Objective falls-risk prediction using wearable technologies amongst patients with and without neurogenic gait alterations: a narrative review of clinical feasibility

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Objectives: The present narrative review aims to collate the literature regarding the current use of wearable gait measurement devices for falls-risk assessment in neurological and non-neurological populations. Thereby, this review seeks to determine the extent to which the aforementioned barriers inhibit clinical use.

Background: Falls contribute a significant disease burden in most western countries, resulting in increased morbidity and mortality with substantial therapeutic costs. The recent development of gait analysis sensor technologies has enabled quantitative measurement of several gait features related to falls risk. However, three main barriers to implementation exist: accurately measuring gait-features associated with falls, differentiating between fallers and non-fallers using these gait features, and the accuracy of falls predictive algorithms developed using these gait measurements.

Methods: Searches of Medline, PubMed, Embase and Scopus were screened to identify 46 articles relevant to the present study. Studies performing gait assessment using any wearable gait assessment device and analysing correlation with the occurrence of falls during a retrospective or prospective study period were included. Risk of Bias was assessed using the Centre for Evidence Based Medicine (CEBM) Criteria.

Conclusions: Falls prediction algorithms based entirely, or in-part, on gait data have shown comparable or greater success of predicting falls than existing stratification scoring systems such as the 10-meter walk test or timed-up-and-go. However, data is lacking regarding their accuracy in neurological patient populations. Inertial measurement units (IMU) have displayed competency in obtaining and interpreting gait metrics relevant to falls risk. They have the potential to enhance the accuracy and efficiency of falls risk assessment in inpatient and outpatient setting.

Keywords: Wearable technologies; inertial measurement units (IMU); gait; falls; neurological disease

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Introduction

Injuries are the fifth largest disease burden in Australia and falls alone account for 40% of injury-related admissions (1). A fall is an event in which a person inadvertently comes to rest on the ground (2). Falls are overrepresented in elderly populations and mostly occur during walking (3). A neurogenic gait alteration (NGA) is an alteration to gait due to abnormalities of the central or peripheral nervous system(s) resulting in changes to ambulation (4). The presence of an NGA doubles an elderly person's risk of falling by altering postural stability, limb dynamics, movement speed, symmetry and smoothness (5). Multiple sclerosis, Parkinson's disease, stroke, cerebral palsy, neurogenic claudication and peripheral neuropathy are common causes of NGA (3). Historically, tests like the Timed Up-and-Go (TUG), Berg-Balance-Scale (BBS), 10-Meter-Walk Test (10MWT) and Physiological Profile Assessment (PPA) were used for clinical assessment of falls-risk. These 'test batteries' require the patient to perform compound movements that assess balance and coordination during walking and completing questionnaires on existing risk-factors. However, they have high inter- and intra-observer variability and only provide an overall falls-risk without identifying which gait metrics are contributing, or where to intervene (6,7). With advances in gait-analysis technology, the gait perturbations prevalent in patients prone to falling can be assessed. Then, accurate capture of a patient's gait metrics in a clinical setting would allow the clinician to make unbiased recommendations for intervention based on the perturbations of gait displayed

Wearable devices capture the 'free-living' gait of unobserved and routine walking behaviours (8). Wearable sensor technology also enables for remote monitoring of many patient metrics by feeding data from small wearable devices to a database on a phone or cloud accessible by the patient and physician (9). For gait analysis, the most common device is a single Inertial Measurement Unit (IMU) or 'single-point' wearable at the pelvis or sternum near the centre of mass (COM), at the ankle or feet for more precise step-recognition, or at multiple points with integrated signals (multi-point wearable sensors) (10). IMUs comprise of at least an accelerometer and gyroscope, sometimes accompanied by magnetometer. Recent IMUs employ tri-axial accelerometers which measure in 3 axes, antero-posterior (AP), medio-lateral (ML) and vertical (VT) (11). IMUs can calculate some gait metrics such as velocity, distance, step and turning occurrences and durations (12), from raw inertial measurements (and accompanying noise). To become the gold-standard clinical falls-risk assessment tool, IMUs must accurately capture and process relevant gait metrics to create falls-risk profiles from short walking bouts (WBs) to generate falls-risk profiles. These falls-risk predictions derived from IMU-derived gait metrics are consequently compared to patient-report of falls over a set retrospective period of time, acquired through a questionnaire and/or interview. This requires prior understanding of literature using quantitative gait assessment comparing fallers and non-fallers to identify which gait parameters are implicated in falls (13). Recent reviews have found that, compared to non-fallers, fallers have reduced gait velocity (GV) (13-17), cadence and step length (SL) (13,16), increased dynamic sway (13) and more variability in gait speed (GSV), step time (STV) and step length (SLV) (16). *Table 1* summarises the gait variables often used to compare fallers and age- and disease-matched non-fallers using these variables and four others, step width (SW), step count (SC), static sway and turning kinematics, that have not been reviewed. For explanation of gait metrics, see *Figures 1-4*. We present the following article in accordance with the Narrative Review reporting checklist (available at https://dx.doi.org/10.21037/mhealth-21-7).

Rationale

This review aims to investigate the application of wearable technology in capturing and processing relevant gait data for falls-risk analysis. In particular, this study aims to explore the presence of three barriers to the implementation of IMU devices in clinical falls-risk assessment: (I) accurately measuring gait metrics which are proven to be associated with high falls risk (mentioned above), (II) identifying differences in these metrics between groups of patients who have fallen, and those who have not, (III) accuracy of falls-prediction algorithms developed from IMU-collected gait metrics (Appendix 1).

Objectives

To perform a narrative review involving collection and critical appraisal of literature pertaining to the use of wearable devices in the prediction of falls, and identify factors limiting clinical implementation of IMU devices in falls-risk assessment.

Table 1 Definitions of all gait metrics which were used from included studies

Simple metric	Definition	Units	Derivative metrics
Daily step count	The number of steps taken over an entire day	N/A	N/A
GV	Average distance travelled in the ambulant direction per second.	Meters per second	GSV, the standard deviation of GV
ST	Average amount of time between two consecutive contacts of the same foot with the ground	Seconds	STV, the standard deviation of ST
Step time	Average amount of time between two consecutive contacts of any foot with the ground.	Seconds	Cadence, average number of steps per minute, Step time variability, the standard deviation of step time, Step time asymmetry, the asymmetry of step times between the left and right feet
SL	Average distance between two consecutive contacts of the same foot with the ground	Meters	SLV, the standard deviation of SL
Step length	Average distance between two consecutive contacts of any foot with the ground	Meters	Step length variability, the standard deviation of step length, Step length asymmetry, the asymmetry of step lengths between the left and right feet
Dynamic balance	Aberrant movement of the centre of mass within a single gait cycle. Several ways to measure.	Several	N/A
Static balance	Movement of the centre of mass whilst standing still with feet together	Meters	N/A
Turning kinematics	Number of steps taken, or time taken to complete a 180-degree turn	s	N/A

See available online: https://cdn.amegroups.cn/static/public/mhealth-21-7-1.xlsx for more details. m, meters; s, seconds; m/s, meters per second; Hz, Hertz (number of steps per second); GV, gait velocity; ST, stride time; SL, stride length; GSV, gait speed variability; STV, stride time variability; SLV, stride length variability.

Methods

Review protocol registered on PROSPERO (Appendix 2).

Eligibility

Included studies comprised of:
(I)   Cohort studies or case-control studies;
(II) Studies with 6 or greater month follow up;
(III) Studies conducting gait analysis with wearable technologies measuring relevant gait metrics and/ or used relevant gait metrics to assess falls-risk with analysis of diagnostic test accuracy;
(IV) Studies written in English and available in full-text.

It should be noted that information could not be presented from papers in which methodology was not adequately discussed, in particular if they failed to provide detailed description of data capture, processing, and statistical analysis. This resulted in one paper being discounted from qualitative synthesis.

Information sources

Databases used to search for articles were Medline, PubMed, Scopus and Embase. All articles with results discussed came from a structured literature search. A similar search strategy was used across all databases for consistency, done in February 2020.

PubMed example: (((acceleromet* OR gyrometer OR magnetometer OR gait analysis) AND (sensor OR tracker OR device OR detector OR wearable) AND (gait OR posture OR ambulation)) AND (falls risk OR fall risk OR fall prediction OR falls prediction)).

Study selection

Studies were collated in EndNote X9 and duplicates removed. Studies were then screened based on inclusion/ exclusion criteria by 2 independent reviewers (CB and DH) on an online reviewing software by Rayyan (Qatar Computing Research Institute). Discrepancies were
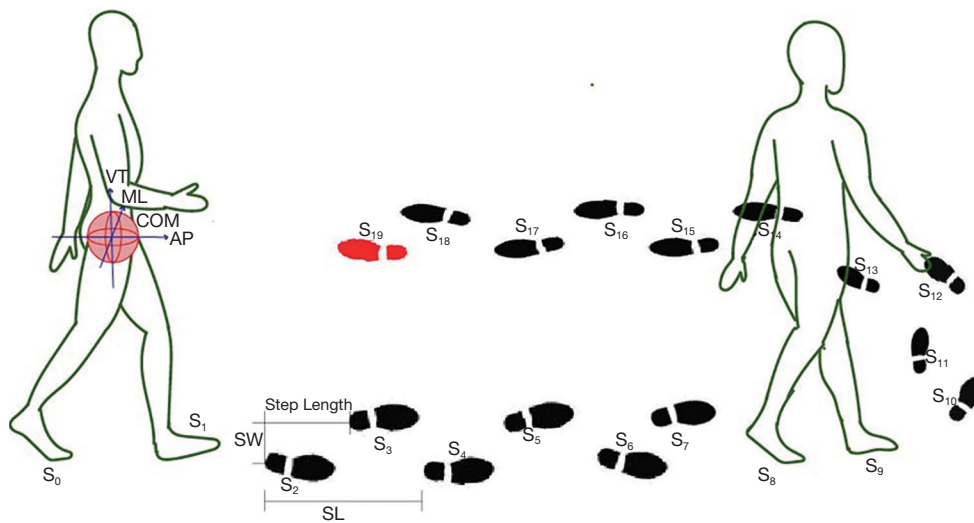
Figure 1 Gait bout. S_0=step that begins measurement window, turning occurs from S_8-S_{14} (7 steps). S_{18} and S_{19} represent a variation in step length. SL, stride length; SW, step width; VT, vertical; ML, medio-lateral; COM, Centre of motion; AP, antero-posterior; S (n), nth step.
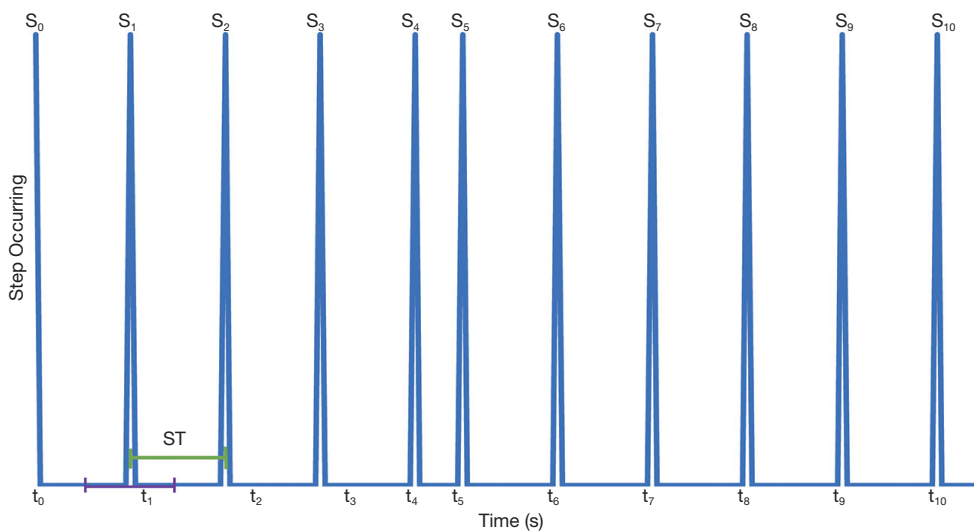

Figure 2 Timing of gait bout in *Figure 1*. S (n)=nth step, t (n)=time at nth step, t_0=time at start. t_4t_5 represents a variation in step time. ST, step time.

resolved by cross-examination until consensus was reached.

Individual analysis of study bias

Critical appraisal of literature was conducted throughout the review process, with summaries concluding each section. For assessment of potential sources of bias, and level of evidence for each article based on criteria from the Centre for Evidence Based Medicine (CEBM) (18,19),

see the available online: https://cdn.amegroups.cn/static/public/mhealth-21-7-1.xlsx.

Data extraction

The following information was collected from each article which met eligibility criteria by 2 independent reviewers (CB and DH), and documented available at available online: https://cdn.amegroups.cn/static/public/mhealth-21-7-1.xlsx :
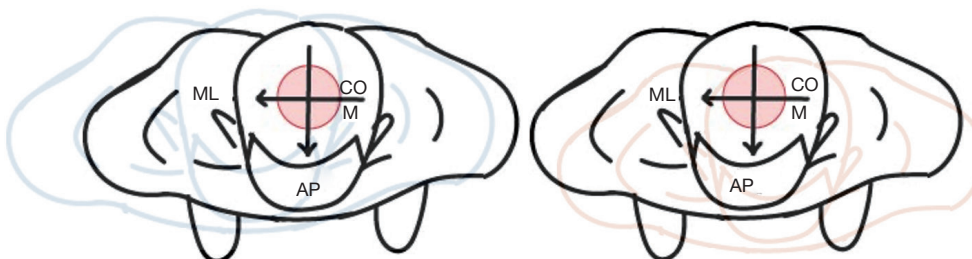
Figure 3 Static balance testing. Blue represents lateral movement of COM relative to the feet, orange represents anterior movement of the COM relative to the feet. ML, medio-lateral; COM, Centre of motion; AP, antero-posterior.

$$Gait\ Velocity = \frac{Path\ length\ (meters)}{Time\ taken\ (seconds)}$$

$$Cadence = \frac{Number\ of\ steps}{Time\ taken\ (minutes)}$$

$$Stride\ time = \frac{1}{Cadence}$$

$$Turning\ steps = \left| S'_f, S_{t1}S_{t2}...S_{tn}, S''_i \right|$$

$$Turning\ time = Time\ for \left(S'_f, S_{t1}S_{t2}...S_{tn}, S''_i \right)$$

Figure 4 Calculations of key gait and balance variables. S'f=final step of first bout, Stn=nth step of turn, S''i=Initial step of second bout.

(I)   Number of subjects.

(II)   Type, number, and placement of IMU device on subjects.

(III)   Gait features that were measured by the IMU device (s) used in the study.

(IV)   Length and setting of WB used to measure gait features.

(V)   Gait features used in the falls-risk algorithm (if any) produced by the study.

(VI)   Tool used to classify subjects into high and low falls-risk group

(VII) Study period over which patients were assessed for falls.

(VIII) Participant demographics, including the presence of any neurological disease affecting gait (NGA).

(IX)   General data from the article such as year of publication, journal, objectives, level of evidence, risk of bias and funding sources.

Data synthesis

Following data collection, studies were sorted into 3 groups pertaining to the barrier to clinical IMU implementation that they addressed, those being device accuracy, device sensitivity, and algorithm predictive accuracy. Qualitative analysis was performed to provide an appreciation of the results of existing literature and discuss whether any barriers remain to implementation.

Results

Characteristics of included studies

Since 2002 (20), researchers have investigated the use of single-point or multi-point IMUs to measure gait metrics (*Table 2*). In total, 46 articles met the eligibility criteria for inclusion in this study (*Figure 5*). While most used single-point IMUs, they examined fewer variables, had more disagreement with gold-standard measurements, and only 5 studied NGAs. Single-point wearables are much easier to use in a clinical setting or home, but they cannot compare data from numerous sensors to reduce false-positive errors in data capture, which may be enhanced in NGAs where movement is less smooth. Inaccuracies also mean that algorithms interpreting the data must provide leeway when identifying steps to avoid false-negative errors in data processing. 17 papers compared IMUs to gold-standard gait-analysis technologies and one (21) assessed test-retest reliability to validate wearables in clinical assessment of relevant gait parameters. 25 papers investigated the ability of IMUs to detect expected gait changes between groups of fallers and age-matched non-fallers. 33 studies used IMUs from 50–100 Hz to distinguish populations of high and low

Table 2 Characteristics of studies validating the use of IMU in falls

Type of study	Total	Single point	Multi -point	Gait metrics studied [n]	Control variables [n]	Medan CEBM level of evidence and risk of bias [Range=a, b]
Validation against gold standard	18	9	9	SL [8], GV [7], cadence [4], SC [4], Turning kinematics [3], dynamic sway [2], static sway [2], STV [1], SLV [1]	3D motion capture [8], gait mats/force plates [6], videography [5]	1b [1b, 4]. Low-moderate [low, moderate-high]
Prediction of falls	12	10	2	SL [3], GV [6], cadence [9], SC [4], turning kinematics [2], dynamic sway [6], static sway [1], STV [5], SLV [4]	N/A	2b [1b, 4] Low [low, moderate]
Classification of faller/non-faller	13	11	2	SL [2], GV [4], cadence [4], turning kinematics [1], dynamic sway [7], static sway [3], STV [1], SLV [1],	N/A	4 [4, 5] Moderate [low, moderate-high]
Classification of high/low falls risk	6	6	0	GV [1], cadence [5], SC [3], turning kinematics [1], dynamic sway [5], static sway [1], STV [2]	TUG [3], PPA [1], BBS [3], STRATIFY [1], Tinetti [1], DGI [1]	4 [4] Moderate [low, moderate-high]

CEBM, Centre for Evidence Based Medicine; GV, gait velocity; SC, daily step count; ST, stride time; SL, stride length; GSV, gait speed variability; STV, stride time variability; SLV, stride length variability; STRATIFY, Ontario Modified Stratify; Tinetti, Tinetti Balance Assessment Tool; DGI, Dynamic Gait Index.
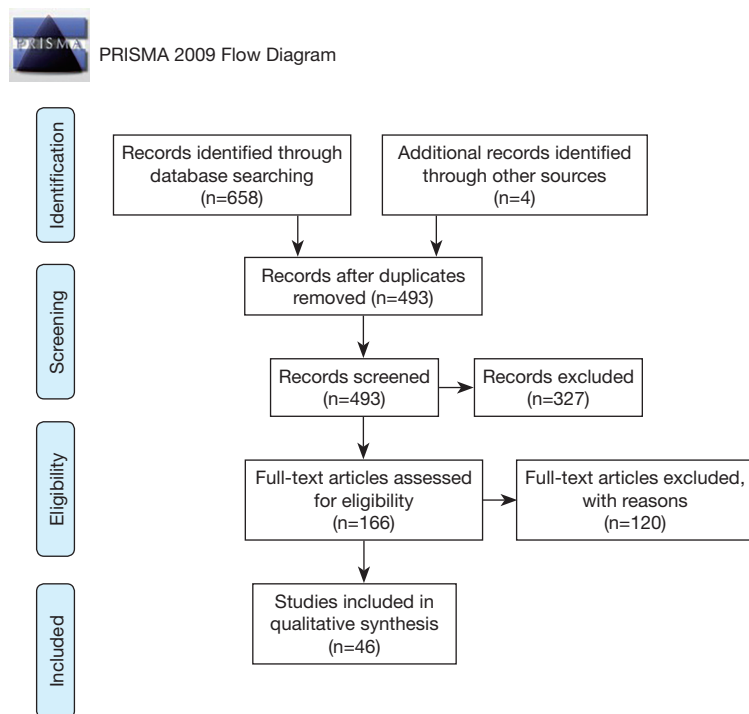

Figure 5 PRISMA flow diagram of the article selection process showing yields at each stage of the process.

falls-risk determined by fall history (22), test battery score or prospective falls. The 46 studies included in the analysis typically presented with a low-to-moderate risk of bias (available online: https://cdn.amegroups.cn/static/public/mhealth-21-7-1.xlsx)

Discussion

Accuracy and reliability in measuring spatiotemporal gait metrics

Studies using multi-point sensors on the limbs and trunk verified that whether accelerometers were used alone (23,24) or with gyroscopes and magnetometers (12,25,26), they could capture gait with comparable accuracy compared to a gold-standard. GV was accurately detected by multi-point IMUs sampling at 32 Hz (24) to 500 Hz (27), SLV and STV at 130 Hz (23), dynamic balance in ML and VT directions at 130 Hz (26) and SC as low as 20 Hz (12). However, one study (27) found a significant discrepancy between IMU data at 500 Hz and force-sensitive treadmill data for cadence and SL, while other studies found IMUs 100–200 Hz to be accurate for cadence (26) and SL (20,23,24). Given otherwise similar methodology and low risk of bias, one possible reason for this discrepancy may be location of sensor placement, which was on the feet in the 500 Hz trials. This may have caused the IMU to detect noise from smaller movements of the foot during a gait cycle, compared to an IMU placed on the trunk which detects overall motion.

Studies using single-point wearables from 31.26–255 Hz (21,28) have more disagreement between gold-standard and sensor data. For example, when compared to the Centre of Pressure sway (COP) from a force plate during static posturography, IMU data (sampled at 52 Hz) captured from the COM had poor correlation (29), while data capture at 200 Hz from the sternum highly correlated (30). It is unlikely the difference sampling rates account for this discrepancy (given both are above the Nyquist sampling thresholds of around 30 Hz for detecting human motion) (31). Perhaps placing the IMU above the COM magnifies small movements in the AP and ML directions, thus being able to distinguish sway from noise. This translates into the sternum being a key location for single-point fixation wearables for gait and falls assessment. When single-point sensors were used to measure SL (8,28,32), cadence (8,28), GV (8), SC (28,33), STV (8), dynamic sway (34) and turning (35), they

demonstrated good-to-excellent agreement with gold-standard methods of gait analysis. The findings of these studies thus suggest the gait metrics measured by wearables have sufficient accuracy and reliability to be used in clinical setting, but the consistency of this agreement from condition-to-condition is yet to be assessed.

Sensitivity in detecting differences between fallers and non-fallers

Regarding the ability to differentiate between groups of age- and disease-matched fallers and non-fallers, studies tended to show that wearable devices were able to detect subtle differences in relevant biomechanical gait metrics between these groups. Overall, IMUs were sensitive enough to detect differences in GV (25,36-42), SL (25,37,39,40), turning kinematics (25,41,43), GSV (39), SLV (37), STV (36,44), cadence (25,36,39-41,45) and postural sway in single (39,46,47) or multiple axes (25,38,40-42,48-50) between fallers and non-fallers. Only one retrospective study did not identify dynamic imbalance during treadmill walking as significantly different between fallers and non-fallers (51). However, it should be noted that past fallers tend to consciously widen their stance for lateral stability, and this effect is enhanced on a treadmill (52). Moreover, this study had a moderate-high risk of bias according to CEBM criteria. Interestingly, most studies assessing SC using single-point IMUs at 50–100 Hz, did not find that fallers had a significantly lower SC than non-fallers (37,39,44,49,50,53), while one did (40). This may be because waist, thigh and wrist-worn high-frequency single-point sensors underestimate SC by 2–10% (54) and SC seems to only be altered in fallers with NGAs, which only one study (50) assessed. IMU devices accurately measure gait factors related to falls-risk and appear able to differentiate between groups of fallers and non-fallers using these factors. However, for clinical implementation this sensitivity in detecting differences in gait metrics needs to be confirmed in continuous real-world data collection in home and community environments.

Classification accuracy of falls-prediction tools

Regarding the accuracy of falls-prediction algorithms developed based on biomechanical data collected by IMUs, studies were considered successful if biomechanical data was used by an algorithm to accurately sort patients into

high- and low-falls-risk groups. In successful studies, these algorithms were developed post-hoc by neural network, machine learning or decision trees, trialling sets of 5–30 gait parameters to determine the most successful combination. Limiting the number of gait parameters trialled at once prevents 'over-training', which increases internal classification accuracy but reduces generalisability (55). Nonetheless, these post-hoc selected 'inputs' into the algorithms increases risk of a 'contextualised' model and its accuracy, reliability and validity to the generalised population of fallers is unknown without validation in external data-sets.

Additionally, there is limited evidence verifying the role of static balance in falls, several papers utilising biomechanical data algorithms to classify fallers performed static posturography. 5 papers utilised static postural stability in their algorithm yielding faller classification accuracies of 71.2–85% (25,56,57) and falls-risk classification accuracies of 90.5% (36) and 97% (58) to Tinetti and STRATIFY scores respectively. While their results seem impressive, it should be noted that multiple measures like SD and CV were used for sway, and the algorithm tested combinations of them until it yielded the highest classification accuracy. By inputting the same variable multiple times, false-positive results are more likely, and this can only be accounted for by testing the algorithm against novel data to test true classification accuracy, known as 'cross-validation' (24,59). The majority of these papers had a moderate risk of bias according to CEBM criteria (36,56-58).

That said, when papers did not include static posturography, classification of fallers was still accomplished. A study by Iluz *et al.*, (38) using a 100 Hz IMU at the COM identified lower GV, and higher sway in AP and VT directions during daily-life sit-to-walk transitions in fallers compared to age-matched adults. Combining this data into a faller identification algorithm yielded a classification accuracy of 88% however, using data captured during lab-based gait yielded 71% accuracy. This may imply that algorithms should be specific to the gait-capture setting. Iluz's paper is one of many to combine dynamic sway with metrics including GV (25,47,60), SL (25,60), turning kinematics (25,59), cadence (25,59-62), STV (60,63), SLV (60) and GSV (60) in algorithms with moderate-good classification accuracies of 68-85%, consistently out-performing existing test batteries (36,38,43,47,56,57). One study (64) used cadence, SL and GV measured by a triaxial accelerometer at 100 Hz at the COM in an algorithm which classified 6-month prospective fallers with an Odds-Ratio of

3.89 if the cut-off value was exceeded. An algorithm using SLV, cadence and turning kinematics from 102.4 Hz sensors at each shank had a predictive accuracy of 2-year prospective falls of 83.02% and another algorithm using SL, STV and turning kinematics had an accuracy of 72.97% (43).

Feasibility and limitations

No studies thus far have attempted falls-risk classification using IMU data from NGA populations. As such, limitations still exist when it comes to the assessment of falls-risk in neurological populations which make up a large portion of hospital inpatients and clinical visitors. Falls-classification tools in elderly populations used single- or multi-point IMUs with various sensor configurations, walking settings and gait-metrics. Although, IMU devices are able to assign falls risk using algorithms developed with gait metrics collected from WBs for non-neurological populations, these are yet to be extensively validated in large external populations. Current falls-prediction tools therefore require validation in external data-sets before clinical implementation Moreover current classification accuracy is limited by comparison against self-report of retrospective falls (over a set period) by patients which is not an accurate nor reliable gold-standard of objective measurement. Additionally, falls-prediction tools constructed from 'walking bouts' may not reflect falls-risk during 'free-living' gait and thus future studies employing gait metrics from continuous monitoring of walking in the community and in the home are warranted.

Despite these limitations, IMUs placed at the COM, chest or limbs, sampling at 50–250 Hz have been validated against gold-standard methods in capturing various gait metrics. They also have the potential to distinguish fallers and non-fallers based on gait deterioration patterns and use this to accurately assign falls-risk. Single-point wearables are more viable in clinical settings but have not been thoroughly tested in NGA populations nor validated for SLV, static sway or GSV. Moreover, the studies have a lot of heterogeneity in methodology, with no clear standard. Finally, our review included insufficient studies of NGA populations and more data is required to justify using single-point IMUs for gait analysis and falls prediction in NGAs, primarily those of spinal origin.

Conclusions

Currently, the literature is divided on metrics like GV

and SL as predictors of falls, and advents such as turning kinetics are in the immature stage of research. In addition, the bulk of studies examine community-dwelling elderly, with few investigating NGAs and none investigating spinal NGAs. Moreover, while the use of sensor technology in falls-risk analysis has been investigated, the studies examine very few gait metrics at once, and comparing studies reveals a wide variety of sensor types in use. Future avenues of research thus include investigations of multiple gait metrics simultaneously especially in NGA and spinal NGA populations.

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Footnotes

Reporting Checklist: The authors have completed the Narrative Review reporting checklist. Available at https://dx.doi.org/10.21037/mhealth-21-7

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://dx.doi.org/10.21037/mhealth-21-7). The authors have no conflicts of interest to declare

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Appendix 1 Research question

A search of the literature was conducted to address the research question "What is the current use of wearable technologies for falls-risk assessment" as shown in the PICO format below. A search strategy was created to identify relevant studies based on the research question below (set out in the PICO format):

Population	Falls-risk individuals in both neurological and non-neurological populations
Intervention	Wearable technology based gait analysis tools for fall-risk assessment
Control (Reference Clinical Tool)	Other clinical fall-risk assessment tools based on gait analysis e.g. laboratory-based 3D motion
Outcome	Successful/accurate falls-risk prediction

A search of Medline, PubMed, Scopus and Embase databases was performed in February 2020. The complete search strategy can be obtained from the attached PROSPERO registration (ID: CRD42020195861)

Included Studies:

Medline, Embase, Pubmed and Scopus were systematically searched from their date of inception to February, 2020. A manual search for other relevant articles was also conducted by examining the references and citations of key papers. Database and bibliographic search identified 662 relevant studies. After removal of duplicates, 493 studies remained. 327 references were excluded on title and abstract screen and 120 references were excluded by full-text analysis, leaving a final 46 studies to be included in qualitative synthesis (see Figure 5 for PRISMA flow chart). Reasons for exclusion during full text review include: not involving falls-risk prediction tool/model (73), not involving wearable technologies (47).

Appendix 2 Review registration

Do fallers walk funny? A systematic review of gait metrics that predict falls in high-risk populations
Callum Betteridge, Daniel Ho

To enable PROSPERO to focus on COVID-19 registrations during the 2020 pandemic, this registration record was automatically published exactly as submitted. The PROSPERO team has not checked eligibility.

Citation

Callum Betteridge, Daniel Ho. Do fallers walk funny? A systematic review of gait metrics that predict falls in high-risk populations. PROSPERO 2020 CRD42020195861 Available from: https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42020195861

Review question

P: In adult patients (normal or neurogenic gait alterations) at risk of falls/with a history of falls
I: Which aspects of gait or posture change
C: Compared to adult patients without falls risk/history of falls
O: And are predictive of falls risk

Searches

MEDLINE, PubMed, EMBASE, Scopus, Search date 28/02/2020

Search strategy

https://www.crd.york.ac.uk/PROSPEROFILES/195861_STRATEGY_20200628.pdf

Types of study to be included

Cohort or case control

Condition or domain being studied

Risk of falls in adults with and without neurological disease

Participants/population

Adult fallers versus non-fallers, with or without neurological disease

Intervention(s), exposure(s)

Changed gait parameters

Comparator(s)/control

Gait parameters in non-fall patients

Main outcome(s)

Main outcome is either history of falls or prospective falls events

* Measures of effect

Relative risks and odds ratios

Additional outcome(s)

None

* Measures of effect

None

Data extraction (selection and coding)

Papers are cohort, with 6 or greater month follow up, or case-control studies comparing groups of age and/or disease-matched fallers and non-fallers with validated methods of gait analysis and be published after January 1st, 2015.
Data collected from articles post-screening documenting which gait variables are measured, and their effects on risk of falls. Additionally, how gait metrics and falls risk were assessed, patient numbers and broad demographics (esp whether or not there was a neurological alteration to gait)

Risk of bias (quality) assessment

Risk of bias and level of evidence for each article is assessed using the Oxford University Centre for Evidence Based Medicine (CEBM) criteria

Strategy for data synthesis

If consistent measures of falls-risk and gait metrics are used, data will be synthesised assuming that there are more than 3 studies for that gait metric.
Method will be using forest plots if this is available.

Analysis of subgroups or subsets

'Subgroups' will be defined by each gait metric, for example for gait velocity, any paper studying it will be examined and the results combined if gait velocity is measured consistently, if falls-risk is measured consistently, and if there are 3 or more applicable studies.

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Collaborators

Professor Ralph Mobbs. University of New South Wales
Mr Wen Jie Choy. University of New South Wales

Type and method of review

Diagnostic, Prognostic, Systematic review

Anticipated or actual start date

01 March 2020

Anticipated completion date

30 July 2020

Funding sources/sponsors

No funding was obtained for this review, it was performed independently

#Conflicts of interest

Language

English

Country

Australia

Stage of review

Review Ongoing

Subject index terms status

Subject indexing assigned by CRD

Subject index terms

MeSH headings have not been applied to this record

Date of registration in PROSPERO

30 July 2020

Date of first submission

28 June 2020

Stage of review at time of this submission

Stage	Started	Completed
Preliminary searches	Yes	Yes
Piloting of the study selection process	Yes	Yes
Formal screening of search results against eligibility criteria	Yes	Yes
Data extraction	No	No
Risk of bias (quality) assessment	No	No
Data analysis	No	No

The record owner confirms that the information they have supplied for this submission is accurate and complete and they understand that deliberate provision of inaccurate information or omission of data may be construed as scientific misconduct.The record owner confirms that they will update the status of the review when it is completed and will add publication details in due course.