Predicting Fall Risk Through Automatic Wearable Monitoring: A Systematic Review

Markey C. Olson[1,2] and Thurmon E. Lockhart[1]

1School of Biological and Health Systems Engineering, Arizona State University

mcolson4@asu.edu
Thurmon.Lockhart@asu.edu

2Muhammad Ali Parkinson's Disease Clinic, Barrow Neurological Institute

ABSTRACT

Falls represent a major burden on elderly individuals and society as a whole. Technologies that are able to detect individuals at risk of fall before occurrence could help reduce this burden by targeting those individuals for rehabilitation to reduce risk of falls. Wearable technologies especially, which can continuously monitor aspects of gait, balance, vital signs, and other aspects of health known to be related to falls, may be useful and are in need of study. A systematic review was conducted in accordance with the Preferred Reporting Items for Systematics Reviews and Meta-Analysis (PRISMA) 2009 guidelines to identify articles related to the use of wearable sensors to predict fall risk. Fifty four studies were analyzed. The majority of studies (98.0%) utilized inertial measurement units (IMUs) located at the lower back (58.0%), sternum (28.0%), and shins (28.0%). Most assessments were conducted in a structured setting (67.3%) instead of with free-living data. Fall risk was calculated based on retrospective falls history (48.9%), prospective falls reporting (36.2%), or clinical scales (19.1%). Measures of the duration spent walking and standing during free-living monitoring, linear measures such as gait speed and step length, and nonlinear measures such as entropy correlate with fall risk, and machine learning methods can distinguish between falls. However, because many studies generating machine learning models did not list the exact factors being considered, it is difficult to compare these models directly. Few studies to date have utilized results to give feedback about fall risk to the patient or to supply treatment or lifestyle suggestions to prevent fall, though these are considered important by end users. Wearable technology demonstrates considerable promise in detecting subtle changes in biomarkers of gait and balance related to an increase in fall risk. However, more large-scale studies measuring increasing fall risk before first fall are needed, and exact biomarkers and machine learning methods used need to be shared to compare results and pursue the most promising fall risk measurements. There is a great need for devices measuring fall risk also to supply patients with information about their fall risk and strategies and treatments for prevention.

https://doi.org/10.36001/IJPHM.2021.v12i4.2958

1. INTRODUCTION

Fall incidents and the resultant injuries, fear of falling, and decreased activity levels present a large issue for the rapidly growing population of older adults. Falls are the leading cause of injuries and death among older Americans, with 1 in 4 seniors falling each year. The total cost of fall injuries in the US was estimated to be $50 billion in 2015 and is expected to rise to $67.7 billion by 2020 (National Council on Aging, 2018). Globally, the cost of falls is expected to exceed $240 billion a year by 2040 (World Health Organization, 2007).

Given the staggering effect of falls on individuals and society, it is not surprising that a number of technologies have been developed in recent years to detect and respond to falls (Aziz, Musngi, Park, Mori & Robinovitch, 2016, Chaudhuri, Thompson & Demiris, 2014, Santo el al, 2019, Bourke et al, 2016, Secerquia, Lopez & Vargas-Bonilla, 2018, Cheffena, 2016, Ejupi, Galang, Aziz, Park, & Robinovitch, 2017, Ozdemir, 2016, Hsieh, Liu, Huang, Chu & Chan, 2017, Yu, Chen & Brown, 2018, and Dubois & Charpillet, 2014). Many of these devices have been designed to be wearable, so that falls can be detected and assistance summoned no matter where the individual is at the time. Home- or location-based technologies such as cameras, motion sensors, and impact/noise detectors have also been utilized. These sensors may help to reduce rates of severe injury and death from falls by ensuring fast response and tracking the circumstances surrounding the fall to allow for lifestyle changes and rehabilitation to circumvent further future falls.

While falls detection is valuable, it still requires that a fall may occur before it can provide aid, meaning injuries are still likely. A better alternative would be to stop falls before they ever occur by monitoring features that often lead to falls and suggesting further action such as rehabilitation, assistive technology, or temporary reduction or change in activities to alleviate this fall risk. It has been shown that assessing and responding to clinical gait and balance metrics associated with falls can lower fall risk (RAND, 2003, Gillespie et al., and Khanuja, Joki, Bachmann & Cuccurullo, 2018), and it is recommended by the American and British Geriatrics Societies that all adults over 65 be assessed for fall risk at clinical visits (Khanuja et al., 2018, American Geriatrics Society, 2011). Assessments at clinical visits are helpful, but the length of time between regular visits and inter-rater differences and inability to document small changes using the clinician-rated tests employed may allow some individuals at fall risk to be missed. More frequent assessment in real-world environments is more likely to detect small changes in gait, balance, activity, and other parameters that indicate degradation in health that might lead to falls.

One method that has been used to monitor and assist elderly individuals both in terms of measuring fall risk and many other features of daily life (Philips et al., 2016, Rantz et al., 2013, Alwan, 2009, Manton et al., 2016, Rantz et al., 2014, Villacorta, Jimenez, Val, & Izquierdo, 2011) is the “smart home” concept. A number of ambient sensors such as cameras, motion/depth detectors, pressure mats, microphones, and latch sensors keep track of daily activity, gait parameters, medication, food, and water intake, and the like to ensure that individuals remain healthy and active. Such a strategy shows promise in allowing elderly individuals to “age-in-place” for longer outside of a care home setting and reduce the rates of falls and other incidents leading to injury.

However, smart home sensors can only provide information about events and warning signs that occur in the home or community care setting. The installation of equipment throughout the house may be costly and time-intensive, may not be approved in certain setting such as rental properties or care homes, may have difficulty identifying and tracking multiple people within the home, and may not be accepted by older individuals unused to technology or those worried about surveillance. Because of these considerations, smart home technology may not be readily available for all individuals or in all situations where they may be needed.

Wearable sensors, on the other hand, can be kept with an at-risk individual at all times, providing constant real-time information. Even within a home or community care setting, wearables may increase the value of smart home features by allowing for improved discrimination of which individuals are being monitored and where they are located. This review aims to present previous work in wearables designed to measure fall risk, evaluate the current state-of-the-art, and discuss the research needed to allow this work to be transferred from the clinical and community-care settings where it has been most-often implemented thus far to allow for easy use by elderly individuals in their daily life both in their home and out in the community.

2. METHODS

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematics Reviews and Meta-Analysis (PRISMA) 2009 guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009). Keyword search was performed in PubMed in August 2019. The search algorithm utilized was (fall* AND ("predict*" OR "prevent*" OR "risk") AND ("app*" OR "wear*" OR "phone" OR “sensor”)). Title and abstract review were performed on all search results.

Those articles meeting the following criteria were included in the review: 1) peer-reviewed journal articles with full-text available in English (conference proceedings were not included) and published within the last decade to reflect recent advances in technological capabilities (2009-2019); 2) prospective studies examining the use of a wearable technology to measure fall risk, directly or indirectly through known and stated correlate; 3) the use of a fully portable system (papers with tethered components such as pressure mats, cameras, and radio antennas were only reviewed if wearable components were able to be used separately and data was given separately); 4) paper investigated assessment of fall risk before the fall occurred, not just fall detection; 5) assessments could be conducted without a physician, therapist, or other expert to allow monitoring outside of clinical settings (or could be modified to do so).

Additional articles were located through a citation search of the articles located in the initial search and through suggestion by peers. Review articles found during the initial search and meeting all eligibility requirements but 2) were also included in the review process and utilized to locate any additional relevant articles not appearing in the PubMed search, but were screened out before the writing of this systematic review to avoid overlapping data.

Articles making it through the review process were screened according to the types of information included: 1) consumer preferences, 2) fall risk standard used for comparison (retrospective history, falls diary, etc.), 3) tasks utilized to determine fall risk, 4) whether assessment was triggered for a set period or using continuous or free-living data, 5) biomarkers analyzed, 6) software algorithm used to determine fall risk, 7) hardware/sensor type, 8) location of sensors on the body, 9) type of feedback given about fall risk, and 10) whether patients were given any advice or treatment to reduce fall risk.

3. RESULTS

3.1. Study Selection

A total of 1529 results resulted from the initial search terms, of which 112 made it through title/abstract review. Most papers were removed because they did not describe wearable methods of ascertaining fall risk, instead using ambient sensors and/or measuring only fall detection. A further 17 articles that met the other search criteria were removed because they were conference proceedings, not peer-reviewed journal articles. 22 of the papers selected were reviews, not controlled studies, and were thus removed from the systematic review, but were still reviewed in the literature search to identify further articles. The literature search revealed 14 additional articles for a total of 104 articles which underwent full-text review. A further 50 articles were excluded because, while fall risk or related measurement was stated as the main aim, it was not classified in the study (most of these studies focused on proof-of-concept showing that free-living or gait activity could be accurately determined by wearable methods), resulting in 54 articles in the systematic review (Aicha, Englebienne, Schooten, Pijnappels & Krose, 2018, Antos, Danilovich, Eisenstein, Gordon & Kording, 2019, Barrois et al., 2017, Bergamini et al., 2017, Brodie, Lord, Coppens, Annegarn & Delbaere, 2015, Brodie et al., 2015b, Brodie et al., 2017, Caby, Kieffer, Hubert, Cremer & Macq, 2011, Cui et al., 2014, Di Rosa et al., 2017, Doheny et al., 2013, Doi et al., 2013, Drover, Howcraft, Kofman & Lemaire, 2017, Ejupi et al., 2017, Ganea, Paraschiv-Ionescu, Bula, Rochat & Aminian, 2011, Gietzalt et al., 2009, Govercin et al., 2010, Greene et al., 2010, Greene et al., 2012, Greene, Doheny, Ohalloran & Kenny, 2013, Greene Doheny, Kenny & Caulfield, 2014, Greene, Redmond & Caulfield, 2017, Greene et al., 2018, Howcroft, Lemaire & Kofman, 2016, Howcroft, Kofman & Lemaire, 2017, Howccroft, Kofman & Lemaire, 2017b, Hsieh, Roach, Wajda & Sosnoff, 2019, Hua et al., 2018, Ihlen, Weiss, Bourke, Helbostad & Hausdorff, 2016, Ihlen et al., 2018, Iluz et al., 2014, Iluz et al., 2015, Latt, Menz, Fung & Lord, 2009, Marschollek et al., 2011, Marschollek, 2011b, Martinez-Ramirez et al., 2011, Mikos et al., 2019, Mohler, Wendel, Taylor-Piliae, Toosizadeh & Najafi, 2016, Najafi, Armstrong & Mohler, 2013, Pazaic, Lindemann, Grebe & Stork, 2016, Rasche et al., 2017, Rasche et al., 2018, Razjouyan et al., 2017, Rezvanian & Lockhart, 2016, Rispens et al., 2014, Riva, Toebes, Rijnappels, Stagni & Dieen, 2013, Schwenk et al., 2014, Simila, Immonen & Ermes, 2017, Soangra & Lockhart, 2018, Stack et al., 2018, Van Schooten et al., 2015, Van Schooten et al., 2016, Weiss et al., 2013, Weiss, Herman, Giladi & Hausdorff, 2014). Figure 1 details the systematic review process.

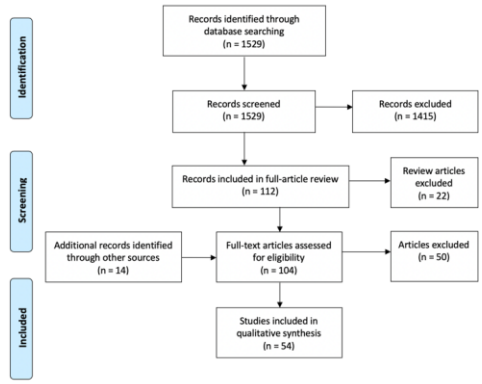

Figure 1: Systematic review process, documenting records perused, excluded, and included at each step.

3.2. Consumer Preferences

Only two studies considered the consumer preferences of fallers and older individuals at risk of future falls. Govercin, et al. (2010) asked focus groups of older adults (at fall risk and not based on clinical scores) and the caregivers of fall-prone individuals to identify features that they would prefer in a fall preventions device. Participants stated that fall prediction was as important as falls detection and that they preferred wearable devices to those that were optical or home-based because they could be used be more widely used. A non-stigmatizing sensor on the wrist, such as a smartwatch-based app, with an emergency button in case of undetected fall was generally preferred.

Rasche, et al. (2018) found that the features most asked for in a fall prevention smartphone app by the 96 older adults in the study were (1) a checklist of typical tripping hazards, (2) an emergency guideline in case of a fall, (3) description of exercises and integrated workout plans that decrease the risk of falling, (4) inclusion of a continuous workout program, and (5) cost coverage by health insurer.

Based on these studies, it is apparent that individuals want a portable device that is not easily noticed as medical equipment and, in addition to detecting and alerting in the case of a fall incident, can give feedback about fall risk on a regular basis and use this information to prescribe potential risk-alleviating measures such as home modifications or exercises.

3.3. Population Characteristics

With the exception of the two consumer preference studies listed above, all of the studied reviewed here implemented a wearable sensor to measure variables that might be correlated with fall incidence or risk, or with a condition known to be linked to falls such as frailty or freezing of gait in Parkinson's disease (PD). The size and characteristics of the populations studied varied widely, as shown in Tables 1 and 2.

Population Size	**Studies (%)**
5-24	15.4% [26, 29, 32, 47, 63, 68, 73, 74]
25-49	19.2% [27, 28, 34, 35, 51, 55, 58, 59, 67, 72]
50-99	32.7% [30, 31, 33, 36, 37, 39, 50, 52, 53, 56, 57, 60, 61, 62, 65, 71, 77]
100-149	13.5% [38, 45, 48, 49, 69, 70, 78]
150-199	3.8% [64, 75]
200-299	9.6% [25, 40, 43, 46, 76]
300+	5.8% [42, 44, 54]

Table 1: Number of Individuals Included Categorized by Study. Bracketed numbers indicate reference number for each paper.

While studies varied greatly by size, the vast majority studied less than 200 individuals. Given the size of data sets generally utilized to train predictive algorithms, the small effect size expected, and the high rate of non-compliance or study withdrawal during home-based recording and fall diary follow-up (Shany, Liu, Redmond, Wang & Lovell, 2015), it is expected that much larger trials are needed including up to several thousand volunteers.

Population/Control Group	**Studies (%)**
Older Adult Fallers/Non-fallers	71.2% [25, 29-43, 45, 46, 48-54, 56, 58-59, 62, 64-67, 69, 70, 74-77]
Older Adult Balance Decline/None	1.9% [72]
Older Adults Frail/Non-frail	3.8% [44, 60]
Older Adults Assisted/Unassisted	1.9% [26]
PD Fallers/Non-fallers	9.6% [47, 55, 57, 74, 78]
PD with FOG/without FOG	3.8% [61, 68]
Demented Fallers/Non-fallers	1.9% [71]
Stroke Fallers/Non-fallers	1.9% [27, 28]
Diabetes Fallers/Non-fallers	1.9% [63]
Cardiac patients Frail/Non-frail	1.9% [73]

Table 2: Breakdown of the experimental population and the control group for each paper.

The majority of studies (71.2%) analyzed potential differences between older adults without other impairment based on whether they were prone to falling. A further 17.3% of studies analyzed fall risk similarly in populations with neurological or other impairment leading to an increased rate of falls. The remaining studies measured the correlation of other variables known to be related to falls such as frailty, PD freezing of gait (FOG), and the use of a prescribed assistive device while walking to determine how they affected measures of gait that could be detected by wearables.

In 20 of 52 (38%) of studies, subjects were excluded if unable to ambulate without an assistive device during testing (Barrois et al., 2017, Bergamini et al., 2017, Brodie et al., 2015, Caby et al., 2011, Di Rosa et al., 2017, Doi et al., 2013, Drover et al., 2017, Ganea et al., 2011, Greene et al., 2014, Greene et al., 2017, Greene et al., 2018, Howcroft et al., 2016, Howcroft et al., 2017, Howcroft et al., 2017b, Hua et al., 2018, Iluz et al., 2014, Rezvanian & Lockhart, 2016, Riva et al., 2013, Stack et al., 2018). This exclusion is often utilized in studies of gait, as the use of a device changes movement patterns. However, the use of assistive devices is common at home in fall-prone individuals and fall risk measurement tools that can account for aids will be important in the future to allow wide-spread use.

3.4. Gold Standard Used to Determine Fall Risk

While most studies analyzed compared wearable features directly to fall incidence/risk, they did not all distinguish fallers from non-fallers in the same way. There were three main ways that fall status was determined: retrospective fall history, prospective fall diary, and clinical measures of fall risk. However, the time period for which falls were monitored (both retrospectively and prospectively) and the clinical measures used varied widely (see Table 3).

48.9% of studies utilized retrospective falls (asking falls history for anywhere from 6 months to 5 years), 36.2% used prospective falls (with follow-up recording of one month to two years), and 19.1% used clinical scales (most commonly the Tinetti scale, with many studies using a combination of several scales). 4.3% of studies analyzed both retrospective and prospective falls and 4.3% analyzed falls and clinical scales. One study intending to measure the beginning of balance decline, which increases fall risk, measured the change in Berg Balance scale scores over one year following wearable assessment (Simila et al., 2017). It is important to note that, though wearables have been tested for use in objective fall detection, no studies were found that have combined measurement of falls and of fall risk. Fall history and diaries were all based on self-report measures.

Studies intending to measure frailty used the Fried Frailty Index (Greene et al., 2013, Martinez-Ramirez et al., 2011) or the STS Frailty Criteria (Razjouyan et al., 2017). PD FOG was measured using video assessment of gait by trained interpreters, with periods with and without FOG used to build classification models for use in wearables (Mikos et al., 2019, Rezvanian & Lockhart, 2016). The use of an assistive device was consistent between users, with each user completing the same number of trials with and without an assistive device (Antos et al., 2019).

Gold Standard	Studies (%)
Retrospective falls history	48.9%
Previous 6 months	8.5% [48, 49, 55, 75]
Previous year	38.3% [25, 29, 30-33, 35, 38, 45, 52, 53, 56, 57, 65, 66, 69, 70, 78]
Previous 5 years	4.3% [42, 46]
Prospective falls occurrence	36.2%
Following month	2.1% [64]
Following 3 months	4.3% [47, 71]
Following 6 months	17.0% [27, 37, 50, 54, 62, 75-77]
Following year	12.8% [30, 36, 58, 59, 76, 78]
Following 2 years	2.1% [43]
Clinical Assessment	19.1%
Aachen Falls Prevention Scale	2.1% [66]
Berg Balance Scale	2.1% [28]
Barthel Index	4.3% [28, 41]
Dynamic Gait Index	2.1% [34]
Functional Ambulation Categories	2.1% [28]
Heinrich II	2.1% [67]
Physiological Profile Assessment	2.1% [51]
Short Physical Performance Battery	2.1% [52]
Tinetti Falls Efficacy Scale	10.6% [28, 34, 39, 63, 66]
Timed Up and Go	4.3% [34, 41]
STRATIFY Falls Risk Assessment	2.1% [40]

Table 3: Methods Used to Determine Fall Risk for Comparison with Biomarkers

There are strengths and weaknesses associated with any measure of fall risk. The most accurate measure of future fall risk, especially if we hope to catch biomarker preceding first fall, is prospective falls occurrence. However, it also requires a follow-up period to the study, which increases study cost and patient withdrawal from data collection. Retrospective fall history also gives an accurate, though less sensitive, measure of fall status and does not require follow-up. Clinical scales provide a correlate measure of fall risk (scales may have been initially compared to either prospective or retrospective falls) and may be collected at the same time as biomarkers, negating the need for follow-up period. However, they do not give a fully accurate picture of whether the individual is or will be a faller. Many of these tests are also subjective and may not be sensitive to early, invisible changes in gait indicative of change in fall risk.

3.5. Wearable Sensors

The majority of studies utilized an accelerometer or inertial measurement unit (IMU) containing an accelerometer in addition to other instruments such as a gyroscope, magnetometer, or barometer. Other sensors used included pressure insoles and electrocardiogram (ECG) and respiratory monitors, as displayed in Table 4. Only one study (Di Rosa et al., 2017) did not utilize an accelerometer, instead relying on pressure insoles alone.

Sensor Used	**Studies (%)**
IMU	98.0%
Accelerometer	98.0% [25-33, 35-40, 42-64, 67-78]
Gyroscope	33.3% [27, 28, 39, 42-47, 55, 60-62, 64, 71, 73, 74]
Magnetometer	5.9% [27, 60, 64]
Barometer	5.9% [29-31, 38]
Pressure Insoles	5.9% [34, 48-50]
ECG	2.0% [67]
Respiratory Monitor	2.0% [67]

Table 4: Types of Sensors Used to Measure Fall Risk

In three studies, no wearable sensor was described. Two studies (Govercin et al., 2010, Rasche et al., 2018) measured only consumer preferences for a potential sensor. Rasche, et al. (2017) used questionnaires and a test of compensatory movement during standing balance, but it was not stated whether the balance test utilized a sensor such as the phone's accelerometer or was measured by self-assessment.

Most studies (58.8%) used a single IMU or other sensor. The remaining used 2 (21.6%), 3 (5.9%), 5 (7.8%), 6 (5.9%), or 10 (2.0%) sensors. This data is broken down by study in Table 5. In most cases, all sensors were of the same type. However, three studies by Howcroft et al. (2016, 2017, 2017b), or 7.8%, utilized four accelerometers in addition to pressure insoles in both shoes.

Number of Sensors	**Studies (%)**
1	58.8% [25, 29-31, 33, 38-40, 51-56, 58-61, 63, 64, 67, 69-73, 75-78]
2	21.6% [26, 34-36, 42-44, 46, 47, 57]
3	5.9% [27, 37, 68]
5	7.8% [28, 45, 62, 74]
6	5.9% [48-50]
10	2.0% [32]

Table 5: Number of Sensors Used on Each Individual During Testing by Study

The position of sensors varied, but the most common location was the lower back (58.0%), followed by the sternum and shins (26% of studies each). Other positions included the upper back, the thigh, the feet, the wrist, the head, and the elbows (see Table 6). One study (Hua et al., 2018) using a single accelerometer did not state where the sensor was located during testing.

Sensor Location	
Lower Back	58.0% [25, 27, 28, 33, 36, 37, 40, 45, 48-50, 53-60, 62, 68-70, 72, 74-78]
Belt Clip/Pocket	4.0% [26, 73]
Upper Back	4.0% [32, 36]
Sternum	26.0% [28-31, 35, 38, 39, 45, 51, 62, 63, 67, 71]
Thigh(s)/Knees(s)	10.0% [32, 35, 45, 62, 68]
Shin(s)	26.0% [28, 37, 42-50, 62, 68]
Feet/Ankle(s)	14.0% [32. 34, 48-50, 61, 74]
Elbow(s)	2.0% [32]
Wrist(s)	8.0% [26, 32, 64, 74]
Head	8.0% [48-50, 57]

Table 6: Positioning of Sensors on the Body by Study

3.6. Biomarkers of Fall Risk

In order to ensure timely updates to fall risk information and remove the burden or remembering and making time to check their status, it would be most helpful for a fall risk device to continuously monitor biomarkers of fall risk and be able to update risk scores without the need for specific guided movements. However, as of this writing, few of the articles identifying biomarkers of fall risk have done so based on continuous, unstructured data (32.7%). All other studies involved structured or semi-structured movements and were generally conducted in a lab-based setting, which is known to affect fall risk results (Rispens et al., 2016, Van Schooten, Rispens, Elders, Dieen & Pijnappels, 2014). Even among the 17 studies that examined continuous locomotor data, the duration over which training data was collected varied widely, which may drastically affect results and accuracy of the resultant models, as shown in Table 7.

Data Duration	**Studies (%)**
1 day	11.8% [67, 71]
3 days	29.4% [53, 55, 56, 77, 78]
1 week	35.3% [25, 31, 54, 64, 75, 76]
2 weeks	17.6% [34, 62, 69]
8 weeks	5.9% [29]

Table 7: Duration of Monitoring for Studies Using Continuous Measurement

The continuous studies primarily looked at biomarkers obtained during periods of locomotion (82.4%), though two studies (11.8%) focused on transitions from sitting to standing or walking and vice versa (Cui et al., 2014, Govercin et al., 2010), and one study focused on classifying activity and heart rate variability (Greene et al., 2013).

All but one (94.1%) of the studies examining biomarkers of fall risk from continuous data analyzed individual biomarkers related to fall risk separately, allowing for direct comparison of those factors that independently influenced fall risk. Table 8 shows the parameters of gait/activity that demonstrated significant differences between fallers and non-fallers in at least one study analyzing continuous data. Those parameters that were also found not to be significantly affected by classification in other studies were noted; however, those factors found to be insignificant in all studies were not included for the sake of brevity.

Walking duration, entropy, amplitude of the dominant frequency (DF) in the vertical direction, and the harmonic ratio in the vertical and anterior-posterior directions were most commonly found to be significant determinants of fall risk. It is important to note that, though nonlinear measures were more often found to show significant differences between fallers and non-fallers, these measures vary considerably based on the number of steps utilized in processing, so a standard processing method breaking walks into smaller segments is needed. Currently, this process differs between groups, making results difficult to compare.

One study analyzing wearable data based both on retrospective and prospective falls (Weiss et al., 2014) found that retrospective fallers demonstrated decreased VT amplitude and increased width of the dominant frequency (all directions), decreased regularity, and decreased harmonic ratio (all components), while prospective falls were correlated with only increased AP dynamic frequency width. Another (Van Schooten et al., 2015) found retrospective falls to be influenced by steps per day, walk duration, and dominant frequency power and prospective falls to be influenced by gait speed, frequency, step length, variability, harmonic ratio, index of harmonicity, and logarithmic divergence, illustrating the need for more studies based on prospective falls to elucidate early signs of increased fall risk.

Only two studies focused on predictive biomarkers in sit-to-stand transitions, making consensus difficult to measure to date. Parameters analyzed in these papers are shown in Table 9. The single study analyzing continuous heart rate variability data (Razjouyan et al., 2017) found that fallers had lower average R-R intervals (time between R waves of the ECG), lower variability in R-R duration, and increased power in the low frequency component of the heart wave during continuous monitoring.

Studies conducted in-lab were generally much more structured and focused than those involving continuous assessment. The Timed Up and Go (TUG) test was the most commonly performed task (45.9%), but measured walks of various lengths/durations, postural stability tests, sit-to-stand, and activities of daily living (ADLs) were also common (see Table 10).

Gait Parameters	Significant	Not Significant
Steps per day	[29, 75]	[31, 62]
Walks per day	[29]	[31, 62]
Average steps per walk	[29, 31, 77]	[62]
Variability walk duration	[71]	
Longest walk	[71]	[29, 31]
Walking Duration	[62,67,71,75]	
Standing Duration	[71]	
Sitting Duration	[62]	
Lying Duration	[62]	
Side Lying	[67]	
Gait speed	[75,76]	
Cadence	[75,76]	[29,31, 62]
Step length	[75,76]	
RMS VT	[76]	[29, 31]
RMS AP	[76]	
Step duration	[77]	
Stride duration	[77]	
Step time variability	[29,31]	
Single support time	[34]	
Double support time	[34]	
Heel contact force slope	[34]	
Average Acceleration ML	[34]	
Index of Harmonicity VT	[69]	
Entropy	[53, 54,76]	
LF%	[69]	
Range AP	[76,77]	
Range ML	[77]	[76]
Local Dynamic Stability VT	[69]	
LDS per stride VT	[69]	
Amplitude DF VT	[69,75-78]	
Amplitude DF ML	[76,77]	[69]
Slope DF VT	[69,77]	
Slope DF ML	[77]	[69]
Width DF VT	[78]	
Width DF AP	[76,78]	
Width DF ML	[78]	
Harmonic ratio VT	[75,76,78]	
Harmonic ratio AP	[75,76,78]	
Harmonic ratio ML	[75,78]	
Index of harmonicity	[75,76]	
Logarithmic divergence	[75,76]	
Missteps (calculation not given)	[55]	

Table 8: Parameters Measured During Continuous. The first column lists parameters measured, the second documents studies finding significant differences between groups, and the third indicates studies in which the parameter was measured but not significant. AP=Anterior-Posterior, ML=Medio-Lateral, VT=Vertical, RMS=Root Mean Square

Sit-to-stand Parameters	Significant	Not Significant
Amplitude arm swing	[64]	
Smoothness VT	[56]	
Smoothness AP	[56]	
Jerk	[64]	[56]
Oscillation ML	[64]	
Entropy VT	[64]	
Energy VT	[64]	
Energy ML	[64]	
Index of Harmonicity VT	[64]	

Table 9: Parameters Demonstrating Significant Differences Between Fallers and Non-fallers During Continuous Analysis of Sit-to-Stand Transitions

Only seventeen studies (45.9%) of structured movement assessments of fall risk provided information about specific biomarkers that were significantly different between fallers and non-fallers. The biomarkers analyzed are shown in Table 11 and 12. The remaining studies utilized machine learning and other algorithms to predict fall risk but did not detail which results were collected and subsequently found to be predictive, by themselves or in conjunction with other factors.

Gait speed was most often found to be significantly different between fallers and non-fallers in structured walking tasks. Step duration, RMS, total time needed to complete the TUG test, and harmonic ratio were also commonly utilized. All of these measures were also found to be useful during continuous testing, suggesting that some of the work that has been used to develop predictive models during structured testing may be usable for continuous testing if an algorithm is able to correctly screen for similar actions during spontaneous activity. For stair climbing, it was found that stability was reduced in prospective fallers, but number of steps and duration to climb stairs were not altered (Brodie et al., 2015b).

Studies of biomarkers of fall risk during postural stability tasks demonstrated conflicting results. Two of the four studies examining postural stability found that there were differences between fallers and non-fallers during normal standing with eyes open or closed in terms of COP radius, area, path length and velocity eyes open (Soangra & Lockhart, 2018) and in total sway (Mohler et al., 2016). However, another study found that path length was not changed in either normal or tandem stance with eyes open or closed and that sway area increased only with eyes closed (Martinez-Ramirez et al., 2011). A final study found that RMS was only significantly predictive in harder conditions (tandem stance and dual-task) and maximum acceleration was not predictive (Hsieh et al., 2019). Further studies are needed to determine what measures are significantly different in normal stance (and may be able to be collected from unstructured data during standing periods) or in stances that can be easily explained and completed safely in a home environment if structured assessment is needed.

Task	
TUG	45.9% [25, 26, 27, 32, 40, 42-47, 58, 59, 61, 63, 72, 74]
Locomotion	59.5%
3-meter walk	2.7% [74]
4-meter walk	2.7% [72]
15-foot (4.57-meter) walk	16.2% [35, 38, 39, 45,73, 74]
5-meter walk	2.7% [73]
25-foot (7.62-meter) walk	8.1% [48-50]
10-meter walk	10.8% [26, 28, 36, 38]
20-meter walk	8.1%[57-59]
25-meter walk	2.7% [32]
400-meter walk	2.7% [52]
1-minute walk	2.7% [77]
3-minute walk	2.7% [70]
6-minute walk	10.8% [26, 27, 48, 50]
Random Walk	8.1% [33, 61, 68]
Tandem Walk	2.7% [74]
Sit-to-Stand	16.2% [35, 38, 39, 45, 73, 74]
Postural Stability	18.9%
Eyes Open	18.9% [32, 45, 51, 60, 62, 65, 73]
Eyes Closed	8.1% [51, 60, 62]
Dual-Task Eyes Open	2.7% [51]
Dual-Task Eyes Closed	2.7% [51]
Tandem Stance	5.4% [51, 60]
One-Legged Stance	5.4% [32, 51]
ADLs	13.5%
Stair Climbing	2.7% [30]
Turning	2.7% [74]
Reaching	2.7% [74]
Walking with Obstacles	2.7% [33]
Not Otherwise Specified	5.4% [38, 68]
Clinical Assessments	5.4%
Berg Balance Scale	2.7% [72]
Falls Questionnaire	2.7% [65]

Table 10: Activities Used for Structured Assessment

As in continuous testing, measures of turning ability were only focused on by a few studies, and consensus on useful parameters was not reached. Interestingly, the parameters found to be significant by structured studies differed for the most part from the results in the continuous studies. It is difficult to tell whether this is due to inherent differences between the way people turn in a naturalized setting, difference in the calculation of parameters between studies, or due to small effect size and population creating conflicting results given the relatively small number of studies using these parameters to date. Further research is needed to isolate the most beneficial parameters to measure sit-to-stand transitions, both in structured and daily life environments.

Gait Parameter	Significant	Not Significant
Gait speed	[28,36, 38,57,73,77]	[62]
Stride length	[28]	[62]
Step duration	[40,77]	
Gait variability	[57]	[40,62]
RMS	[28,40]	
Attenuation coefficients	[28]	
Symmetry	[28]	
TUG time	[27,63]	
Steps to turn 180	[27]	
Step Stability Index	[33]	
Harmonic ratio	[36,57]	
Energy expenditure	[40]	
Pelvis sway	[40]	
Entropy	[73]	

Table 11: Parameters Demonstrating Significant Differences Between Fallers and Non-fallers During Structured Gait Analysis

Sit-to-stand Parameter	Significant	Not Significant
Duration	[35,63]	[39]
Variability		[35]
RMS ML	[35]	
Spectral Edge Frequency AP	[35]	
Maximum acceleration	[38]	
Maximum velocity	[38]	
Peak power	[38]	
Fractal dimension	[39]	

Table 12: Parameters Demonstrating Significant Differences Between Fallers and Non-fallers During Structured Analysis of Sit-to-Stand Transitions

3.7. Software/Algorithms

Thirty-seven (71.2%) articles utilized machine learning or regression to classify fallers vs non-fallers. Most of these studies listed the types of classification algorithms that best fit their data but did not list the features that were fed into these algorithms, making even similar algorithms by different groups difficult to compare. Many of these studies (24.3%) also failed to list accuracy values, merely stating that algorithms using measures obtained from wearables were as accurate or more accurate that those obtained by clinical means or were more accurate than other classification methods tried. Machine learning algorithms used to classify fallers vs non-fallers, along with the average accuracy of each of these methods and the accuracy noted in each study, are shown in Table 13.

Method Used	**Average Accuracy**	**Accuracy by Study**
Linear Regression	76.7%	53.9% [35], 81.0% [36], 75.0% [42], 89.7% [56], 70.0% [58], 88.2% [62], 72.5% [70], 77.1% [71], 78.0% [72], 82.0% [75], NL [26]
Wavelet	82.1%	82.1% [68], 93.1% missteps [55], NL [30,31,38,60,63]
Support vector machine	72.9%	67.6% [37], 80.6% [45], 84% [48], 78% [49], 54.5% [50], NL [32]
Neural Network	66.2%	74% [25], 84.0% [48], 75.3% [49], 57.0% [50], 92.9% [61]
Naïve Bayesian	66.2%	80% [48], 68.3% [49], 50.2% [50], NL [32]
Random Forest	75.6%	77.5% [37], 73.7% [52]
K-Nearest Neighbor	71.8%	71.8% [37], NL [32]
Classification Regression Tree	80%	80% [59]
Partial Least Squares	83%	83% [54]
Long Short-Term Memory	91%	91% [25]
Principal Component Analysis	NA	NL [60,76]
Empirical mode decomposition	NA	NL [33]
Radial basis function network	NA	NL [32]
Multiple Together	NA	90% [25], 99.2% use of assisted device [26]
Machine Learning/Feature Selection NOS	NA	69% [34], 90.5% [40], 79.6% [43], 73.6% [46], 73.3% [47]

Table 13: Machine Learning Classification Accuracies. The first column documents different methods used, the second lists the average accuracy given by all studies using that method, accounting for all studies that gave accuracy information. NA was used when no study utilizing that method gave accuracy information and for the bottom two columns, in which studies used multiple algorithms together or failed to specify the type of machine learning used to allow for comparison to similar techniques. The third column lists individual accuracies for each study. NL = no accuracy information given, NOS = Not Otherwise Specified.

Several studies gave more in-depth information comparing linear regression models using clinical and wearable biomarkers of fall risk. In general, these studies found that wearable features were more accurate at determining fall risk than clinical metrics, but that models combining both sets of features were the most accurate. Iluz, et al. (2015) found that data collected by a monitor worn for three days of unstructured activity was 88% accurate at classification, clinical data was 71% accurate, and 89.7% accuracy was achieved when information was combined. Marshollek, et al. (2011) found STRATIFY to have an accuracy of 48%, TUG 50%, clinical assessment 55%, an algorithm taking all three conventional measures into account 72%, and sensor data 70% and in another study (2011b) that clinical regression trees were 80% accurate using accelerometer data alone and 78% combining accelerometer data with clinical, but linear regression was 65% accurate using accelerometer data and 70% combined. Van Schooten, et al. (2015) obtained 68% accuracy using clinical data, 71% using wearable data, and 82% with both.

To allow for clearer comparison and analysis of potentially promising fall risk algorithms in the future, it is urgent that more information be provided about specific parameters supplied to described models and the resultant accuracy. Without knowledge of specific parameters and descriptions of the types of machine learning used to generate discerning algorithms, it is nearly impossible for scientists to work together to maximize accuracy of future iterations. It is also highly important that more information be given about accuracy, including information about both sensitivity and specificity. The accuracy numbers given by the majority of studies listed failed to document these numbers separately, which makes it difficult to determine the relative contributions of Type I and Type II error. While both types of error present concerns, they should be handled differently. Type I error, or false positives, can quickly lead to over-diagnosis and treatment, which is costly both in terms of health-care expenditure and aggravated anxiety and fear of falling in those patients falsely identified as fall risks. However, such systems can still be used well as a first line of defense in conjunction with further testing. For example, an automatic home-based fall risk screening wearable with high sensitivity but low specificity might indicate to the patient that they should schedule an appointment with their physician for a more in-depth fall risk assessment. If the physician finds reason for concern about fall risk, further treatment can then be suggested. Alternatively, the same device may suggest targeted home-based exercise to reduce fall risk that will provide low-cost benefit to the patient even in the case of a false positive. In contrast, devices with high specificity but low sensitivity to fall risk may still be useful for tracking patients already known to be at risk to measure sudden changes indicative of need for immediate action.

3.8. Feedback About Fall Risk

Only two studies measuring fall risk with wearables provided feedback to their users about fall risk in real time. Mikos, et al. (2019) used vibration feedback supplied to the ankle to alert PD patients in the case of FOG. Rasche, et al. (2017) gave users visual feedback of their fall risk upon completion of a fall risk assessment including questionnaires and standing balance.

3.9. Fall Risk Intervention/Treatment

Two studies delivered treatment to ease fall risk. Mikos, et al. (2019) delivered vibration biofeedback during FOG episodes to alert patients to the incorrect stepping pattern and encourage correct stepping. Simila, et al. (2017) randomized patients at fall risk to receive computer-based exercise plans and activity/falls monitoring, paper-based exercise plans and activity diary, or no exercise/monitoring, though the effects of these interventions were not considered.

4. ARTICLES IN PERIODICALS

Falls present a devastating and rapidly growing problem for our aging society. Currently, fall risk assessment may be conducted using short, subjective, clinical measures during regular physician appointments, but guidance to prevent falls is very general and targeted treatments such as physical therapy are often reserved for individuals who have already fallen and are in need of rehabilitation. Technology may help to improve fall risk assessment and response in multiple ways, including allowing for more regular fall risk screening at home, isolating more objective parameters that may be indicative of more subtle changes related to fall risk, and providing more targeted treatments and lifestyle changes based on the exact types of degradation noted. The same sensors used to assess fall risk may be usable to measure suggested at-home therapy routines. Both home-based systems such as the Kinect (Hondori & Khademi, 2014, Su, Chiang & Huang, 2014) and wearables (Dobkin & Dorsch, 2011, Yurtman & Barshan, 2013) have been shown to be effective at tracking and guiding therapy-related exercise.

End-user studies of the preferences of elderly individuals (some of whom are known fallers) and their care-givers demonstrate the need for a device that can subtly track fall risk and then supply feedback about both risk and treatment and lifestyle changes that can actually help to reduce this risk. Patients do not wish to receive a fall risk assessment if they feel helpless to change the results. However, while all of the studies reviewed here were specifically designed to measure fall risk, only two articles each made a point to present fall risk results directly to subjects or to provide treatment to try to improve fall risk or a related factor. One of these studies, which provided feedback about FOG in PD in real-time, is incredibly helpful but can only be targeted to a fraction of the individuals who fall each year. Clearly, interventions and suggestions specifically targeted to fall risk profile and readily accessible following assessment is an area in which research, development, and innovation are gravely needed.

The available research has demonstrated that wearable sensors are a viable way of determining biomarkers of fall risk, that data may be collected by sensors in a number of locations (many of which allow the sensor to be easily hidden against the body, beneath clothing, or disguised as a watch or other traditional accessory to encourage frequent wear), and that data from simple tasks such as walking and standing may be useful in collecting these biomarkers. Based on these facts, the need for such tasks as practiced in many clinical scales of fall risk such as the Tinetti or the Berg Balance Scale, which must be attended by a trained practitioner, can be significantly alleviated. However, further research is still needed before home-based fall risk assessment using wearables is feasible. There is still a need for studies of both continuous and structured assessments conducted in home and community environments over the period of several weeks or months to note variations in parameters that might be more indicative of change in scenery or task than decline in gait or balance function. For example, individuals may walk differently in tight spaces, when carrying something or conducting another task, or when wishing to look at something along their path. Longer assessment times, combined with prospective falls monitoring, may also help pick up subtle changes leading up to a fall, both over the term of several weeks to allow for treatments to be recommended and in the preceding few minutes to warn the patient and ask them to sit or otherwise reduce their immediate risk of fall.

If structured assessments are to be used, several factors will need to be taken into account to design a user-friendly system. Any tasks to be completed should be simple, easily explained, and safely and readily completed within a small space, and minimal if any outside equipment should be required. It should be considered that many elderly individuals at risk for falls suffer from comorbidities such as cognitive or sensory impairment, which could drastically reduce the ability of individuals to understand and carry out instructions requiring more than a few sequential steps. Simple walks or standing are likely feasible, but dual tasks or complicated stances would be difficult to implement. Safety is also paramount, so exercises such as single-leg balance should not be requirements for assessment. If used in therapy, precautions such as advising someone else be present to assist and a mat or other padding be placed on the floor, should be made clear. Finally, all assessments should be easily completed in a small space, which may restrict the length of walking tasks, and should not require the use of outside tools such as tape lines to mark off a set distance, as this would likely drastically reduce compliance.

In other words, while studies to date have laid important groundwork in establishing the feasibility of using IMUs and other wearables to track features of gait and balance related to fall risk, they have still suffered from important limitations.

Very few studies have considered user feedback or risk reduction. Most research thus far has been completed in controlled environments, and data may not easily transfer to daily life. Longer trial durations are needed to account for normal variability in sensor placement and movement patterns and to allow for closer temporal comparison with fall events. Trials using measures other than IMUs, especially those tracking vital signs such as ECG, respiration, blood pressure, or production of metabolic factors such as insulin, which have all been linked to falls in some cases, are also needed. Given the nearly infinite number of models that could possibly be tested, it is important that there be large scale (>1000-1500 individual) trials of those parameters deemed most viable based on current research. To facilitate this process and subsequent endeavors, greater transparency in research methodology is urgently needed so all parameters of interest may be known.

These longer, large-scale trials and the eventual release of fall risk assessment and treatment tools into the population will create several technical challenges to overcome. First, battery life must be considered. Most wearables currently marketed for consumer use last a maximum of 12-18 hours, meaning most charge these devices overnight. While this may be feasible, removal of the sensor during sleep may lose important information, such as transitions from lying to standing or a degradation in vital signs overnight. It may also be difficult for some seniors to remember to reapply the sensor the following morning. Thus, batteries lasting longer periods (such as that of the Dynaport, a research IMU which lasts a week) while still retaining consumer features, and possibly alerting the patient once the charge cycle is complete, would be greatly helpful. Another technical challenge, which is currently being experienced in may arenas due to the boom in big data and artificial intelligence, is the need to store, sort through, and analyze very large amounts of information, and to do as much of this analysis as possible in real-time and on the user's devices to prevent delays in areas without wireless signal.

As with any systematic review, there are limitations to this study. It is impossible to review every paper, even within specific fields such as wearables or fall risk, necessitating the use of search terms to limit and filter results. As such, it is likely that some papers that would helpfully contribute to this discussion were left out of the literature search and analysis. This paper also did not conduct a meta-analysis regarding the comparative efficacy of different parameters or algorithms in determining fall risk, largely due to the wide and different designs used in the cited studies and the lack of needed information given about these variables by a sizable minority of them. In the future, continued research may make such an analysis possible.

5. CONCLUSIONS

Falls represent a huge and expanding threat to our aging population, and the measurement of fall risk (with subsequent action) shows promise in reducing the number of fall incidents. Technology such as wearable monitors can measure biomarkers related to fall risk (thus far, identified markers have mainly been features of gait). However, further research is still needed to reach a consensus on the best parameters to measure, the best positioning for sensors (both in terms of accuracy and user acceptance), types of interface consumers prefer and best understand, and what treatment options or lifestyle changes best improve rates of falls subsequent to an increase in measured fall risk.

REFERENCES

[1] National Council on Aging. (2018, June 4). Falls Prevention Facts. Retrieved from https://www.ncoa.org/news/resources-for-reporters/get-the-facts/falls-prevention-facts/

[2] World Health Organization, WHO Global Report on Falls Prevention in Older Age, WHO Press, 2007 (Department of Aging and Life Course).

[3] Aziz, O., Musngi, M., Park, E. J., Mori, G., & Robinovitch, S. N. (2016). A comparison of accuracy of fall detection algorithms (threshold-based vs. machine learning) using waist-mounted tri-axial accelerometer signals from a comprehensive set of falls and non-fall trials. *Medical & Biological Engineering & Computing*, *55*(1), 45–55. doi: 10.1007/s11517-016-1504-y

[4] Chaudhuri, S., Thompson, H., & Demiris, G. (2014). Fall Detection Devices and Their Use With Older Adults. *Journal of Geriatric Physical Therapy*, *37*(4), 178–196. doi: 10.1519/jpt.0b013e3182abe779

[5] Santos, G., Endo, P., Monteiro, K., Rocha, E., Silva, I., & Lynn, T. (2019). Accelerometer-Based Human Fall Detection Using Convolutional Neural Networks. *Sensors*, *19*(7), 1644. doi: 10.3390/s19071644

[6] Bourke, A. K., Klenk, J., Schwickert, L., Aminian, K., Ihlen, E. A. F., Mellone, S., … Becker, C. (2016). Fall detection algorithms for real-world falls harvested from lumbar sensors in the elderly population: A machine learning approach. *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. doi: 10.1109/embc.2016.7591534

[7] Sucerquia, A., López, J., & Vargas-Bonilla, J. (2018). Real-Life/Real-Time Elderly Fall Detection with a Triaxial Accelerometer. *Sensors*, *18*(4), 1101. doi: 10.3390/s18041101

[8] Cheffena, M. (2016). Fall Detection Using Smartphone Audio Features. *IEEE Journal of Biomedical and Health Informatics*, *20*(4), 1073–1080. doi: 10.1109/jbhi.2015.2425932

[9] Ejupi, A., Galang, C., Aziz, O., Park, E. J., & Robinovitch, S. (2017). Accuracy of a wavelet-based fall detection approach using an accelerometer and a barometric pressure sensor. *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. doi: 10.1109/embc.2017.8037280

[10] Özdemir, A. (2016). An Analysis on Sensor Locations of the Human Body for Wearable Fall Detection Devices: Principles and Practice. *Sensors*, *16*(8), 1161. doi: 10.3390/s16081161

[11] Hsieh, C.-Y., Liu, K.-C., Huang, C.-N., Chu, W.-C., & Chan, C.-T. (2017). Novel Hierarchical Fall Detection Algorithm Using a Multiphase Fall Model. *Sensors*, *17*(2), 307. doi: 10.3390/s17020307

[12] Yu, S., Chen, H., & Brown, R. A. (2018). Hidden Markov Model-Based Fall Detection With Motion Sensor Orientation Calibration: A Case for Real-Life Home Monitoring. *IEEE Journal of Biomedical and Health Informatics*, *22*(6), 1847–1853. doi: 10.1109/jbhi.2017.2782079

[13] Dubois, A., & Charpillet, F. (2014). A gait analysis method based on a depth camera for fall prevention. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. doi: 10.1109/embc.2014.6944627

[14] RAND, Falls prevention intervention in the medicare population, Evidence Report and Evidence-Based Recommendations, (2003).

[15] L.D. Gillespie, et al., Interventions for preventing falls in older people living in the community

[16] Khanuja, K., Joki, J., Bachmann, G., & Cuccurullo, S. (2018). Gait and balance in the aging population: Fall prevention using innovation and technology. *Maturitas*, *110*, 51–56. doi: 10.1016/j.maturitas.2018.01.021

[17] (2011) Summary of the Updated American Geriatrics Society/British Geriatrics Society clinical practice guideline for prevention of falls in older persons. *Journal of the American Geriatric Society*, 59 (1), 148-157.

[18] Phillips, L. J., Deroche, C. B., Rantz, M., Alexander, G. L., Skubic, M., Despins, L., … Koopman, R. J. (2016). Using Embedded Sensors in Independent Living to Predict Gait Changes and Falls. *Western Journal of Nursing Research*, *39*(1), 78–94. doi: 10.1177/0193945916662027

[19] Rantz, M. J., Skubic, M., Abbott, C., Galambos, C., Pak, Y., Ho, D. K., … Miller, S. J. (2013). In-Home Fall Risk Assessment and Detection Sensor System. *Journal of Gerontological Nursing*, *39*(7), 18–22. doi: 10.3928/00989134-20130503-01

[20] Alwan, M. (2009). Passive in-home health and wellness monitoring: Overview, value and examples. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. doi: 10.1109/iembs.2009.5333799

[21] Manton, J. D., Hughes, J. A. E., Bonner, O., Amjad, O. A., Mair, P., Miele, I., … Kaminski, C. F. (2016). Development of an open technology sensor suite for assisted living: a student-led research project. *Interface Focus*, *6*(4), 20160018. doi: 10.1098/rsfs.2016.0018

[22] Rantz, M. J., Skubic, M., Popescu, M., Galambos, C., Koopman, R. J., Alexander, G. L., … Miller, S. J. (2014). A New Paradigm of Technology-Enabled �Vital Signs for Early Detection of Health Change for Older Adults. *Gerontology*, *61*(3), 281–290. doi: 10.1159/000366518

[23] Villacorta, J. J., Jiménez, M. I., Val, L. D., & Izquierdo, A. (2011). A Configurable Sensor Network Applied to Ambient Assisted Living. *Sensors*, *11*(11), 10724–10737. doi: 10.3390/s111110724

[24] Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Bmj*, *339*(jul21 1). doi: 10.1136/bmj.b2535

[25] Aicha, A. N., Englebienne, G., Schooten, K. V., Pijnappels, M., & Kröse, B. (2018). Deep Learning to Predict Falls in Older Adults Based on Daily-Life Trunk Accelerometry. *Sensors*, *18*(5), 1654. doi: 10.3390/s18051654

[26] Antos, S. A., Danilovich, M. K., Eisenstein, A. R., Gordon, K. E., & Kording, K. P. (2019). Smartwatches Can Detect Walker and Cane Use in Older Adults. *Innovation in Aging*, *3*(1). doi: 10.1093/geroni/igz008

[27] Barrois, R. P.-M., Ricard, D., Oudre, L., Tlili, L., Provost, C., Vienne, A., … Yelnik, A. P. (2017). Observational Study of 180° Turning Strategies Using Inertial Measurement Units and Fall Risk in Poststroke Hemiparetic Patients. *Frontiers in Neurology*, *8*. doi: 10.3389/fneur.2017.00194

[28] Bergamini, E., Iosa, M., Belluscio, V., Morone, G., Tramontano, M., & Vannozzi, G. (2017). Multi-sensor assessment of dynamic balance during gait in patients with subacute stroke. *Journal of Biomechanics*, *61*, 208–215. doi: 10.1016/j.jbiomech.2017.07.034

[29] Brodie, M. A., Lord, S. R., Coppens, M. J., Annegarn, J., & Delbaere, K. (2015). Eight-Week Remote Monitoring Using a Freely Worn Device Reveals Unstable Gait Patterns in Older Fallers. *IEEE Transactions on Biomedical Engineering*, *62*(11), 2588–2594. doi: 10.1109/tbme.2015.2433935

[30] Brodie, M. A., Wang, K., Delbaere, K., Persiani, M., Lovell, N. H., Redmond, S. J., … Lord, S. R. (2015b). New Methods to Monitor Stair Ascents Using a Wearable Pendant Device Reveal How Behavior, Fear, and Frailty Influence Falls in Octogenarians. *IEEE Transactions on Biomedical Engineering*, *62*(11), 2595–2601. doi: 10.1109/tbme.2015.2464689

[31] Brodie, M. A., Coppens, M. J., Ejupi, A., Gschwind, Y. J., Annegarn, J., Schoene, D., … Delbaere, K. (2017). Comparison between clinical gait and daily-life gait

assessments of fall risk in older people. *Geriatrics & Gerontology International*, *17*(11), 2274–2282. doi: 10.1111/ggi.12979

[32] Caby, B., Kieffer, S., Hubert, M. D. S., Cremer, G., & Macq, B. (2011). Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry. *BioMedical Engineering OnLine*, *10*(1), 1. doi: 10.1186/1475-925x-10-1

[33] Cui, X., Peng, C.-K., Costa, M. D., Weiss, A., Goldberger, A. L., & Hausdorff, J. M. (2014). Development of a new approach to quantifying stepping stability using ensemble empirical mode decomposition. *Gait & Posture*, *39*(1), 495–500. doi: 10.1016/j.gaitpost.2013.08.036

[34] Di Rosa, M., Hausdorff, J. M., Stara, V, Rossi, L., Glynn, L., Casey, M., … Cherubini, A. (2017). Concurrent validation of an index to estimate fall risk in community dwelling seniors through a wireless sensor insole system: A pilot study. *Gait & Posture*, *55*, 6–11. doi: 10.1016/j.gaitpost.2017.03.037

[35] Doheny, E. P., Walsh, C., Foran, T., Greene, B. R., Fan, C. W., Cunningham, C., & Kenny, R. A. (2013). Falls classification using tri-axial accelerometers during the five-times-sit-to-stand test. *Gait & Posture*, *38*(4), 1021–1025. doi: 10.1016/j.gaitpost.2013.05.013

[36] Doi, T., Hirata, S., Ono, R., Tsutsumimoto, K., Misu, S., & Ando, H. (2013). The harmonic ratio of trunk acceleration predicts falling among older people: results of a 1-year prospective study. *Journal of NeuroEngineering and Rehabilitation*, *10*(1), 7. doi: 10.1186/1743-0003-10-7

[37] Drover, D., Howcroft, J., Kofman, J., & Lemaire, E. (2017). Faller Classification in Older Adults Using Wearable Sensors Based on Turn and Straight-Walking Accelerometer-Based Features. *Sensors*, *17*(6), 1321. doi: 10.3390/s17061321

[38] Ejupi, A., Brodie, M., Lord, S. R., Annegarn, J., Redmond, S. J., & Delbaere, K. (2017). Wavelet-Based Sit-To-Stand Detection and Assessment of Fall Risk in Older People Using a Wearable Pendant Device. *IEEE Transactions on Biomedical Engineering*, *64*(7), 1602–1607. doi: 10.1109/tbme.2016.2614230

[39] Ganea, R., Paraschiv-Ionescu, A., Büla, C., Rochat, S., & Aminian, K. (2011). Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people. *Medical Engineering & Physics*, *33*(9), 1086–1093. doi: 10.1016/j.medengphy.2011.04.015

[40] Gietzelt, M., Nemitz, G., Wolf, K.-H., Schwabedissen, H. M. Z., Haux, R., & Marschollek, M. (2009). A clinical study to assess fall risk using a single waist accelerometer. *Informatics for Health and Social Care*, *34*(4), 181–188. doi: 10.3109/17538150903356275

[41] Govercin, M., Költzsch, Y., Meis, M., Wegel, S., Gietzelt, M., Spehr, J., … Steinhagen-Thiessen, E. (2010). Defining the user requirements for wearable and optical fall prediction and fall detection devices for home use. *Informatics for Health and Social Care*, *35*(3-4), 177–187. doi: 10.3109/17538157.2010.528648

[42] Greene, B. R., Donovan, A. O., Romero-Ortuno, R., Cogan, L., Scanaill, C. N., & Kenny, R. A. (2010). Quantitative Falls Risk Assessment Using the Timed Up and Go Test. *IEEE Transactions on Biomedical Engineering*, *57*(12), 2918–2926. doi: 10.1109/tbme.2010.2083659

[43] Greene, B. R., Doheny, E. P., Walsh, C., Cunningham, C., Crosby, L., & Kenny, R. A. (2012). Evaluation of Falls Risk in Community-Dwelling Older Adults Using Body-Worn Sensors. *Gerontology*, *58*(5), 472–480. doi: 10.1159/000337259

[44] Greene, B. R., Doheny, E. P., Ohalloran, A., & Kenny, R. A. (2013). Frailty status can be accurately assessed using inertial sensors and the TUG test. *Age and Ageing*, *43*(3), 406–411. doi: 10.1093/ageing/aft176

[45] Greene, B. R., Doheny, E. P., Kenny, R. A., & Caulfield, B. (2014). Classification of frailty and falls history using a combination of sensor-based mobility assessments. *Physiological Measurement*, *35*(10), 2053–2066. doi: 10.1088/0967-3334/35/10/2053

[46] Greene, B. R., Redmond, S. J., & Caulfield, B. (2017). Fall Risk Assessment Through Automatic Combination of Clinical Fall Risk Factors and Body-Worn Sensor Data. *IEEE Journal of Biomedical and Health Informatics*, *21*(3), 725–731. doi: 10.1109/jbhi.2016.2539098

[47] Greene, B. R., Caulfield, B., Lamichhane, D., Bond, W., Svendsen, J., Zurski, C., & Pratt, D. (2018). Longitudinal assessment of falls in patients with Parkinson’s disease using inertial sensors and the Timed Up and Go test. *Journal of Rehabilitation and Assistive Technologies Engineering*, *5*. doi: 10.1177/2055668317750811

[48] Howcroft, J., Lemaire, E. D., & Kofman, J. (2016). Wearable-Sensor-Based Classification Models of Faller Status in Older Adults. *Plos One*, *11*(4). doi: 10.1371/journal.pone.0153240

[49] Howcroft, J., Kofman, J., & Lemaire, E. D. (2017). Feature selection for elderly faller classification based on wearable sensors. *Journal of NeuroEngineering and Rehabilitation*, *14*(1). doi: 10.1186/s12984-017-0255-9

[50] Howcroft, J. D., Kofman, J. D., & Lemaire, E. D. (2017b). Prospective Fall-Risk Prediction Models for Older Adults Based on Wearable Sensors. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(10), 1812–1820. doi: 10.1109/tnsre.2017.2687100

[51] Hsieh, K. L., Roach, K. L., Wajda, D. A., & Sosnoff, J. J. (2019). Smartphone technology can measure postural stability and discriminate fall risk in older adults. *Gait & Posture*, *67*, 160–165. doi: 10.1016/j.gaitpost.2018.10.005

[52] Hua, A., Quicksall, Z., Di, C., Motl, R., Lacroix, A. Z., Schatz, B., & Buchner, D. M. (2018). Accelerometer-based predictive models of fall risk in older women: a pilot study. *Npj Digital Medicine*, *1*(1). doi: 10.1038/s41746-018-0033-5

[53] Ihlen, E. A., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorff, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of Biomechanics*, *49*(9), 1420–1428. doi: 10.1016/j.jbiomech.2016.02.055

[54] Ihlen, E. A. F., Schooten, K. S. V., Bruijn, S. M., Dieën, J. H. V., Vereijken, B., Helbostad, J. L., & Pijnappels, M. (2018). Improved Prediction of Falls in Community-Dwelling Older Adults Through Phase-Dependent Entropy of Daily-Life Walking. *Frontiers in Aging Neuroscience*, *10*. doi: 10.3389/fnagi.2018.00044

[55] Iluz, T., Gazit, E., Herman, T., Sprecher, E., Brozgol, M., Giladi, N., … Hausdorff, J. M. (2014). Automated detection of missteps during community ambulation in patients with Parkinson's disease: a new approach for quantifying fall risk in the community setting. *Journal of NeuroEngineering and Rehabilitation*, *11*(1), 48. doi: 10.1186/1743-0003-11-48

[56] Iluz, T., Weiss, A., Gazit, E., Tankus, A., Brozgol, M., Dorfman, M., … Hausdorff, J. M. (2015). Can a Body-Fixed Sensor Reduce Heisenberg's Uncertainty When It Comes to the Evaluation of Mobility? Effects of Aging and Fall Risk on Transitions in Daily Living. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *71*(11), 1459–1465. doi: 10.1093/gerona/glv049

[57] Latt, M. D., Menz, H. B., Fung, V. S., & Lord, S. R. (2009). Acceleration Patterns of the Head and Pelvis During Gait in Older People With Parkinsons Disease: A Comparison of Fallers and Nonfallers. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *64A*(6), 700–706. doi: 10.1093/gerona/glp009

[58] Marschollek, M., Rehwald, A., Wolf, K.-H., Gietzelt, M., Nemitz, G., Schwabedissen, H. M. Z., & Schulze, M. (2011). Sensors vs. experts - A performance comparison of sensor-based fall risk assessment vs. conventional assessment in a sample of geriatric patients. *BMC Medical Informatics and Decision Making*, *11*(1). doi: 10.1186/1472-6947-11-48

[59]Marschollek, M., Rehwald, A., Wolf, K. H., Gietzelt, M., Nemitz, G., Schwabedissen, H., & Haux, R. (2011b). Sensor-based Fall Risk Assessment – an Expert 'to go.' *Methods of Information in Medicine*, *50*(05), 420–426. doi: 10.3414/me10-01-0040

[60] Martínez-Ramírez, A., Lecumberri, P., Gómez, M., Rodriguez-Mañas, L., García, F., & Izquierdo, M. (2011). Frailty assessment based on wavelet analysis during quiet standing balance test. *Journal of Biomechanics*, *44*(12), 2213–2220. doi: 10.1016/j.jbiomech.2011.06.007

[61] Mikos, V., Heng, C.-H., Tay, A., Yen, S.-C., Chia, N. S. Y., Koh, K. M. L., … Au, W. L. (2019). A Wearable, Patient-Adaptive Freezing of Gait Detection System for Biofeedback Cueing in Parkinsons Disease. *IEEE Transactions on Biomedical Circuits and Systems*, *13*(3), 503–515. doi: 10.1109/tbcas.2019.2914253

[62] Mohler, M. J., Wendel, C. S., Taylor-Piliae, R. E., Toosizadeh, N., & Najafi, B. (2016). Motor Performance and Physical Activity as Predictors of Prospective Falls in Community-Dwelling Older Adults by Frailty Level: Application of Wearable Technology. *Gerontology*, *62*(6), 654–664. doi: 10.1159/000445889

[63] Najafi, B., Armstrong, D. G., & Mohler, J. (2013). Novel Wearable Technology for Assessing Spontaneous Daily Physical Activity and Risk of Falling in Older Adults with Diabetes. *Journal of Diabetes Science and Technology*, *7*(5), 1147–1160. doi: 10.1177/193229681300700507

[64] Pozaic, T., Lindemann, U., Grebe, A.-K., & Stork, W. (2016). Sit-to-Stand Transition Reveals Acute Fall Risk in Activities of Daily Living. *IEEE Journal of Translational Engineering in Health and Medicine*, *4*, 1–11. doi: 10.1109/jtehm.2016.2620177

[65] Rasche, P., Mertens, A., Bröhl, C., Theis, S., Seinsch, T., Wille, M., … Knobe, M. (2017). The "Aachen fall prevention App" – a Smartphone application app for the self-assessment of elderly patients at risk for ground level falls. *Patient Safety in Surgery*, *11*(1). doi: 10.1186/s13037-017-0130-4

[66] Rasche, P., Mertens, A., Brandl, C., Liu, S., Buecking, B., Bliemel, C., … Knobe, M. (2018). Satisfying Product Features of a Fall Prevention Smartphone App and Potential Users' Willingness to Pay: Web-Based Survey Among Older Adults. *JMIR MHealth and UHealth*, *6*(3). doi: 10.2196/mhealth.9467

[67] Razjouyan, J., Grewal, G. S., Rishel, C., Parthasarathy, S., Mohler, J., & Najafi, B. (2017). Activity Monitoring and Heart Rate Variability as Indicators of Fall Risk: Proof-of-Concept for Application of Wearable Sensors in the Acute Care Setting. *Journal of Gerontological Nursing*, *43*(07), 53–62. doi: 10.3928/00989134-20170223-01

[68] Rezvanian, S., & Lockhart, T. (2016). Towards Real-Time Detection of Freezing of Gait Using Wavelet Transform on Wireless Accelerometer Data. *Sensors*, *16*(4), 475. doi: 10.3390/s16040475

[69] Rispens, S. M., Schooten, K. S. V., Pijnappels, M., Daffertshofer, A., Beek, P. J., & Dieën, J. H. V. (2014). Identification of Fall Risk Predictors in Daily Life Measurements. *Neurorehabilitation and Neural Repair*, *29*(1), 54–61. doi: 10.1177/1545968314532031

[70] Riva, F., Toebes, M., Pijnappels, M., Stagni, R., & Dieën, J. V. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require

step detection. *Gait & Posture*, *38*(2), 170–174. doi: 10.1016/j.gaitpost.2013.05.002

[71] Schwenk, M., Hauer, K., Zieschang, T., Englert, S., Mohler, J., & Najafi, B. (2014). Sensor-Derived Physical Activity Parameters Can Predict Future Falls in People with Dementia. *Gerontology*, *60*(6), 483–492. doi: 10.1159/000363136

[72] Similä, H., Immonen, M., & Ermes, M. (2017). Accelerometry-based assessment and detection of early signs of balance deficits. *Computers in Biology and Medicine*, *85*, 25–32. doi: 10.1016/j.compbiomed.2017.04.009

[73] Soangra, R., & Lockhart, T. (2018). Inertial Sensor-Based Variables Are Indicators of Frailty and Adverse Post-Operative Outcomes in Cardiovascular Disease Patients. *Sensors*, *18*(6), 1792. doi: 10.3390/s18061792

[74] Stack, E., Agarwal, V., King, R., Burnett, M., Tahavori, F., Janko, B., … Kunkel, D. (2018). Identifying balance impairments in people with Parkinson's disease using video and wearable sensors. *Gait & Posture*, *62*, 321–326. doi: 10.1016/j.gaitpost.2018.03.047

[75] Van Schooten, K. S., Pijnappels, M., Rispens, S. M., Elders, P. J. M., Lips, P., & Dieën, J. H. V. (2015). Ambulatory Fall-Risk Assessment: Amount and Quality of Daily-Life Gait Predict Falls in Older Adults. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *70*(5), 608–615. doi: 10.1093/gerona/glu225

[76] Van Schooten, K. S., Pijnappels, M., Rispens, S. M., Elders, P. J. M., Lips, P., Daffertshofer, A., … Dieën, J. H. V. (2016). Daily-Life Gait Quality as Predictor of Falls in Older People: A 1-Year Prospective Cohort Study. *Plos One*, *11*(7). doi: 10.1371/journal.pone.0158623

[77] Weiss, A., Brozgol, M., Dorfman, M., Herman, T., Shema, S., Giladi, N., & Hausdorff, J. M. (2013). Does the Evaluation of Gait Quality During Daily Life Provide Insight Into Fall Risk? A Novel Approach Using 3-Day Accelerometer Recordings. *Neurorehabilitation and Neural Repair*, *27*(8), 742–752. doi: 10.1177/1545968313491004

[78] Weiss, A., Herman, T., Giladi, N., & Hausdorff, J. M. (2014). Objective Assessment of Fall Risk in Parkinsons Disease Using a Body-Fixed Sensor Worn for 3 Days. *PLoS ONE*, *9*(5). doi: 10.1371/journal.pone.0096675

[79] Shany, T., Liu, Y., Redmond, S. J., Wang, K., & Lovell, N. H. (2015). Review: Are we stumbling in our quest to find the best predictor? Over-optimism in sensor-based models for predicting falls in older adults. *Healthcare Technology Letters*, *2*(4), 79–88. doi: 10.1049/htl.2015.0019

[80] Rispens, S. M., Dieën, J. H. V., Schooten, K. S. V., Lizama, L. E. C., Daffertshofer, A., Beek, P. J., & Pijnappels, M. (2016). Fall-related gait characteristics on the treadmill and in daily life. *Journal of NeuroEngineering and Rehabilitation*, *13*(1). doi: 10.1186/s12984-016-0118-9

[81] Van Schooten, K. S.., Rispens, S. M., Elders, P. J., Dieën, J. H. V., & Pijnappels, M. (2014). Toward ambulatory balance assessment: Estimating variability and stability from short bouts of gait. *Gait & Posture*, *39*(2), 695–699. doi: 10.1016/j.gaitpost.2013.09.020

[82] Hondori, H. M., & Khademi, M. (2014). A Review on Technical and Clinical Impact of Microsoft Kinect on Physical Therapy and Rehabilitation. *Journal of Medical Engineering*, *2014*, 1–16. doi: 10.1155/2014/846514

[83] Su, C.-J., Chiang, C.-Y., & Huang, J.-Y. (2014). Kinect-enabled home-based rehabilitation system using Dynamic Time Warping and fuzzy logic. *Applied Soft Computing*, *22*, 652–666. doi: 10.1016/j.asoc.2014.04.020

[84] Dobkin, B. H., & Dorsch, A. (2011). The Promise of mHealth. *Neurorehabilitation and Neural Repair*, *25*(9), 788–798. doi: 10.1177/1545968311425908

[85] Yurtman, A., & Barshan, B. (2013). Detection and Evaluation of Physical Therapy Exercises by Dynamic Time Warping Using Wearable Motion Sensor Units. *Information Sciences and Systems 2013 Lecture Notes in Electrical Engineering*, 305–314. doi: 10.1007/978-3-319-01604-7_30

Thurmon E. Lockhart is a human locomotion biomechanist specializing in fall accidents and the Director of the Locomotion Research Laboratory at the Arizona State University where he is a Professor of Biomedical Engineering and Biological Design. His research focuses on the identification of injury mechanisms and quantification of sensorimotor deficits and movement disorders associated with aging and neurological disorders on fall accidents utilizing wearable biosensors and nonlinear dynamics. His research interest include wearable biomedical devices, gait and posture, chaos and ergonomics.

Markey C. Olson is a PhD Candidate at the Arizona State University, School of Biological and Health Systems Engineering. Her research focuses on the measurement and treatment of biomechanical factors, especially those related to gait and balance, of fall risk and neurological disease.