Accelerometry applications and methods to assess standing balance in older adults and mobility-limited patient populations: A narrative review

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Abstract

Accelerometers provide an opportunity to expand standing balance assessments outside of the laboratory. The purpose of this narrative review is to show that accelerometers are accurate, objective, and accessible tools for balance assessment. Accelerometry has been validated against current gold standard technology, such as optical motion capture systems and force plates. Many studies have been conducted to show how accelerometers can be useful for clinical examinations. Recent studies have begun to apply classification algorithms to accelerometry balance measures to discriminate populations at risk for falls. In addition to healthy older adults, accelerometry can monitor balance in patient populations such as Parkinson's disease, multiple sclerosis, and traumatic brain injury. The lack of software packages or easy-to-use applications have hindered the shift into the clinical space. Lack of consensus on outcome metrics has also slowed the clinical adoption of accelerometer-based balance assessments. Future studies should focus on metrics that are most helpful to evaluate balance in specific populations and protocols that are clinically efficacious.

Keywords: accelerometry, balance, fall risk, accessibility

Statements and Declarations

The authors declare no conflicts of interest.

1 Introduction

Over one quarter of adults over the age of 65 fall every year; and of those falls, 10% of them result in injury [1]. The highest rates of injury-related hospitalizations and death for older adults are due to falls [2]. Annually, $50 billion is spent on fall-related healthcare costs in the United States [3]. Further, many older adults develop a fear of falling, whether or not they have a history of falls. Fear of falling can lead to decreases in socialization, independence, mobility, quality of life, and life expectancy [4]. With the national population of older adults expected to increase by 40% by 2030 [1], the impact of falls will only increase without better detection and prevention. Declines in static balance performance have been associated with falls [5]. While many studies examine gait of individuals to assess fall risk, standing balance assessment is easier to perform and administer, requiring less of the individual and of the testing environment. Static, standing balance only requires the individual to keep their center of gravity over an immobile base of support, meaning the feet are not moving. Standing balance measurements have the potential to minimize burden on the patient and the clinician. Using accelerometry will additionally reduce that burden by providing objective measurements in a noninvasive manner. Recent systematic reviews have explored accelerometry for balance assessment in older adults as a method of early diagnosis [6], in children to monitor psychomotor development [7], in patient populations [8, 9], as well as for comparisons to alternative cost-effective devices for gait assessment [10]. This narrative review provides a broader exploration of how accelerometry is currently used for measuring balance characteristics, comparisons to laboratory technology and clinical assessments, and brief explorations into different applications for various patient populations.

Accelerometry is becoming more ever-present in society as most people carry around at least one smart device that has embedded accelerometers. This highlights the potential of accelerometry to be better utilized in clinical settings for balance assessments. With every smart device such as phones, tablets, and watches having pre-installed accelerometers, these sensors have never been more available or more affordable. Technological advancements have led to increased sensitivity of these devices [11]. Accelerometers have been used to measure standing balance through the recording and processing of sway accelerations. Most studies have been conducted in the laboratory setting; however, there is now the potential to transition this methodology to the clinic. Current clinical evaluations of balance are heavily reliant on subjective observations by a physician and often suffer from ceiling and floor effects. Accelerometers can provide objective measurements with higher granularity for diagnostic tests and patient monitoring.

Accelerometers are portable, opening the possibility to move beyond a laboratory setting. They also allow for more freedom of movement for the subject. In contrast, traditional methods of evaluating balance with motion capture systems and force plates require a fixed environment and only allow for minimal subject movement [11]. This portability thus allows for more freedom in experimental design and provides the opportunity for assessments to take place in less controlled settings. Increasingly, accelerometers have been implemented to assess fall risk, detect falls, and diagnose and monitor changes in mobility conditions [12–17]. Incorporating technology, like sensory biofeedback or exergames, into fall prevention and mobility interventions is also an area of expanding research [18–20]. Developing and implementing new technologies for early detection, diagnosis, and fall prevention are important steps in reducing falls. In addition to their portability, accelerometers are affordable, easy to use, and allow for more continuous and close monitoring of changes over time.

We propose that accelerometers have an advantage over current standard practices as they provide objective quantification of balance that is highly correlated with several clinical and laboratory balance assessments while also being economical and accessible. Here we review the emerging literature on the use of accelerometers to assess balance to demonstrate their potential for clinical use.

This review focuses on accelerometry methods for standing balance. The different metrics calculated from the collected acceleration time-series are described, including emerging data analytic techniques used to classify high and low fall risk. We discuss the different patient populations where accelerometry measures of standing balance are being used. We conclude with a discussion of current limitations and future applications.

2 Methods

Publications for this narrative review were obtained using Google Scholar, PubMed, and Web of Sciences databases. Groups of search terms were used to find publications that focused on accelerometry to assess balance in older adults. The following groups of search terms were used: 1) “accelerometry” “postural control” and 2) “accelerometry” “community” “balance” “older adults”. Publications were included if they were experimental studies using accelerometry to measure balance published in English. Other inclusion criteria were: 1) outcome metrics were derived from acceleration signals; AND 2) study population performed static, standing balance tasks which includes standing on one or both legs, in any stance, on compliant surfaces; AND either 3) study population focused on older adults or mobility-limited, adult, patient populations; OR 4) accelerometers or smart devices using accelerometry were compared to force plates, motion capture systems. We also included publications that used accelerometers or smart devices using accelerometry to 5) compare or predict scores of clinical balance assessments OR 6) provide sensory (e.g., auditory, visual, vibrotactile) feedback of balance performance. If these criteria were not met, publications were excluded. Publications that focused on gait assessment were not considered unless the study included postural control assessments as well. The data collection, analysis, and interpretation of the included publications were conducted by a single reviewer (K.Bohlke). The search was completed on May 26th of 2023.

3 Standing Balance Overview

Balance is defined as the ability to keep the center of gravity over the base of support. Good balance means that your body’s position can be controlled and well maintained in static and dynamic conditions [21]. Static balance is defined by having a base of support that is not moving, but postural adjustments are still required to keep the center of gravity over the base of support. Upright standing is the most common posture. Walking, on the other hand, is defined as a “dynamic” balance task that requires postural adjustments to keep the center of gravity over a moving base of support [21]. Postural control requires several neural systems to work together. The motor system and several sensory systems form the control pathway for balance, as well as other deeper motor systems like the basal ganglia and the cerebellum [22].

Somatosensory, visual, and vestibular information combine to help the nervous system maintain balance. The sensory systems detect the status of the body, monitoring the current state of balance. This information undergoes sensory integration within the brain. The sensory feedback helps inform motor commands that are sent back to the body [23]. Breakdowns in any aspect of this control system can lead to balance deficits and increase the risk of falling.

As adults age, they are more likely to fall due to various reasons: muscle weakness, joint pain, poor vision, neuropathy, and pathologies like vestibular disorders, Parkinson's disease, and dementia. However, postural stability declines with age, even without overt disease pathology [24]. This age-related decline is being studied in various ways to see how balance becomes less automatic, requiring more cognitive resources to perform what was once automatic [24–26]. Additionally, research has indicated that older adults may have deficits in sensory integration, or an inability to reweight sensory inputs [27]. Detecting balance changes early enough is imperative to develop effective preventative care. There are many different balance assessments, some relying only on clinicians and others requiring laboratory equipment. With an increasingly aging population, fall prevention will become that much more important, necessitating an increase in balance assessment accessibility.

Modeling the body as a single inverted pendulum is the basis for most static balance measurements, particularly when using force plates. This model also assumes that the body acts as a single link about the ankle. The center of mass (CoM) of that link is defined by the anthropometry of the individual and is approximately at the level of the navel. The center of pressure (CoP), measured using force plates, is reflective of the torques about the angle that control the position of the CoM against gravity [11]. Force plates track under-foot CoP by measuring the location of the resultant vertical ground reaction force vector [28]. The difference between CoP and CoM is proportional to CoM movement [29, 30]. The difference between CoP and CoM is reflective of the torque response required to maintain upright balance. In this inverted pendulum model, the sensory sytems involved in balance (vision, proprioception, and vestibular) are used to establish the position and velocity of movement of the body about the ankle and ankle torques are generated (reflected in the CoP) to control the CoM position to maintain stability [29, 30].

The single inverted pendulum model is an approximation. In reality, the other joints of the body (e.g. hip, knee) also can play a role. For example, movement about the hip as well as the ankle can be used to control upright stance. Different balance strategies, ankle strategy versus hip strategy, result in different movement relationships [31]. Ankle strategy, i.e. control about the ankle, is more likely to be used by younger, healthier individuals, whereas hip strategy is more common in older adults and in pathological cases like vestibular problems, peripheral neuropathy [32], or ankle sprains [33].

4 Accelerometry

A uniaxial accelerometer measures acceleration in one direction. Tri-axial accelerometers measure acceleration in three orthogonal directions which are commonly aligned along medial-lateral, vertical, and anterior-posterior axes respectively. Most modern accelerometers are developed using micro-electromechanical systems (MEMS) technology[34]. MEMS accelerometers can be classified by how acceleration is sensed: capacitive, piezoresistive, piezoelectric, optical, inductive, etc. [35]. These methods for measuring acceleration are all based on simple mass-spring systems and Hooke's Law [36] (**Fig. 1a**). **Fig. 2b** shows a simplified example of how this mass-spring system would look in a capacitive MEMS accelerometer. As the mass in the system moves, the distance between electrodes changes. The difference between in the capacitance of the two capacitors is proportional to the acceleration the sensor is experiencing [34].

Accelerometry can monitor the approximate accelerations of the CoM of the human body when affixed to the low back. Many studies have used the lower back as the location for their accelerometer placement, with several describing the location as the L3 level of the spine [28, 37–48]. However, some researchers also use the L4 [49–59], L5 [60–78], or S2 [79–82] levels. Other studies use a range from L3-L5 [83–87], L5-S1 [88, 89], or describe the sensor placement as the lower back [63, 90–105], waist [11, 106–111], or sacrum [112–114]. Additional common accelerometer placements on the body include the chest [44, 64, 70, 94, 109, 110, 115–126], the shins [63, 64, 68, 70, 88, 89, 94, 103, 127], and the thighs [50, 63, 68, 70, 82, 125, 128, 129]. Howcroft *et al.* tested faller classification models based on accelerations recorded from different locations. The best single-accelerometer classifiers were from head and pelvis accelerometers. However, the pelvis location was better for the dual-task experiments classification model because the head often makes non-balance related movements during cognitive tasks [103]. Additional accelerometers can be added to allow for more joints to be included in biomechanical model assumptions, allowing for double-link [92] and even triple-link models [63] (**Fig. 2**). For the double-link model, accelerometers are placed on the trunk and the shank, accounting for the ankle and hip joints [92]. The knee joint can be added for the triple-link model by placing another sensor on the thigh [63].

5 Balance Measures

In this review, we focused on experimental papers that measured features directly from acceleration signals during standing balance. The most common outcome measures for accelerometry-based balance assessments are in the medial-lateral (ML) and anterior-posterior (AP) directions. Some studies use the resultant vector which combines the ML and AP signals into signal in the transverse plane. The most reported metrics used in the studies in this review are root-mean-square, jerk, normalized path length, 95% confidence ellipse area, 95% power frequency, and sample entropy (and additional variables derived from sample entropy like multiscale entropy and complexity index) (**Table 1**).

6 Comparison of Accelerometry to Laboratory Measurements

6.a Gold Standard Laboratory Technology

In the laboratory setting, researchers use a variety of technologies to evaluate balance. Motion capture systems and force plates are by far the most common and are considered the gold standard. The following describes studies that compare accelerometry measures to those taken with force plates and motion capture.

Force plates are the most common balance evaluation technology used in research laboratories. Changes in CoP location during standing can show how the body adjusts to different postural conditions. Accelerometry measurements have been compared many times to force plate measurements [11, 33, 42, 44, 60, 63, 72–74, 76, 77, 79, 98, 104, 115–117, 124, 128, 130], some of which have found that accelerometers have comparable or higher reliability than force plates [11, 44]. Force plate CoP metrics and accelerometry measurements are not perfectly correlated. Even in studies where both accelerometers and force plates can distinguish between patient populations [74, 115, 116] or task conditions [72, 79], correlations range from 0.37-0.92, depending on the conditions [72, 74, 79, 115, 116]. The explained variance tends to be low to moderate. One study reported that accelerometry was more correlated to motion capture (r=0.887) than to force plate measurements (r=0.793) – which showed only a moderate coefficient of determination (r^2=0.6294) [76]. Accelerometer measures and CoP differ due to the relationship between the ankle torques, reflected in the CoP, and the movements of the CoM that are in response to the torques. Another reason could be that standing balance is not a perfect inverted pendulum system with just one joint (ankle), as force plate CoP measurements assume [32, 77]. Accelerometers may be useful in patient populations that are more likely to compensate with hip strategy, such as patients with hip fractures [77], ankle sprains [33], or Parkinson's disease [74].

Optical motion capture systems image a whole room or interior environment using a large set of cameras that are installed in the laboratory space. Reflective markers are placed on different segments of the body to track body movements and joint angles. These systems are very expensive and require a specialized set up and trained staff to run. The benefit of this big system is that markers can be attached to different parts of the body to monitor complex movements. The markers are tracked from several angles, so the output is a 3D reconstruction of how the body is moving. Despite not providing positional (location in space) information like motion capture, accelerometry balance assessments have been validated against motion capture systems by comparing measurements made by each system [76, 89, 108]. Root-mean-square of resultant acceleration magnitudes showed high correlations between motion capture and accelerometry (r=0.88, p<0.001) when subjects performed various standing tasks like quiet stance, tandem stance with eyes closed, and tandem stance on foam with eyes open [76]. Olsen *et al*. found that a smartphone application that used accelerometry showed excellent validity compared to motion capture outcomes (r=0.98, 95% confidence interval = 0.98-0.99) [89]. Another study developed a sway meter using accelerometers that calculated center of mass sway angles that were significantly correlated to those measured by a motion capture system (r=0.98, p<0.01) [108].

6.b Laboratory Balance Tasks

Two of the most common balance tasks performed while on a force plate are the Romberg test and the Sensory Organization Test; the latter requires the force plate to be integrated into a dynamic posturography system. Romberg tests involve subjects standing with the feet close together [14]; often subjects perform the Romberg test on solid and foam surfaces. The Sharpened Romberg test has the feet aligned heel-to-toe. Normally, the Romberg test is performed with eyes open and eyes closed. People with poor balance are more easily discriminable because their performances diverge more from healthy individuals during challenging balance tasks than easy balance tasks. In general, the more difficult the task, the more discriminable the sway measure outcomes are [37, 49, 92, 123]. Computerized dynamic posturography systems allow researchers to eliminate different sensory systems for the subject. Computerized dynamic posturography allows the visual surrounding to be "sway-referenced", meaning the surrounding moves at the same speed and angle as the subject. This creates the condition where the visual system does not detect movement. Additionally, the platform the subject is standing on can be rotated about the ankle such that the ankle angle is sway-referenced. Platform sway-referencing is used to make ankle proprioceptive information unreliable for balance control [131]. Computerized dynamic posturography protocols, termed the Sensory Organization Test, include six different conditions: 1) fixed stance and eyes open, 2) fixed stance and eyes closed, 3) fixed stance and sway-referenced vision, 4) sway-referenced platform and eyes open, 5) sway-referenced platform and eyes closed, and 6) both sway-referenced platform and vision [132]. These tasks are considered even more difficult than the Romberg tasks because they involve dynamic postural perturbations, or the illusion of postural perturbations, that require the subject to compensate to maintain balance. Romberg test conditions, by comparison, are all static. The measures during force plate tests are usually based upon the center of pressure. Recently, accelerometers are also being used. A study by Whitney *et al*. compared force plate and accelerometry balance measurements during the Sensory Organization Test conditions and found significant correlations for the six conditions [11]. Normalized path length measurements had the greatest coefficients of correlation compared to root-mean-square and peak-to-peak measurements. Across each measurement, correlations were greater as task difficulty increased [11]. Another study compared CoM accelerations derived from force plate measurements to those recorded using an accelerometer. The CoM estimation from force plates assumes a single inverted pendulum model. The signal traces showed moderate to strong correlations (r=0.65-0.76) in both ML and AP directions for conditions 4-6 [112].

In addition to the Sensory Organization Test, researchers have compared accelerometry to force plate measurements during various single-leg stances [33, 42, 72, 104, 115, 124], tandem stances [72, 104, 115], and dynamic movements [72, 117] (**Table 2)**. Some studies found significant correlations between force plate and accelerometry parameters during single leg stances [42, 72, 124], but other studies had contradicting findings [104, 115]. In Abe *et al*., only healthy subjects had correlated parameters between measurement modalities [33]. Additionally, only accelerometry parameters were significantly different between ankle sprain subjects and healthy controls [33]. Doherty *et al*. failed to find significant correlations between accelerometry and force plates for single leg stances but were able to use accelerometry to detect failures during the single-leg (AUC =0.91, 95% CI=0.86-0.96) and tandem (AUC=0.91, 95% CI=0.85-0.96) stances of the Balance Error Scoring System [104]. While Hsieh *et al*. were unable to differentiate between assisted device users and non-users from the single-leg stances, the semi-tandem stance was successful with accelerometry parameters outperforming force plate parameters (AUC=0.77-0.85 for accelerometry, AUC=0.72-0.78 for force plate) [115]. For dynamic tasks, the specific movement seems to have a lot of weight when comparing accelerometry and force plate measurements. Janssen *et al*. found moderate to high correlations between force plate and accelerometry root-mean-square and area-under-the-curve when subjects were asked to perform sit-to-stand tests [117]. Using the balance conditions from the Dynamic Postural Stability Index, Heebner *et al*. concluded that the two modalities were measuring different aspects of balance and body position [72].

7 Algorithms and Smart Devices

The lack of transformed, easy-to-understand outcomes has prevented widespread accelerometry adoption in the clinic. Clinicians need user-friendly signal analysis software to interpret raw values. Different studies have tried to tackle this problem by developing algorithms and classifier models for distinguishing between individuals with balance disorders, testing subjects using commercially available accelerometers in smart devices, or building their own systems.

Work toward developing software packages and classifier algorithms is underway to discern which features are most important for differentiating between populations with good and poor balance [55, 83, 102, 118, 128]. Accelerometry-derived TUG times were used in a binary logistic regression for distinguishing between fallers and non-fallers [83]. Another study used two classification methods for determining high or low fall risk: an artificial neural network and a linear model. The artificial neural network and the linear model displayed misclassification errors of 0.11 and 0.21, respectively [118]. Fall risk predictors have been developed using machine learning techniques, where accelerometry data is the input. Examples of these techniques include linear least squares model [84], lasso regression model [84, 118], leave-one-out cross-validation model [102], and hybrid-convolutional recurrent neural network model [55]. These predictions are then compared to various clinical assessments [84, 118] or occurrence of falls [55]. These techniques can assist in classifying and predicting fall risk for older adults should help in making accelerometry-based balance assessments more popular in the clinic and community.

Many groups are starting to look to smart devices such as phones and tablets that contain accelerometers to monitor balance instead of force plates or research-grade accelerometers that are used in laboratory settings [41, 44, 56, 79, 89, 115, 116, 128]. One study measured sit-to-stand movements and found peak force and total movement duration were highly correlated between a smartphone and a force plate ($r=0.86$ and $r=0.98$) and, in addition to peak power, had high reliability (intra-class correlations=0.86-0.93) [44]. A different research group found smartphone root-mean-square measurements were correlated to force plate velocities and sway ellipse during challenging balance tasks (e.g., semi-tandem, tandem, single-leg standing). Vertical and AP root-mean-square receiver operating characteristic curves were able to distinguish between older adults with low and high fall risk ($p=0.01$-0.04) [116]. That research group later found significant correlations between root-mean-square and sway ellipse measurements from a smartphone, force plate, and research-grade accelerometer. All smartphone measurements were able to discriminate between assisted device users and non-users ($p<0.0001$-0.02) [115]. Another study compared an iPod touch to an accelerometer and found high cross-correlations between devices (≥ 0.88) [41]. Additionally, root-mean-square and sway area had high intra-class correlations for iPod validity (≥ 0.97) and test-retest reliability (≥ 0.81) [41]. The use of smart devices to analyze postural stability has also been explored in patient populations. Accelerometry measurements from a smartphone were able to discriminate between individuals with and without Parkinson's disease from Sensory Organization Test conditions while the equilibrium score from this test was unable to discriminate [112]. Additionally, impaired and non-impaired wheelchair users were distinguished by smartphone accelerometry [126]. These smart devices are commercially available, making them a cheap and accessible assessment tool. Transitioning from research-grade accelerometers to commercially available devices that are already in high-use is imperative for bringing balance assessment outside of the laboratory.

8 Clinical Settings

8.a Clinical Examinations

In the clinical setting, healthcare providers evaluate balance using a variety of methods. Many research studies have focused on comparing or integrating accelerometry into these methods like the Berg Balance Scale [14, 37], TUG (Timed Up and Go) test [37, 83, 133], or the 5-times sit-to-stand [84, 125]. The Berg Balance Scale involves 14 different tasks that require the subjects to perform different static poses and dynamic movements to evaluate the individual's balance [134]. Examples of static poses are sitting, standing with eyes closed, and standing on one leg. Reaching, retrieving an object from the floor, and turning to look behind are some of the dynamic movements. Each task is scored from 0 of 4 and the individual task scores are added up to a maximum of 56 [37, 134]. The TUG test has subjects start sitting, rise from the chair, walk 3 meters, turn and return to the chair, and sit down again. The main outcome of this assessment is the time to complete the whole TUG test [37, 83, 135]. 5-times sit-to-stand measures how long it takes subjects to stand from a seated position and return to sitting five times [125, 136]. Most of these balance assessments rely on subjective observations from the clinician and often floor and ceiling effects result in poor granularity [14]. It is important to note that the TUG test and 5-times sit-to-stand are not strictly balance assessments, although balance is heavily involved in the tasks. These evaluations were included in this review as some of the studies related accelerometry features from TUG or 5-times sit-to-stand to other clinical balance assessment scores.

Experiments have been conducted to compare these different evaluations to balance as assessed by accelerometry, to see if the scores of the different tests align with various accelerometry signal variables. Some experiments focus on comparing accelerometry outcomes to the scores of the clinical exams [37, 71] or using accelerometry to estimate clinical exam scores [48, 84, 87, 93, 99, 102] (**Table 3**). Godfrey *et al*. compared accelerometry-derived times to stopwatch times for TUG [71]. No significant differences were detected between accelerometry and TUG times, suggesting accelerometry is a feasible method for balance assessment [71]. A study conducted by O'Sullivan *et al*. showed that accelerometry root-mean-square had strong negative correlations with the Berg Balance Scale and strong positive correlations with TUG scores while subjects stood on a foam mat with their eyes open. Low Berg Balance scores and high TUG scores indicate poor balance, as does high root-mean-square [37]. Similarly, another study found that larger summed magnitude area of resultant accelerometry signals corresponded to higher Berg Balance Scale scores and lower TUG scores [99]. A previous study by the same group estimated Berg Balance Scale scores from accelerations recorded during the assessment. Classifiers using the estimated scores showed high performance (89.5%) when identifying individuals with high fall risk [102]. Subjects in a study by Shahzad *et al*. performed TUG, 5-times sit-to-stand, and alternative step test while features were extracted from the accelerometry data to be used in various machine learning algorithms to produce Berg Balance Scale estimates. Shahzad was able to find strong correlations (ρ=0.86) between the average of two estimates and the standard Berg Balance Scale assessment score [84].

Other studies have focused on using the accelerometry measures from the assessments (particularly TUG) to classify adults as having better or worse balance performance [48, 55, 70, 83, 85–87, 111, 125, 133, 137]. These studies break down the tests into different segments, instead of just using overall TUG time to classify patients. One study even had access to a dedicated, commercial software that automatically detected the different segments [137]. Weiss *et al*. found that accelerometry-derived TUG duration was different between non-fallers and fallers while standard stopwatch TUG duration did not show significant differences [83]. Additionally, a model using three different accelerometry-derived metrics (jerk during sit-to-stand, standard deviation, step duration) correctly classified 87.8% of the subjects, compared to just 63.4% from the stopwatch duration [83]. Low and high fall risk subjects were more discriminable using accelerometry metrics, specifically signal complexity and jerk, from segmented TUG than traditional TUG measurements [85, 86]. Similar results were found in a study classifying frail and non-frail adults [133]. Another study using 5-times sit-to-stand had better classification using four accelerometry-derived metrics (74.4%) compared to overall time (59.0%) [125]. The results from these studies provide support for instrumenting balance assessments because accelerometers can provide additional, useful information to detect balance changes.

There are other types of balance assessments for specific patient populations that have also been assessed in relation to accelerometry. For example, the Balance Error Scoring System is often used to evaluate concussed individuals [67, 72, 104, 106] and the Unified Parkinson's Disease Rating Scale (UPDRS) III has its own Postural Instability and Gait Disorders (PIGD) subscore [74].

8.b Patient Populations

8.b.i Neurodegenerative Disorders

Parkinson's disease causes significant deficits in balance and researchers have been using accelerometry to explore this postural control decline [61, 68, 73–75, 78, 91, 94, 138, 139]. Accelerometry signals can successfully distinguish between Parkinson's patients and healthy controls. Additionally, accelerometry-derived outcomes correlate significantly to the PIGD [73] and are more sensitive to Parkinsonian progression compared to Motor UPDRS, PIGD, bradykinesia and rigidity sub-scores [75]. Similarly, accelerometers are also being used to detect balance deficits in patient populations such as multiple sclerosis [51, 64, 110, 115], Huntington's disease [62, 65], stroke [95, 140], lower back pain [52, 53, 82], spinal cord injury [109, 114], osteoarthrosis [80], and arthropathy [58]. For people with multiple sclerosis, assisted device usage is an important risk factor for falls. Hsieh *et al*. found that root mean square and 95% ellipse area were able to successfully discriminate between assisted device users and non-users in people with Multiple Sclerosis ($AUC=0.77-0.89$, $p<0.001-0.03$) [115]. Another study found that sway amplitude and jerk significantly improved in people with multiple sclerosis after completing a 10-week balance intervention [110]. For people with Huntington's disease, the premanifest stage occurs prior to motor diagnosis; however, patients display deficits that are not apparent in clinical assessments. In a study conducted by Porciuncula *et al*., jerk and sway amplitude of low back accelerations were able to differentiate among manifest Huntington's disease, premanifest Huntington's disease, and controls [62]. Individuals with chronic lower back pain exhibit acceleration signals with higher energy spectral density than healthy controls [53], which can be reduced with supervised or laser-guided exercise therapies [52].

8.b.ii Concussions and Sports Injuries

Balance performance is also a common assessment for concussion patients, as poor balance is a major symptom of traumatic brain injury. Several studies of accelerometry-measured balance have thus focused on individuals with concussions [54, 67, 104–106, 122]. Researchers have been using accelerometers during the Balance Error Scoring System when evaluating athletes after concussions. One study found that normalized path length (from the NIH Balance Accelerometry Measure) underperformed in comparison to the Balance Error Scoring System [106]; however, the Balance Accelerometry Measure was not developed for concussion testing. Conversely, Doherty *et al*. showed that 95% sway volume during bilateral stance was significantly different between concussed and healthy subjects [104]. Detecting differences in the bilateral stance is important as subjects often do not make errors during that condition, meaning that the Balance Error Scoring System suffers from ceiling effects. Additionally, this study showed that accelerometers could identify when an error occurred (AUC=0.91) which could be useful for providing objective assistance to the clinical assessment [104]. Another study found that accelerometry values were significantly different between patients mild and persistent concussion symptoms, unlike scores from the Balance Error Scoring System [67]. Other sports injuries that affect balance also benefit from using accelerometry as a measurement tool. Abe *et al.* compared healthy controls to individuals with a history of ankle sprain, using accelerometers on the head and foot, and found that the healthy controls had a lower head-to-foot acceleration ratio than the ankle sprain subjects [33].

8.b.iii Sensory Deficit Patients and Feedback Systems

The balance system relies on inputs from visual, somatosensory, and vestibular systems. Some studies have focused on poor balance resulting from damage to the vestibular system [46, 59, 88, 107]. The NIH's Balance Accelerometry Measure was tested to see if it could accurately differentiate between healthy subjects and patients with vestibular disorders [107]. The results showed that four of the six conditions of the Balance Accelerometry Measure were reliable in vestibular subjects and the composite score output by the test showed high sensitivity and specificity to discriminate between vestibular and healthy groups [107]. Another type of balance deficit can occur with the loss of somatosensory information from peripheral limbs. Individuals with diabetic peripheral neuropathy have reduced sensitivity in their feet which reduces the amount of sensory feedback that the postural control system can use to adjust balance. Turcot *et al.* found that patients with diabetic peripheral neuropathy had higher accelerations and worse postural stability than controls and diabetic patients without peripheral neuropathy [88].

Patients with poor balance may see improvements when using artificial feedback systems [60, 65, 66, 69, 90, 119, 138]. These feedback systems rely on accelerometers to monitor the subject's balance and then that sway information is relayed, processed, and output in some other modality as an additional form of sensory feedback. Vibrotactile feedback [90], auditory feedback [65], and visual feedback [138] have been successful for people with vestibulopathic conditions, Huntington's disease, and Parkinson's disease respectively. Artificial feedback can also help subjects that have good balance [60, 66, 69, 119]. Audio feedback conveyed sway accelerations in two directions by modulating frequency (AP), left/right audio balance (ML), and volume (magnitude of acceleration). The audio feedback helped subjects improve their balance, particularly when posture was challenged by reducing sensory feedback (closing eyes or standing on foam) [60]. Visual biofeedback also enhanced postural control learning in healthy individuals that underwent single leg stance training [119]. This research shows that not only can accelerometry be used as an assessment tool but also as a component of balance treatment or enhancement.

9 Community Settings

Accelerometers allow researchers and clinicians to assess subjects and patients at their residence and in their daily life, without the bias of a laboratory or clinical setting. There have not been many balance studies conducted in community settings with accelerometers, but those that do exist have shown promising results [85, 100, 101, 120, 121, 128, 129]. Alqahtani *et al*. used accelerometers to assess participants' balance in their residence facility to analyze the reliability and validity of accelerometers in a community setting. They found that accelerometers had good to excellent intra-class correlations in all but one of their test conditions (AP semi-tandem stance). They also found that normalized path length had the best test-retest reliability [101]. This group had previously found that accelerometry root-mean-square and normalized path length were significantly correlated to the Duke Comorbidity Index [100]. In residential communities in Taiwan, Wu *et al*. was able to discriminate between low and high fall risk residents and their accelerometry features outperformed traditional assessment measurements [85]. Another study investigated application-based balance tests in laboratory settings and self-administered at home and found that the balance features from the application were sensitive to age and task condition in both testing locations [128]. Self-administered, smartphone-based balance tests were also used to explore the relationship between subjective balance confidence and objective sway measurements. The authors concluded that older adults at higher fall risk display greater postural sway on days with higher balance confidence [120]. Conducting balance assessments within the home or residential communities increases healthcare access for underserved populations, mobility-impaired patients, and individuals unable to get transportation to clinics.

10 Conclusion

In this narrative review, the literature demonstrates that accelerometry is highly correlated with or outperforms several clinical and laboratory balance assessments. Accelerometers can be used to monitor changes in balance due to general aging or from different types of pathology. The portability of accelerometers and their sensitivity to different task and disease conditions show that this technology can reduce burden on clinicians and patients, particularly patients that already have mobility deficits. Commercially available smart devices are being shown to be useful in measuring balance and thus expanding accessibility further to patients and use in community or residential settings.

This review has a few limitations. The heterogeneity of many of the studies in terms of sensor placement, outcome, and balance tests employed make comparisons across studies difficult. Additionally, only papers published in English were considered, reducing the variety of study populations. Many of these studies also lacked diverse samples, particularly in terms of race and education, which limits the generalizability of these conclusions. Additionally, male participants were more common than female participants especially for studies that focused more on comparing accelerometers to other technologies and not on a particular study population. Lastly, a single reviewer was responsible for the data search, extraction, and analysis. As a result, studies could have been missed or omitted that should have been included. Despite these limitations, this narrative review does give a comprehensive overview of accelerometry methods and applications for standing balance assessment.

Accelerometers have been used in many different studies for balance assessment. They have been compared to laboratory technology like force plates and motion capture. Accelerometers provide additional information to clinical assessments like the Berg Balance Scale, TUG test, and 5-times sit-to-stand. They have been used with numerous patient populations, such as Parkinson's disease, Huntington's disease, Multiple Sclerosis, and concussion. Additionally, many studies now are looking at activity monitoring, using accelerometers in fitness watches or other smart devices to monitor function of community-dwelling older adults in their daily lives [141–145]. Despite the potential of these devices, the current literature is limited because it is difficult to make comparisons across studies as the field has not yet agreed on standardized outcomes to measure and report. It is also important to consider whether older adults will use this technology in their community or whether it should be used mostly in the clinic. Studies do not currently examine how older adults feel about incorporating this technology. A previous review has looked into older adults' perceptions of technology and their conclusions point to the importance of older adults thinking the technology is useful and non-invasive [146]. With the rise in activity monitoring and commercially available accelerometers in smart devices, balance assessments should move to the community, not requiring a trip to a clinic. However, accelerometers are not yet part of the clinical diagnostic process despite the breadth of clinically relevant uses, diagnostic sensitivity, and widespread accessibility of commercially available devices. For accelerometers to move into the clinical space, a consensus on relevant outcomes is necessary as well as a reliable, user-friendly signal analysis software that clinicians can use in the balance assessment process.

Overall, accelerometers provide additional insight to current standard clinical assessments and diagnostics for patients, but their full potential is not yet realized. Accelerometers offer clinicians an objective, portable, and cost-effective measurement tool that could increase accessibility to balance assessments for older adults in an increasingly aging population.

11 Author Contributions

The authors confirm contribution to the paper as follows: review conception and design: K. Bohlke, E. Sejdic, A. L. Rosso; data collection, analysis, and interpretation of literature: K. Bohlke; draft manuscript preparation: K. Bohlke, A. L. Rosso, M. S. Redfern, E. Sejdic. All authors reviewed the results and approved the final version of the manuscript.

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14 Figure Legends

Fig. 1 A Diagram of a mass-spring system and Hooke's Law, where F is force, k is the spring constant, x is the displacement, m is the mass, and a is the acceleration **B** Simplified diagram of a capacitive micro-electromechanical accelerometer where m is the mass, k_1 and k_2 are springs, and C_1 and C_2 are capacitors.

Fig. 2 Diagram of the single-link (left), the double-link (center), and the triple-link (right) biomechanical models.

15 Tables

Table 1 Description of the most commonly reported outcome metrics calculated from acceleration signals from the experimental studies discussed in this review.

Feature	**Calculation**	**Relationship to Balance**	**Number of Studies that Measured Feature**
Root-Mean-Square	$= \sqrt{\frac{\left(\sum_{j=1}^{N-1} ACC_j\right)^2}{N}}$ Where N is the total number of data points, and ACC_j is the acceleration data at sample j.	Measure of spread of accelerations, relates to amount of postural sway [101].	54 [11, 33, 37, 38, 40, 41, 43, 45, 46, 48, 49, 56–61, 66, 67, 69–76, 78, 79, 81, 84, 87, 88, 93–97, 100, 101, 109–117, 120, 123, 125, 126, 128, 130]
Jerk	$= \frac{1}{2}\int_0^t \left(\frac{dACC}{dt}\right)^2$ Where t is the total time, ACC is the acceleration signal.	Measures the change in acceleration (slope) and indicates postural control smoothness [73].	25 [48, 54, 55, 57, 61, 62, 68, 71, 73–75, 78, 83, 84, 86, 87, 94, 96, 97, 109, 110, 114, 119, 122, 124, 125]
Normalized Path Length	$= \frac{1}{t}\sum_{j=1}^{N-1} \lvert ACC_{j+1} - ACC_j \rvert$ Where t is the total time, N is the total number of data points, and ACC_j is the acceleration data at sample j.	Measure of speed, similar to integrating acceleration [101].	12 [11, 45, 48, 56, 68, 74, 100, 101, 106, 107, 112, 128]
95% Ellipse Area	Area containing 95% of accelerations in transverse plane (anterior-posterior and medial-lateral).	Planar measure of spread of accelerations, relates to the amount of postural sway [78].	11[a] [48, 61, 71, 77, 78, 104, 112, 113, 115, 120, 126]
95% Power Frequency	95% of power is present below this frequency.	Measure of frequency content of the acceleration signal [125].	10 [48, 60, 61, 70, 71, 73–75, 78, 125]

Sample Entropy	$= -ln\left(\frac{C^{m+1}(r)}{C^{m}(r)}\right)$ Where $C(r)$ is the conditional probability that two sequences match for length $m + 1$ or m, r is the tolerance for match acceptance which is usually defined as a percentage of the standard deviation.	Measure of complexity/regularity of acceleration signals [85, 147].	8[b] [43, 54, 58, 85, 86, 91, 118, 122]

[a] One study [104] used ellipsoid volume instead of ellipsoid area and included the vertical acceleration signal.

[b] Some groups used just sample entropy [43, 91, 118], others went further to find multiscale entropy [85, 86] and then additionally to calculate the complexity index [85, 86, 122].

Table 2 Studies comparing accelerometers to force plates that required subjects to perform single-leg standing, tandem stances, or dynamic movements.

Paper	**Accelerometer Location**	**Activity**
Abe *et al*. 2014 [33]	Forehead, dominant ankle	Single-leg standing
Adlerton *et al*. 2003 [42]	L3	Single-leg standing during resting and fatigued conditions
Dewan *et al*. 2019 [124]	Midsternum level	Double leg standing, single-leg standing, anterior-posterior sway, medial-lateral sway
Doherty *et al*. 2017 [104]	Lower back	Bilateral stance, tandem stance, unilateral stance (single-leg) from the Balance Error Scoring System
Heebner *et al*. 2015 [72]	L5	Dynamic postural stability index, forward jump over hurdle to one leg, lateral jump over hurdle to one leg, double leg stance on firm and foam, tandem stance, single-leg standing
Hsieh *et al*. 2021 [115]	Sternum	Eyes open and closed bilateral stance, semi-tandem stance, tandem stance, and single-leg standing
Janssen *et al*. 2008 [117]	Sternum	Sit-to-stand on firm, foam, and balance board surface, sit-to-stand rising on single dominant leg

Table 3 Studies that focused on comparing accelerometry to or predicting scores of clinical examinations.

Paper	**Tasks Completed with Accelerometer**	**Clinical Examination**	**Main Takeaway**

Godfrey *et al*. 2015 [71]	TUG	TUG	TUG times detected with accelerometry were not significantly different from stopwatch times, indicating algorithm could replace stopwatch timing.
McManus *et al*. 2022 [48]	Standing on firm and foam surfaces in a semitandem stance, with eyes closed in a narrow stance, TUG	Berg Balance Scale, TUG	The Balance Score developed from accelerometry features was significantly correlated to TUG time (ρ = 0.30, 0.34; p<0.001). Accuracy was higher for fall risk assessment classifiers that used accelerometry data (66%, 68%) than classifiers using just TUG time (59%) or Berg Balance Scale scores (59%).
Narayanan *et al*. 2010 [93]	Physiological Profile Assessment, TUG, Alternative Step Test, 5 times Sit-to-Stand	Physiological Profile Assessment	A model developed mostly using accelerometry features from the Alternative Step Test and Sit-to-Stand was highly correlated to the Physical Profile Assessment (ρ = 0.81, p < 0.001).
O'Sullivan *et al*. 2009 [37]	Standing on firm and foam surfaces with eyes open and closed	Berg Balance Scale, TUG	Acceleration root-mean-square during standing on foam with eyes open was significantly correlated with Berg Balance Scale (ρ = -0.829, p < 0.001) and TUG (r = 0.621, p < 0.01).
Shahzad *et al*. 2017 [84]	TUG, Alternative Step Test, 5 times Sit-to-Stand	Berg Balance Scale	The average of Berg Balance Scale score estimation models that were trained using accelerometry features was strongly correlated to standard Berg Balance Scale scores (ρ = 0.86, p < 0.001).
Similä *et al*. 2014 [102]	Berg Balance Scale, 10m Walk	Berg Balance Scale	The gait-based Berg Balance Scale estimation model was most accurate in identifying high fall risk subjects (77.8%) and low fall risk subjects (96.6%); the balance task estimation model performed better with high fall risk (89.5%) than low fall risk (62.1%).
Similä *et al*. 2017 [99]	Romberg test, Berg Balance Scale, TUG, 5 times Sit-to-Stand, 4m Walk	Berg Balance Scale, TUG, 5 times Sit-to-Stand	Results from the estimation models using accelerometry features averaged normalized root-mean-square errors of 0.28 for Berg Balance Scale scores, 0.18 for TUG times, and 0.22 for 4m walk times. Standard deviation of vertical acceleration could predict decline in

			Berg Balance Scale (AUC = 0.82, sensitivity = 80%, specificity = 73%).
Yu *et al*. 2021 [87]	TUG	Short Form Berg Balance Scale	Accelerometer features from TUG performance were the inputs to an estimation model for Short Form Berg Balance Scale scores, with an elastic net regression model performing the best (mean absolute error = 2.12, root-mean-square error = 2.68). Predicted subtask scores were also able to discriminate between fall risk levels (AUC = 0.72-0.79).

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