axivity AX3 sensor (Axivity, York, UK) located over L5.	To determine validity against an instrumented walkway and reliability of a single-point IMU and associated algorithms to assess gait in older and younger healthy adults at different speeds.	Step duration, stride duration, GV estimated, methods from McCamley, 2012. SL, methods from Zijlstra, 2003.	Sensor and algorithm arrangement are valid and reliable for quantifying gait in both younger and older adults.	Healthy cohort limit applicability to pathological cohorts.
Collett *et al.*, 2014	IMU device (Pi-node, Philips, Netherlands) containing a tri-axis accelerometer fitted over L4.	To determine test-retest reliability of spatio-temporal parameters and non-linear (phase plot) measures in HD patients and healthy controls.	GV, step time, step time variability, cadence, stride length, stride length variability, methods from Zijlstra, 2003. Non-linear measures (gait variability and symmetry).	There was no significant difference between any measure between tests.	Straight-walking in a laboratory limits external validity to daily-living. Only six cycles were used to calculate variability, which may have contributed to no difference being found in spatial temporal variability.
Trojaniello *et al.*, 2014	IMU (Opal™, APDM) featuring a 3-axis accelerometer and 3-axis gyroscope. Positioned at S2, L3, waist-level, L5 or right-side waist depending on algorithm employed.	To assess the performance of five methods McCamley, 2012; Zijlstra, 2003; Gonzalez, 2009; Kose, 2012 ; Shin, 2011 for detecting GEs and determining temporal parameters from a trunk/waist IMU compared to stereophotogrammetry and force platforms.	HS, TO, step time, stride time, swing time, double support time, stance time.	No statistically significant difference was found between all methods for stride and step duration and the standard. However, methods that detect TO in conjunction with HS that allow determination of stance, swing and double support time, showed a statistically significant difference in these measures against a standard.	Used sensors of different mass to the original study design and a barefoot walking protocol which differs from those originally employed. Healthy cohort limit applicability to pathological cohorts.
Godfrey *et al.*, 2015	Axivity AX3 sensor (Axivity, York, UK) fixed over L5.	To validate gait parameters from an IMU in a large cohort of young and older adults against an instrumented walkway.	Step count, step time, stride time, GV determined by methods from McCamley, 2012. SL using an inverted pendulum model from Zijlstra, 2003. Gait variability/asymmetry of each spatio-temporal parameter.	Step count and mean spatio-temporal characteristics had excellent/good agreement with laboratory references. There was poor agreement between methods for estimates of left/right step data, variability and asymmetry. Determined it was due to inherent differences between the systems rather than inability of the sensor to measure the gait characteristics.	Healthy cohort limit applicability to pathological cohorts. IMU and instrumented walkway different data conversion principles may impact results. Instrumented walkway was not a gold standard for validating the IMU system with respect to gait variability and asymmetry.
Grimpampi *et al.*, 2015	IMU (FreeSense, Sensorize s.r.l Rome) positioned over lower lumbar spine.	To assess the reliability of gait variability measures in healthy older subjects from lower trunk accelerations.	Stride time variability, methods from Zijlstra, 2003.	Gait variability analysis from lower trunk acceleration data is reliable in older individuals.	Limited number of strides so assessment was based only on linear techniques.
Park & Woo, 2015	Tri-axial accelerometer (G-Walk, BTS Bioenginering S.p.A., Italy) attached over L5.	To determine the relationship between an accelerometer and foot pressure sensors for measuring gait characteristics in healthy subjects.	GV, step count, cadence, stride length, stride duration, swing time, stance time, single support time, double support time, stride velocity, methods from Zijlstra, 2003.	Significant and high correlation between the two systems with respect to GV and cadence. Stride length from the accelerometer was significantly and highly correlated with stride length and stride velocity from the foot pressure system.	Healthy cohort limit applicability to pathological cohorts. Straight-walking in a laboratory limits external validity to daily-living.
Trojaniello *et al.*, 2015	IMU (Opal™, APDM) featuring a 3-axis accelerometer and 3-axis gyroscope. Positioned at S2, waist-level or L5 depending on algorithm.	To assess the performance of three methods McCamley, 2012; Zijlstra, 2003; Shin, 2011 for determining GEs and gait temporal parameters from a single IMU in elderly, post-stroke, PD and HD subjects against an instrumented walkway.	HS, TO, GV, stride time, step time, stance time, swing time.	A universal decrease in accuracy of GE detection and temporal parameters compared to healthy subjects. No statistically significant differences in temporal parameter measurement between IMU methods in any cohort; apart from PD subjects for which methods from Zijlstra, 2003 outperformed.	Limitations include using sensors of different mass to the original study design and a barefoot walking protocol which differs from those originally employed. Limited parameters.
Byun *et al.*, 2016	FITMETER® (FitLifeInc, Suwon, Korea, hereafter FITMETER) containing a tri-axial accelerometer over L5.	To investigate the validity and test-retest reliability of spatio-temporal gait parameters measured with a single tri-axial accelerometer compared to an instrumented walkway.	Cadence, GV, step time, step time variability and asymmetry, methods from McCamley, 2012. SL, methods from Zijlstra, 2013.	Gait parameters from a single accelerometer were reliable and valid with advantages over the walkway system for measuring gait variability and asymmetry.	Length of the active instrumented walkway was too short to capture enough consecutive steps to allow reliable variability measures. Inclination of the accelerometer was not considered. Instrumented walkway was not a gold standard for validating the IMU system with respect to gait variability and asymmetry.
Hickey *et al.*, 2016	Axivity AX3 sensor (Axivity, York, UK) located on L5.	To examine the validity of a single wearable for deriving spatio-temporal gait characteristics in spinocerebellar ataxia type-6 and control cohorts against an instrumented walkway.	GV, SL, swing time variability, step time, swing time, stance time, step time variability, SL variability, stance time variability, swing time asymmetry, step time asymmetry, stance time asymmetry and step length asymmetry, methods from McCamley, 2012.	Mean gait characteristics can be accurately measured using an accelerometer-based wearable in people with SCA6. Although, gait variability and asymmetry showed poor agreement between the two systems.	Instrumented walkway was not a gold standard for validating the IMU system with respect to gait variability and asymmetry. IMU and instrumented walkway different data conversion principles may impact results. Straight-walking in a laboratory limits external validity to daily-living.
Sejdic *et al.*, 2016	Tri-axial accelerometer (MMA7260Q, Freescale Semiconductor) secured over the L3.	To validate a proposed algorithm against a motion capture system for healthy elderly, PD and peripheral neuropathy subjects.	Stride time, HS, TO, stance time, double support duration, single support duration, swing percentage and HR.	Demonstrated the proposed algorithm can accurately extract heel and toe events from gait accelerometry signals.	Treadmill protocol limits validity to overground walking and daily-life scenarios. Treadmill acted as an external pacer which greatly aided the gait of PD subjects which could alter results.
Storm *et al.*, 2016	IMUs (Opal™, APDM) containing a 3-axis accelerometer, 3-axis gyroscope, and a 3-axis magnetometer. Positioned on L5. The other two IMUs positioned at each ankle, just above the malleoli.	To evaluate the accuracy of two algorithms versus pressure insoles for the detection of gait events and temporal parameters based on two shank-worn inertial sensors, and the other based on one waist-worn sensor.	HS, TO, stride time, step time and stance time, methods from McCamley, 2012.	Despite the multi-sensor shank method performing better, both methods showed small differences in GE timing and temporal parameter estimation, for both mean and variability measures, between different environments and different walking protocols.	Small sample size (n=10) of healthy subjects limits applicability to pathological cohorts. Limited parameters.
Lim & Lee, 2017	Tri-axial accelerometer (G-Walk, BTS Bioengineering S.p.A., Italy).	To determine the correlation between accelerometer and treadmill-based analysis of gait parameters during comfortable walking in healthy young adults.	Cadence, GV, step count, step time, stride time, stance phase time, swing phase time and double support time, methods from Zijlstra, 2003.	Measures from the accelerometer strongly correlated with those from the treadmill-based system.	Small sample size (n=23) of healthy adults was a limitation and limits applicability to pathological cohorts. Treadmill-based walking limits external validity to daily-living scenarios.
Oyake *et al.*, 2017	Tri-axial accelerometer (WAA-006; Wireless Technologies Inc., Japan) at L3.	To evaluate the validity of step time and length asymmetries using an accelerometer against force plate measurements in hemiparetic stroke subjects.	GV, step time asymmetry and SL asymmetry.	Step time asymmetry and SL asymmetry estimated from trunk accelerations significantly correlated to that measured using force plates.	Small sample size (n=24). Straight-walking in a laboratory limits external validity to daily-living. Limited parameters.
Storm *et al.*, 2018	Tri-axial accelerometer (MoveMonitor, Version 2.8.1, Mc Roberts, The Hague, The Netherlands) positioned at the lower back. The other two IMUs positioned at each ankle, just above the malleoli.	To characterise gait in both laboratory and daily life conditions for patients with MS. Algorithms to characterise gait from wearable inertial sensors data were also validated.	HS, TO, stride time, step time, stance time, swing time, stride time variability, step time variability, stance time variability, swing time variability, step count and GV, methods from McCamley, 2012.	Validated trunk accelerometry methods to quantify gait in MS subjects and showed how gait characteristics.	Variability measures were highly overestimated. Small sample size (n=14).
Zago *et al.*, 2018	Tri-axial accelerometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L5.	To determine if a commercial IMU can reliably provide the main spatiotemporal gait parameters in PD subjects compared to optical motion capture standard.	Cadence, GV, stride length, stride duration, step duration, stance phase duration, swing phase duration and double support phase duration, methods from Zijlstra, 2003.	Most spatio-temporal gait parameters detected by the IMU were not statistically different. GV was significantly higher when measured with the wearable system. Stride length and step duration and double support duration, although not statistically different, showed moderate RMS and mean absolute errors.	Difference detected in some parameters was probably due to the different algorithm used in the two devices to detect gait events. Small sample size (n=22). Straight-walking in a laboratory limits external validity to daily-living.
De Ridder *et al.*, 2019	Tri-axial accelerometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L5.	To confirm the test-retest reliability and concurrent validity of a commercially available accelerometer for spatio-temporal gait parameters with an instrumented walkway standard.	GV, cadence, stride length, stride duration, stance duration, swing duration, double support, and single support, methods from Zijlstra, 2003.	Accelerometer is reliable for all measured spatio-temporal parameters. Excellent validity shown for GV, cadence, stride length and stride duration. Cautious interpretation necessary for temporal parameters based on final foot contact (stance, swing and single/double support time).	Measured spatio-temporal parameters at a single speed might have an impact on accuracy. Straight-walking on a treadmill limits external validity to daily-living. Healthy cohort limit applicability to pathological cohorts.
Waist					
Kose *et al.*, 2012	IMU (FreeSense, Sensorize®) containing a tri-axial accelerometer and two bi-axial gyroscopes attached to right-side of waist.	To validate a proposed method for SL estimation on healthy subjects at various speeds against stereophotogrammetry.	HS, step duration, SL and distance travelled.	Step length was estimated for all subjects with less than 3% error. Traversed distance was assessed with less than 2% error.	Accuracy discrepancies between left and right steps, hypothesised to be due to asymmetrical sensor placement and fixation to the subject's belt rather than skin. Small sample size (n=9). Limited parameters. Healthy cohort limit applicability to pathological cohorts.
Ear					
Atallah *et al.*, 2014	e-AR sensor. (containing a tri-axial MEMS accelerometer) fitted behind the ear.	To validate an ear-worn accelerometer against a force-plate treadmill for detection of stride duration and step time asymmetry in older adults and orthopaedic patients.	Stride duration and step time asymmetry.	Ear-worn accelerometer was capable of determining gait cycle time, and step-period asymmetry with good correspondence to a force-plate treadmill regardless of inclines or speed.	Fixed speeds and inclines on a treadmill could lead to less asymmetry and gait cycle time variability and alter validity. Did not analyse individual variability only group means based on condition. Straight-walking on a treadmill limits external validity to daily-living. Limited parameters.
Jarchi *et al.*, 2014	e-AR sensor. (containing a tri-axial MEMS accelerometer) fitted behind the ear.	To determine quantitative accuracy of the e-AR sensor for detection of GEs against an in-shoe pressure detection system.	HS and TO.	The e-AR sensor is valid for the detection of GEs in straight walking conditions. With higher accuracy for HS than TO.	Straight-walking protocol limits external validity to daily-living. Healthy cohort limit applicability to pathological cohorts. Small sample size (n =10). Limited parameters.
Jarchi *et al.*, 2015	e-AR sensor. (containing a tri-axial MEMS accelerometer) fitted behind the ear.	Determine detection of GEs in PD patients from an e-AR sensor compared to motion capture.	HS, TO and step frequency.	Good agreement between e-AR sensor and motion capture for detection of GEs and step frequency.	Straight-walking protocol limits external validity to daily-living. Small sample size (n =9). Limited parameters.
Jarchi *et al.*, 2016	e-AR sensor. (containing a tri-axial MEMS accelerometer) fitted behind the ear.	Determine detection of GEs in orthopedic patients from an e-AR sensor compared to an in-shoe pressure detection system.	HS and gait asymmetry.	Good agreement between e-AR sensor and in-shoe pressure system for detection of GEs and step frequency.	Straight-walking protocol limits external validity to daily-living. Small sample size (n =8). Limited parameters.
Shank					
Li *et al.*, 2010	IMU (bi-axial accelerometer and a gyroscope) attached to the lateral aspect of the calf.	To study the feasibility of estimating GV using a shank mounted IMU versus treadmill.	GV.	Speed estimation method worked well across treadmill speeds and slopes. It also worked well during overground walking. Accuracy is comparable to that achieved from foot-mounted sensors.	Healthy cohort limit applicability to pathological cohorts. Straight-walking on a treadmill limits external validity to daily-living. Small sample size (n =8). Inability to assess asymmetry. Limited parameters.
Maqbool *et al.*, 2017	IMU consisting of a tri-axis accelerometer and a tri-axis gyroscope over the shank. Gyroscope signal is the only used.	To validate a shank IMU against pressure insoles for gait event detection in lower limb amputees when performing level ground and ramp activities.	HS and TO.	IC and TO events accurately detected using the proposed system in control subjects and amputees when performing activities of daily living.	Small cohort of two amputees. Protocol of only straight-walking. Need for the instrumented shank to take the first step to allow first TO detection. Inability to assess asymmetry. Limited parameters.
Foot					
Sabatini *et al.*, 2005	IMU (one biaxial accelerometer and one gyroscope) attached to superior aspect of a single shoe.	To determine accuracy of the foot inertial sensing approach in assessing walking speed and the incline on a treadmill.	HS, TO and GV.	Foot inertial sensing is a promising tool for the reliable identification of subsequent gait cycles and the accurate assessment of walking speed and incline.	Difficult attachment of the IMU to the shoe and an accuracy decrease with increasing incline further limit clinical application. Healthy cohort limit applicability to pathological cohorts. Straight-walking on a treadmill limits external validity to daily-living. Small sample size (n =5). Inability to assess asymmetry. Limited parameters.
Song & Kim, 2018	IMU (tri-axis accelerometer, gyroscope) attached to the rear of a single shoe.	To propose a foot IMU and algorithm aimed to classify gait activities and to determine accuracy of gait parameters when compared to motion capture.	Stride length, stride time, GV and step count.	Proposed system is simple and effective for daily-life gait analysis, including gait activity classification and gait parameter estimation for each activity.	Difficulties were present with detecting tip-toed stair walking with lack of evident HS. Inability to assess asymmetry. Limited parameters.
Smart Device					
LeMoyne *et al.*, 2010	iPhone 3G attached above lateral malleolus of left ankle.	To establish the capacity of an iPhone accelerometer to accurately acquire gait parameters.	Time averaged acceleration and step cycle time.	The iPhone accelerometer has the capacity to accurately quantify gait parameters accurately.	Unrealistic attachment of the device above the lateral malleolus does not accurately reflect phone placement in everyday life, limiting applicability Healthy cohort limit applicability to pathological cohorts. Straight-walking in laboratory conditions limits external validity to daily-living. Small sample size (n=1). Limited parameters.
Pepa *et al.*, 2017	iPhone 4s placed at approximately L3-4 and lateral waist.	To assess smartphone performance in different locations in heel strike, step count, step period, and step length estimation compared to stereophotogrammetry.	Step count, HS, Step time and SL.	High correlations found between smartphone and stereophotogrammetry measures. Error ranges comparable to those in the literature. Smartphone placement did not affect the performance.	Device orientation had an effect on step count sensitivity. SL estimation means need for calibration of individual correction factor. Phone positioning on lumbar spine and lateral waist does not accurately reflect phone placement in everyday life, limiting applicability. Healthy cohort limit applicability to pathological cohorts. Straight-walking in laboratory conditions limits external validity to daily-living. Small sample size (n=11). Limited parameters.
Silsupadol *et al.*, 2017	Vivo X5 one of five locations: 1) Over L3; 2) in a shoulder bag on the right hip; 3) above the front right pant pocket horizontal orientation; 4) in the right hand, held in a telephone speaking position; 5) in the front right pant pocket placed in a vertical orientation.	To assess the reliability and validity of a smartphone-based accelerometer in quantifying spatio-temporal gait parameters when attached to the body or in a bag, belt, hand, and pocket compared with instrumented walkway.	SL, GV, step time and cadence.	Smartphone-based assessments of gait are reliable and valid when placed on the body, bag, or belt, particularly in comfortable and fast walking conditions.	Limitations in assessing gait at slow speeds reduces application to pathological groups. Straight-walking with only 5-9 steps per trial in laboratory conditions limits external validity to daily-living. Healthy cohort limit applicability to pathological cohorts. Limited parameters.

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Table S2 Summary of clinical application studies

Reference	Sensor(s)/Placement	Application	Parameters Measured
Trunk			
Auvinet *et al.*, 2003	Locometrix (tri-axial accelerometer) over L3-4.	Gait abnormalities in elderly fallers versus healthy controls.	GV and stride frequency, length, symmetry and regularity.
Moe-Nilssen *et al.*, 2003	Triaxial, piezoresistant accelerometer (Logger Technologi, Malmö, Sweden) over lower back.	Discriminate between children with dyslexia and healthy controls based on gait.	GV, cadence and SL.
Houdijk *et al.*, 2008	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	Assessment of spatiotemporal parameters of amputee gait.	Step count, SL, step duration and GV.
Mizuike *et al.*, 2009	Tri-axial accelerometer (RF-H48C, Hitachi Metals, Ltd., Japan) over L3.	Describe gait of stroke patients delineate from healthy controls.	GV, SL, stride duration, cadence, stride regularity and RMS.
Maquet *et al.*, 2010	Locometrix (tri-axial accelerometer) over L3-4.	Delineation of elderly, Alzheimer's and mild cognitive impairment subjects by gait analysis under single and dual task protocols.	GV, stride frequency, stride length, stride symmetry and stride regularity.
Lamoth *et al.*, 2010	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer over L3.	Differentiate transfemoral amputees and healthy controls based on gait.	GV, stride time, stride time variability, non-linear measures (variability, regularity, stability) and RMS.
Bautmans *et al.*, 2011	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over S2.	Delineating healthy elderly and young subjects from elderly fallers from gait.	GV, step time, step time symmetry, step regularity and stride regularity.
Esser *et al.*, 2011	IMU (MTx, Xsens, The Netherlands) containing a Tri-axial accelerometer, gyroscope and magnetometer, attached over L4.	PD, muscular dystrophy, MND, stroke survivors and healthy subjects.	Step time, SL and GV.
Lamoth *et al.*, 2011	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer over L3.	Effect of dual task conditions on gait in Dementia subjects and healthy controls.	GV, stride time, stride time variability, stride frequency and non-linear measures (gait regularity, gait stability).
Meijer *et al.*, 2011	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	Gait in post-stroke patients versus healthy controls.	GV, cadence, gait symmetry and bilateral coordination of gait.
Bolink *et al.*, 2012	MicroStrain® Inertia-Link® was used containing gyroscopes and accelerometers. Attached over dorsal side of the pelvis between both posterior superior iliac spines.	Objective assessment of total knee replacement in osteoarthritis patients and differentiating from healthy controls.	GV, cadence, SL, step time, step time variability and step time asymmetry.
De Bruin *et al.*, 2012	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over S2.	Determining severity of peripheral neuropathy in diabetics.	SL, GV, step duration and cadence.
Hojan *et al.*, 2014	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	External breast prosthesis effect on gait after mastectomy.	GV, SL, step time, cadence and step time asymmetry.
Dalton *et al.*, 2013	AD_BRC sensor (triaxial accelerometer) attached to upper sternum.	Differentiating between pre-manifest HD, manifest HD and healthy controls.	SL, stride length, cadence, step time, GV, Step time/SL/stride length variability, step asymmetry and step/stride regularity.
Doi *et al.*, 2013	Tri-axial accelerometer (MVP-RF8, MicroStone, Nagano, Japan) attached to L3.	Effect of multicomponent exercise on gait in elderly with MCI.	GV, stride time, stride length and HR.
Esser *et al.*, 2013	IMU (Pi-Node, Philips, Netherlands) over L4.	Differentiate PD patients and healthy controls.	Cadence, stride length, GV, cadence variability, stride length variability and non-linear measures (gait variability).
Iosa *et al.*, 2013	FreeSense (Sensorize s.r.l., Rome, Italy) containing a tri-axial accelerometer at L2-3.	Differentiating Cerebral Palsy children from healthy controls during running and walking.	GV, SL, step duration, RMS and HR.
Manikowska *et al.*, 2013	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	Gait patterns in pre and post-menopausal women.	GV, SL, cadence, stance phase duration, swing phase duration, single support duration, double support duration and SL variability.
Manikowska *et al.*, 2013	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer. Over posterior sacrum at body's centre of mass.	Effect of hippotherapy on gait in cerebral palsy children.	GV, cadence, SL, stride length and left-right symmetry.
Collett *et al.*, 2014	IMU device (Pi-node, Philips, Netherlands) containing a tri-axis accelerometer fitted over L4.	Delineating HD patients from healthy controls and determining disease severity using gait.	GV, step time, step time variability, cadence, stride length, stride length variability and non-linear measures (gait variability and symmetry).
Herman *et al.*, 2014	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer fixed over the lower back.	Quantify motor differences in PD subtypes and propose a classification scheme.	Step count, GV, stride time variability, stride regularity and cadence.
Pau *et al.*, 2014	Tri-axial accelerometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L4-L5.	Effect of physical activity on balance and gait of older adults.	SL, GV, gait cycle duration, stance duration, swing duration and double support duration.
Saether *et al.*, 2014	(MTx. XSens, Enschede, NL) attached over L3 contains tri-axial units of accelerometers, gyroscopes, and magnetometers.	Gait characteristics in cerebral palsy versus healthy children.	GV, cadence, SL, step time, stride regularity and symmetry.
Arvin *et al.*, 2015	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed over L5.	Effect of unilateral hip abductor muscle fatigue on gait in older adults.	Stride time, stride time variability, step symmetry, stance time, HR and non-linear measures (gait stability).
Demonceau *et al.*, 2015	Locometrix (tri-axial accelerometer) over L3-4.	Delineating PD patients from healthy controls and determining disease severity.	Cadence, SL, gait regularity and symmetry.
Martinez-Ramirez *et al.*, 2015	IMU (MTx, Xsens, The Netherlands) containing a Tri-axial accelerometer, gyroscope and magnetometer over the lumbar spine.	Frailty assessment based on gait assessment.	GV, cadence, step regularity, stride regularity, gait symmetry, step time, step time variability, RMS and HR.
Matsushima *et al.*, 2015	Triaxial accelerometer (Jukudai Mate; Kissei Comtec Co., Ltd., Matsumoto, Japan) fixed over L3.	Delineating Ataxia patients from healthy controls and determining disease duration.	GV, cadence, SL, gait regularity and RMS.
Perrochon *et al.*, 2015	Locometrix (tri-axial accelerometer) over L3-4.	Effects of exercise on gait in dementia patients.	GV, stride frequency, stride length, gait symmetry and gait regularity.
Rapp *et al.*, 2015	IMU (Humotion, Münster, Germany) featuring a tri-axis accelerometer and tri-axis gyroscope attached over L4-5.	Efficacy of rehabilitation for patients after hip arthroplasty.	GV and gait symmetry.
Terrier & Reynard, 2015	Tri-axial accelerometer (Physilog® System, Gaitup, Lausanne, Switzerland) 5cm below sternal notch.	Effect of aging on gait parameters.	GV, non-linear measures (gait stability), RMS and walk-ratio.
Awotidebe *et al.*, 2016	IMU containing tri-axial accelerometer, gyroscope and magnetometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L5.	Delineating between type 2 diabetes patients and healthy controls.	GV, SL, stride length and cadence.
Barden *et al.*, 2016	Triaxial accelerometer (GENEActiv, Cambridgeshire, UK) attached over L3.	Compare regularity and symmetry of gait between knee osteoarthritis (OA) and healthy controls.	Stride time, step time, stride regularity, step regularity and gait symmetry.
Clermont *et al.*, 2016	tri-axial accelerometer (GENEActiv, Cambridge, UK), attached near COM.	Delineating between knee osteoarthritis patients and age-matched controls.	Step count, stride time, stride time variability, step time, step time variability and non-linear measures (gait variability).
Del Din *et al.*, 2016	Tri-axial accelerometer (Axivity AX3, York, UK) over L5.	Delineating between PD patients and age-matched controls.	GV, SL, swing time variability, GV variability, SL variability, stpe time variability, stance time variability, step time, swing time, stance time, step time symmetry, swing time symmetry, stance time symmetry and SL symmetry.
Gillain *et al.*, 2016	Locometrix (tri-axial accelerometer) over L3-4.	Determining risk of developing AD from MCI based on gait.	Stride frequency, SL, gait symmetry and regularity.
Hatanaka *et al.*, 2016	triaxial accelerometer (Mimamori-Gait® System, LSI Medience Corp., Tokyo, Japan) back of waist.	Gait comparison in Progressive Supranuclear Palsy and PD and delineating from healthy controls.	GV, SL, cadence, step time, step time variability and double support time.
Henderson *et al.*, 2016	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer placed on lower trunk.	Effect of rivastigmine on gait variability in PD.	GV and step time variability.
Hickey *et al.*, 2016	Axivity AX3 sensor (Axivity, York, UK) located on L5.	Differentiating patients with spinocerebellar ataxia type-6 from healthy controls.	GV, SL, swing time variability, step time, swing time, stance time, step time variability, SL variability, stance time variability, swing time asymmetry, step time asymmetry, stance time asymmetry and step length asymmetry.
Martinez-Ramirez *et al.*, 2016	Tracker MTx (XSENS; Xsens Technologies B.V. Enschede, The Netherlands) featuring tri-axis accelerometer, tri-axis gyroscope, tri-axis magnetometer fixed over L3.	Dual task walking performance in frail populations with and without MCI against controls.	GV, step and stride regularity, gait symmetry, step time variability, RMS, gait stability and HR.
Mutoh *et al.*, 2016	Tri-axial accelerometer (MG-M1110-HW, LSI Medience, Tokyo, Japan) over L3.	Effects of hippotherapy on gait and balance ability of children and adolescents with cerebral palsy.	Cadence, SL and GV.
Pau *et al.*, 2016	IMU containing tri-axial accelerometer, gyroscope and magnetometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L4-5.	Gait measures in MS and correlation with patient-reported outcomes. Determining MS severity.	Stride length, GV, cadence, stance duration, swing duration and double support duration.
Van Schooten *et al.*, 2016	DynaPort MiniMod (McRoberts BV, The Hague, The Netherlands) consisting of a triaxial accelerometer over L5.	Gait characteristics as a predictor of falls in older subjects.	Stride length, GV, stride time variability, GV variability, stride length variability, stride length, gait symmetry, gait variability, non-linear measures (gait smoothness, complexity, intensity) and stride frequency.
Del Din *et al.*, 2017	Tri-axial accelerometer (Axivity AX3, York, UK) on the lower back.	Gait characteristics in fallers and non-fallers with and without PD.	Step count, mean bout length, step time, swing time, stance time, step time asymmetry, swing time asymmetry, stance time asymmetry, SL asymmetry, step velocity, SL, swing time variability, step time variability, stance time variability, GV and SL variability.
Pau *et al.*, 2017	Triaxial accelerometer fixed to participant's sacrum.	Gait in early MS subjects compared to healthy control.	Cadence, speed, stride length, stance, swing and double support phase duration.
Esser *et al.*, 2018	IMU (tri-axial accelerometer and gyroscope) fixed to the lower back.	Gait analysis to detect peripheral neuropathy in diabetes patients.	Step time, cadence, stride length, GV and non-linear measures (gait control variables).
Pau *et al.*, 2018	Tri-axial accelerometer (G-Walk, BTS Bioengineering S.p.A., Italy) attached over L4-5.	Effect of texting while walking on gait in MS patients compared to healthy controls.	Stride length, GV, cadence, stance duration, swing duration and double support duration.
Storm *et al.*, 2018	Tri-axial accelerometer (MoveMonitor, Version 2.8.1, Mc Roberts, The Hague, The Netherlands) positioned at the lower back. The other two IMUs positioned at each ankle, just above the malleoli.	Characterise gait in MS patients in laboratory and free-living conditions and determine severity.	HS, TO, stride time, step time, stance time, swing time, stride time variability, step time variability, stance time variability, swing time variability, step count, GV
Tanigawa *et al.*, 2018	MVP-RF-8, MicroStone Co., Nagano, Japan) that contained a triaxial angular rate gyroscope and a linear accelerometer were attached to a fixed belt at the level of the L3.	Relationship of lumbopelvic pain with gait in pregnant patients.	Gait symmetry and stride variability.
Waist			
Terrier *et al.*, 2009	Physilog system (BioAGM, Switzerland), triaxial accelerometer lateral waist.	Assess the effect of prescription footwear on gait quality in patients after ankle/foot fractures.	Stride regularity and stride symmetry.
Yang *et al.*, 2011	Tri-axial accelerometer at lateral waist.	Differentiating PD and healthy controls.	Cadence, step regularity, step symmetry and stride regularity.
Terrier *et al.*, 2017	Actigraph wGT3X-BT activity monitor (Actigraph, Pensacola, FL, USA) lateral waist.	Delineating patients with chronic pain of lower limbs and healthy controls from free-living gait.	Cadence, stride regularity and non-linear measures (intensity, dynamic stability).
Foot			
Chung *et al.*, 2012	Triaxial accelerometer on superior aspect of right foot.	Delineating patients with Alzheimer's disease (AD) from healthy controls.	Stride length, stride frequency, GV, cadence, stance phase duration and stance phase variability.
Angthong & Veljkovic, 2018	Foot pod (Garmin Ltd., Kansas City, USA) strapped to dorsum of foot.	Relationship of patient-reported outcomes and quality-of-life with gait characteristics in patients with foot-ankle conditions.	Distance travelled, step count, SL, cadence and GV.
Ear			
Atallah *et al.*, 2014	e-AR sensor (containing a tri-axial MEMS accelerometer) fitted behind the ear.	Post-operative recovery of orthopaedic patient.	Stride duration and step time asymmetry.
Jarchi *et al.*, 2016	e-AR sensor (containing a tri-axial MEMS accelerometer) fitted behind the ear.	To assess recovery in anterior cruciate ligament injury patients after surgery.	Gait asymmetry.
Smart device			
Kosse *et al.*, 2016	iPod touch G4 (iOS 6, Apple Inc.) fixed over L3.	Assess gait variability changes related to aging.	Stride time, stride time variability, GV, RMS and non-linear measures (gait stability).
Mobbs *et al.*, 2018	Apple Watch (Apple, San Francisco, CA, USA) on the wrist.	Gait analysis for objective recovery measures following lumbar microdiscectomy.	GV.
Soangra & Lockhart, 2018	Apple iPhone 5 (iPhone 5, Apple Inc., Cupertino, CA, USA) on lateral waist.	Identifying CVD patients likely to have post-operative adverse outcomes based on gait analysis.	GV and non-linear measures (gait variability).

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Table S3 Risk of bias assessment of validity and reliability studies

Article (author, year)	Patient Selection				Index Test			Reference Standard			Flow and Timing			Overall
	1.1	1.2	1.3	1.4	2.1	2.2	2.3	3.1	3.2	3.3	4.1	4.2	4.3	5.1
Atallah *et al.*, 2014	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Bautmans *et al.*, 2011	CS	Y	Y	Y	NA	NA	Y	NA	NA	NA	NA	NA	Y	++
Brandes *et al.*, 2006	CS	Y	Y	Y	Y	NA	Y	CS	Y	CS	Y	Y	Y	+
Bugane *et al.*, 2012	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Byun *et al.*, 2016	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Dalton *et al.*, 2013	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
De Bruin *et al.*, 2012	N	Y	Y	CS	NA	NA	Y	NA	NA	NA	NA	NA	N	+
De Ridder *et al.*, 2019	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Esser *et al.*, 2012	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Godfrey et al, 2014	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Godfrey et al, 2015	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	N	+
Grimpampi *et al.*, 2015	CS	Y	Y	Y	NA	NA	Y	NA	NA	NA	NA	NA	Y	++
Hartmann *et al.*, 2009	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Hartmann *et al.*, 2009 (different surfaces)	CS	Y	Y	Y	NA	NA	Y	NA	NA	NA	NA	NA	N	+
Henriksen *et al.*, 2004	CS	Y	Y	Y	NA	NA	Y	NA	NA	NA	NA	NA	Y	++
Hickey *et al.*, 2016	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Houdijk *et al.*, 2008	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Jarchi *et al.*, 2014	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Jarchi *et al.*, 2015	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	N	+
Jarchi *et al.*, 2016	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Köse *et al.*, 2012	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
LeMoyne *et al.*, 2010	N	Y	Y	CS	NA	NA	Y	NA	NA	NA	NA	NA	Y	+
Li *et al.*, 2010	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Lim & Lee, 2017	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Maqbool *et al.*, 2017	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
McCamley *et al.*, 2012	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Oyake *et al.*, 2017	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Park & Woo, 2015	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	CS	+
Pepa *et al.*, 2017	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	CS	+
Sabatini *et al.*, 2005	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Sejdic *et al.*, 2016	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Silsupadol *et al.*, 2017	CS	Y	Y	CS	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Song & Kim, 2018	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Storm *et al.*, 2016	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Storm *et al.*, 2018	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	N	+
Trojaniello *et al.*, 2014	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Trojaniello *et al.*, 2015	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Zago *et al.*, 2018	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	CS	++
Zijlstra & Hof, 2003	CS	Y	Y	Y	Y	NA	Y	Y	Y	Y	Y	Y	Y	++
Zijlstra & Zijlstra, 2013	CS	Y	Y	Y	Y	NA	Y	Y	CS	Y	Y	Y	Y	++
Collett *et al.*, 2014*	Assessed using NOS													
Esser *et al.*, 2011*	Assessed using NOS													

Y, yes; N, no; NA, not applicable; CS, can't say; "+" denotes acceptable quality in minimizing bias; "++" denotes high quality in minimizing bias; NOS, Newcastle-Ottawa Scale. *, refer Appendix 1.

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Appendix 1 Risk of bias assessment of clinical applicability studies

Study (Author, Year)	Selection	Comparability	Exposure	Results
Angthong, 2018	2	2	2	Fair
Atallah, 2014	2	1	2	Fair
Auvinet, 2003	3	0	2	Poor
Awotidebe, 2016	4	1	2	Good
Barden, 2016	3	2	2	Good
Bautmans, 2011	4	2	2	Good
Bolink, 2012	3	1	2	Good
Chung, 2012	1	1	2	Poor
Clermont, 2016	3	1	2	Good
Collett, 2014	3	2	2	Good
Dalton, 2013	3	2	2	Good
De Bruin, 2012	2	2	2	Fair
Del Din, 2016	3	1	2	Good
Del Din, 2017	3	1	2	Good
Demonceau, 2015	3	2	2	Good
Esser, 2011	1	0	1	Poor
Esser, 2013	4	2	2	Good
Esser, 2018	3	1	2	Good
Gillain, 2016	2	2	2	Fair
Hatanaka, 2016	3	1	2	Good
Herman, 2014	3	2	2	Good
Hickey, 2016	4	1	2	Good
Hojan, 2014	3	1	2	Good
Iosa, 2013	2	2	2	Fair
Jarchi, 2016	2	1	1	Poor
Kosse, 2016	3	1	2	Good
Lamoth 2011	3	1	2	Good
Lamoth, 2010	3	1	1	Poor
Manikowska, 2013 (postmenopausal women)	3	1	2	Good
Maquet, 2010	3	2	2	Good
Martinez-Ramirez, 2015	3	1	1	Poor
Martinez-Ramirez, 2016	3	1	2	Good
Matsushima, 2015	2	1	2	Fair
Meijer, 2011	3	2	2	Good
Mizuike, 2009	4	1	2	Good
Moe-Nilssen, 2003	4	2	3	Good
Pau, 2016	4	0	2	Poor
Pau, 2017	4	0	2	Poor
Pau, 2018	3	1	2	Good
Perrochon, 2015	2	2	2	Fair

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Rapp, 2015	3	2	1	Poor
Saether, 2014	4	2	2	Good
Soangra, 2018	2	1	2	Fair
Storm, 2018	3	1	2	Good
Tanigawa, 2018	3	0	2	Poor
Terrier, 2009	1	2	2	Poor
Terrier, 2015	3	1	2	Good
Terrier, 2017	3	1	2	Good
Van Schooten, 2016	3	2	2	Good
Yang, 2011	3	0	2	Poor

Randomised control trials (RCT)												
Study (Author, Year)	Internal validity											Overall assessment
	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8		1.9	1.10	
								I(%)	C(%)			
Doi, 2013*	Y	CS	CS	CS	Y	Y	Y	4	8	Y	NA	+
Henderson, 2016*	Y	Y	Y	Y	CS	CS	Y	15	11	Y	NA	++
Pau, 2014*	Y	Y	CS	CS	CS	Y	Y	0	0	Y	NA	+

Not assessed	
Houdijk, 2008	Assessed using SIGN
Arvin, 2015	Self-controlled before-after study
Manikowska, 2013	Case series
Mobbs, 2018	Case report
Mutoh, 2016	Case series

NOS interpretation:

Good quality: ≥3 stars in selection domain AND ≥ 1 star in comparability domain AND ≥2 stars in outcome/exposure domain.

Fair quality: 2 stars in selection domain AND ≥ 1 star in comparability domain AND ≥ 2 stars in outcome/exposure domain.

Poor quality: ≤ 1 star in selection domain OR 0 stars in comparability domain OR ≤ 1 star in outcome/exposure domain.

Y, yes; N, no; NA, not applicable; CS, can't say; "+" denotes acceptable quality in minimizing bias; "++" denotes high quality in minimizing bias; I (%), percentage dropout in intervention group; C (%), percentage dropout in control group. *, RCTs were assessed using SIGN checklist for RCTs.

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