Evaluation of Wearable Sensors as an Older Adult Fall Risk Assessment Tool

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Dr. Jonathan Kofman and Dr. Edward Lemaire, as Jennifer Howcroft's supervisors, assisted with project conceptualization, and creation of the data collection and analysis protocols. They also participated in writing and editing manuscripts submitted and published in peer-reviewed journals that served as the basis for Chapters 2.3.3.1, and 3 to 7 and editing all thesis Chapters. The first draft was always written by Jennifer Howcroft, and she was involved in the editing process at all stages.

Dr. William McIlroy assisted in modifying and finalizing the data collection protocol. He also participated in editing manuscripts submitted and published in peer-reviewed journals that served as the basis for Chapters 4 to 5.

Jennifer Howcroft recruited all participants, performed all data collections, and performed all data analyses presented in the thesis.

Abstract

Falls are common in the geriatric population, with approximately one third of older adults falling each year. Falls can result in lasting physical and psychological consequences and cost approximately $20 billion per year in the United States. Wearable sensors can be used for quantitative, gait-based, point-of-care fall risk assessment that can be easily and quickly implemented in clinical care and older adult living environments.

The objectives of this study were to evaluate eyes open and eyes closed static posturography in older adults; provide in-depth analysis of the differences between single-task and dual-task gait in elderly individuals and the relation to faller status; generate models for wearable-sensor-based fall risk classification in older adults and identify the optimal sensor type, location, combination, and modelling method for walking with and without a cognitive load task; and compare wearable-sensor-based fall risk classification performance to clinical assessment-based and posturography-based fall risk classification outcomes.

A convenience sample of 100 older individuals (75.5 ± 6.7 years; 76 non-fallers, 24 fallers based on 6 month retrospective fall occurrence; 47 non-fallers, 28 fallers based on 6 month prospective fall occurrence with retrospective fallers excluded) walked 7.62 m under single-task (ST) and dual-task (DT) conditions while wearing pressure-sensing insoles and tri-axial accelerometers at the head, pelvis, and left and right shanks. Participants also completed the Activities-specific Balance Confidence scale, Community Health Activities Model Program for Seniors questionnaire, six minute walk test, static posturography with eyes open and closed, and ranked their fear of falling. Fall risk classification models were assessed for all sensor combinations and three model types: multi-layer perceptron neural network, naïve Bayesian, and support vector machine. Feature selection was performed using Relief-F, Fast Correlation-Based Filter (FCBF), and Correlation based Feature Selection (CFS).

For static posturography, measures sensitive to anterior-posterior motion and medial-lateral centre of pressure (CoP) velocity were greater under eyes closed compared to eyes open conditions for prospective non-fallers, fallers, and multi-fallers. For prospective multi-fallers, medial-lateral range and root-mean square distance from the mean were also greater when visual input was removed, suggesting that assessment of medial-lateral balance control may be particularly important for evaluating the risk of multiple falls. Differences were found between

prospective fallers and non-fallers for Romberg Quotient (RQ) anterior-posterior range and root-mean square distance from the mean. Differences between prospective multi-fallers and non-fallers were for eyes closed and RQ anterior-posterior and vector sum magnitude velocity. This suggests that RQ calculations are particularly relevant for elderly fall risk assessments.

Measures that changed between ST and DT walking conditions, including non-temporal measures related to movement frequency and abnormal body segment movements, were identified. Increased gait variability under DT conditions was indicated by increased posterior CoP stance path deviations, medial-lateral CoP stance path deviation durations, and CoP stance path coefficient of variation; and decreased Fast Fourier Transform quartiles and ratio of even to odd harmonics. Decreased gait velocity and decreased pelvis and shank acceleration standard deviations (SD) could represent compensatory gait strategies to counter the increased gait variability and thus maintain stability. Differences between prospective fallers and prospective non-fallers were related to movement frequency and variability.

Fall risk classification models that used Relief-F feature selection achieved the best performance. With feature selection, the best model for prospective faller classification contained ten features (four pressure-sensing insole features, six left shank accelerometer features) and used a support vector machine classifier. This model achieved an accuracy of 94%, F1 score of 0.923, and Matthew's Correlation Coefficient (MCC) of 0.866. The posterior pelvis accelerometer provided strong single-sensor performance (83% accuracy, F1 score 0.769, MCC 0.645), although lower than the best multi-sensor model performance, and should be considered if a single-sensor system is necessary to reduce assessment cost and complexity at the point-of-care. Neural networks and support vector machines both achieved strong classification performance and outperformed naïve Bayesian classifiers. Sensor-based models outperformed clinical assessment-based models and posturography-based models for both retrospective and prospective fall risk classification. Wearable sensors provided strong fall risk classification performance and should be considered for point-of-care assessment of elderly fall risk.

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Dedication

To my supervisors, Dr. Jonathan Kofman and Dr. Edward Lemaire, who have been constant sources of guidance, wisdom, and insight into the many complexities of a successful research project. They have inspired me to strive for excellence throughout this journey and in my future endeavours.

To my husband, family, and friends who have provided me with constant support and encouragement throughout my whole life. Their confidence in my ability to persevere and succeed, and their pride in my accomplishments have been a huge motivator throughout this journey. I would like to thank my husband in particular for helping me through the hard days, celebrating the wonderful days, and being by my side for all the days in between.

To my friends and colleagues who have provided advice and support; I wish great happiness and success in all their future activities.

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List of Abbreviations

6MWD: Six-minute walk test distance

6MWT: Six-minute walk test

ABC: Activities-specific Balance Confidence scale

AP: Anterior-posterior

AUC: Area under curve

BBS: Berg Balance Scale

CA: Clinical assessment measures

CBMS: Community Balance and Mobility Scale

CFS: Correlation-based feature selection

CHAMPS: Community Health Activities Model Program for Seniors

CoP: Centre of pressure

CoV: Coefficient of variation

CTSIB: Clinical Test of Sensory Integration and Balance

DT: Dual-task

FCBF: Fast correlation based filter

FFT: Fast Fourier Transform

FN: False negative

FP: False positive

H: Head accelerometer

HR: Harmonic Ratio

I: Pressure-sensing insole

ICC: Intraclass Correlation Coefficient

L: Linear

LS: Left shank accelerometer

Max: Maximum

MCC: Matthew’s Correlation Coefficient

MET: Metabolic Equivalent of Task

Min: Minimum

ML: Medial-lateral

MLE: Maximum Lyapunov Exponent

NB: Naïve Bayesian

NN: Neural network

NPV: Negative predictive value

P: Pelvis accelerometer

PCA: Principal component analysis

PF: Prospective faller

PMF: Prospective multi-faller

PNF: Prospective non-faller

PPA: Physiological Profile Assessment

PPV: Positive predictive value

PS: Pressure-sensing

Q: Quadratic

REOH: Ratio of even to odd harmonics

RF: Retrospective faller

RNF: Retrospective non-faller

ROC: Receiver-Operator Characteristic Curve

RMS: Root-mean square

RQ: Romberg Quotient

RS: Right shank accelerometer

SAFE: Survey of Activities and Fear of Falling in the Elderly

SD: Standard deviation

SOT: Sensory Organization Test

SP: Static posturography measures

SR: Summed Ranking

ST: Single-task

SVM: Support vector machine

TN: True negative

TP: True positive

TUG: Timed Up and Go

Vel: Velocity

VSM: Vector sum magnitude

WBB: Wii Balance Boards

Chapter 1 Introduction

Falls are common for people beyond middle age, with approximately one third of people over 65 years of age falling each year [1,2]. This fall rate increases with age [3,4] and for people in long-term care [5]. Fall related injuries among people older than 65 years cost approximately $20 billion per year in the United States [6]. Furthermore, the direct-care costs of injuries due to falls could reach $32.4 billion per year by 2020 [7].

Falls can result in lasting physical and psychological consequences, including injury [3,8], long-term disability [9], reduced activity and mobility levels [4,8,10,11], admission to long-term care institutions [4,11,12], fear of falling [8,11], reduced self-confidence [4,13], and death [11,14]. Fear of falling is a particularly worrisome consequence since fear can lead to a cyclical pattern of deterioration, social isolation, and decreased quality of life [15], even without a fall occurring.

The serious physical, psychological, and economic consequences of falling has led to two approaches to avoid these consequences. The first approach uses physical monitoring devices to detect falls and allow immediate care once a person has fallen. However, this approach can only reduce the severity of the consequences, not eliminate them. Another approach is to prevent fall occurrence through interventions such as exercise [16,17], improved footwear [16], assistive devices [17], adaptation or modification of home environment [16,17], review and modification of medications [16], and increased surveillance and care by caregivers [17]. To be the most effective in preventing falls, these interventions must be provided early to elderly individuals at risk of falling. Therefore, timely fall risk assessment is important for identifying those at risk of falling and to aid in determining the most appropriate intervention to ultimately reduce or eliminate falls [17].

Several clinical assessment tools (i.e., tools based on observational assessment or questionnaires that are used clinically) have been used to assess fall risk; including, timed walking tests, Timed Up and Go (TUG), Berg Balance Scale, Community Balance and Mobility Scale (CBMS), and Tinetti Assessment Tool (described in Chapter 2.2). These assessments often involve a specific task-duration threshold or other threshold value that classifies the individual as at fall risk and the clinician's subjective judgement can affect the overall score. Sensors that objectively provide quantitative measurements could eliminate the subjective influences in fall risk assessment. Many of these sensors measure in flat ground environments (e.g., force platforms, pressure platforms, and instrumented walkways). On the other hand, wearable sensors allow measurement in a variety of environments (e.g., accelerometers, gyroscopes, pressure-sensing insoles). The most appropriate wearable sensors and sensor-derived measurements for elderly fall risk have yet to be determined. The goal of this research is to develop a wearable-sensor-based fall risk assessment tool that can predict elderly fall risk.

1.1 Rationale

As previously stated, many older adults are at risk of falling and a fall can have serious and lasting physical, psychological, and economic consequences. A variety of clinical techniques have been used to determine fall risk proactively and inform the clinician when prescribing appropriate interventions to reduce fall risk.

While a properly designed clinical tool based on observational assessment or questionnaires can provide a standardized fall risk assessment, many clinical tools are limited by ceiling or floor effects, low resolution, and subjective elements [18,19]. Clinical tools can oversimplify fall risk in older populations to a summation of disease-specific symptoms instead of a complex interaction of multiple diseases [20]. Furthermore, if younger populations are the comparator, healthy elderly can be incorrectly classified as at fall risk due to normal, age-related changes that do not correlate with increased falls [20].

Some clinical tools, such as the Gait and Balance Scale [21], STRATIFY [22,23], and interRAI Home Care Assessment [24], include fall history due to its strong predictive power for future falls [5,13,17,25-27]. While this approach is good, at least one fall must occur to classify an individual as at risk. Past falls could result in negative consequences, such as injury and fear of falling, before diagnosis and subsequent interventions. The goal of this thesis research was to determine biomechanical gait features that are linked to fall risk, and to develop a fall risk model that can be used to identify fall risk in individuals without a recent fall history. This could result in earlier intervention and reduce the chance of falls occurring, and thereby avoid the associated negative consequences of falling.

Laboratory-based equipment can provide a complete, quantitative assessment of body kinematics and dynamics. Unfortunately, this equipment is expensive and time consuming for data collection and analysis, limiting its role in clinical practice [28]. Furthermore, force plates limit assessments to the laboratory environment and one step, level ground movements [29]. Instrumented walkways are available in clinical facilities, but the analyses are limited to temporal and foot position on level ground.

Wearable sensors overcome some laboratory-based equipment limitations since they are not bound to a specific environment, allowing assessment in a variety of locations such as stairs, ramps, home, and outdoors. While wearable sensors such as footswitches and pedometers do not provide biomechanical signals for complex movement analyses, sensors such as accelerometers and pressure-sensing insoles provide richer data that can be used to better understand mobility.

Inertial sensors, primarily accelerometers, have been applied in the past to older adult fall risk prediction (reviewed in detail in Section 2.3.3) and previously developed models have reached high levels of accuracy (47-100%), sensitivity (0-100%), and specificity (15-100%). However, these previous fall risk prediction models could be improved by identifying fallers prospectively, using separate training and testing data sets, and performing intra-study sensor-site comparisons instead of inter-study comparisons. Inter-study comparisons can have different participants and protocols, thereby introducing outcome data changes that are not related to the sensors or modelling methods.

The F-Scan pressure-sensing insole is a thin grid of pressure measurement cells that can be placed inside a shoe between the foot and shoe insole. This sensor has not been applied to fall risk assessment for older populations, but has been successfully used to assess simulated instability and transtibial amputee dynamic stability (reviewed in detail in Section 2.3.3.2). This is the first study to investigate plantar pressure analysis for older adult fall risk assessment. It is important to determine whether insoles provide data relevant to fall risk and different fall risk information than accelerometers, to avoid redundancy that hinders data collection efficiency and cost.

1.2 Objectives

The objectives of this research were to:

1. Evaluate eyes open and eyes closed posturography in elderly people.

a. Determine whether posturography measures can differentiate between elderly fallers and non-fallers and determine whether these posturography measures can be used to create a viable screening tool for older people at fall risk.
b. Determine if differences could be detected between eyes open and eyes closed static posturography conditions.

2. Evaluate single-task (ST) and dual-task (DT) walking in elderly people using pressure-sensing insoles and accelerometers.
   a. Determine whether pressure-sensing insole and accelerometer wearable sensors can detect biomechanical differences in gait that occur with a secondary cognitive task.
   b. Determine whether ST or DT gait data from pressure-sensing insole and accelerometer wearable sensors can differentiate between elderly fallers and non-fallers.
3. Develop and evaluate elderly fall risk prediction models using plantar pressure and accelerometer-based features.
   a. Determine the most appropriate plantar pressure measures, accelerometer measures, and accelerometer sites.
   b. Use the measures in 3(a) to assess and classify elderly fall risk.
   c. Compare wearable-sensor-based fall risk classification to clinical-assessment-based fall risk classification and posturography-based fall risk classification.
   d. Use feature selection to identify smaller feature sets for fall risk classification from wearable accelerometer and pressure-sensing insole gait data and compare the results to fall risk classification results obtained without feature selection.

1.3 Contributions

This research provides a substantial knowledge contribution to the field of older adult fall risk management and advances the application of wearable sensors in this field. The following novel contributions were made:

1. <u>Identified the importance of Romberg Quotient (RQ) calculations for elderly fall risk assessments that use static posturography</u>. This is the first study to use the RQ to identify posturography differences between older adult fallers and non-fallers. Differences were

found between prospective fallers and non-fallers for RQ anterior-posterior range and root-mean square distance from the mean. Differences between prospective multi-fallers (i.e. multiple falls) and non-fallers were for eyes closed and RQ anterior-posterior and vector sum magnitude velocity. This suggests that RQ calculations are particularly relevant for elderly fall risk assessments. Therefore, postural balance should be tested with and without visual input and RQ should be calculated to provide fall risk-relevant information, for both single and multi-fallers, when assessing an older adult population.

2. <u>Increased the knowledge base of gait changes that occur with a secondary task and are detectable using wearable sensor-derived measures</u>. Previous studies had only investigated swing time and gait speed measures using force-sensing insoles [30-32] and walking speed, stride time, leg rotation, and gait variability measures using accelerometers [33-35]. In this thesis research, pressure-sensing insole data provided new measures associated with centre of pressure (CoP) stance path, stride events, and impulse. Increased gait variability under DT conditions was evident from increased CoP stance path deviations and coefficients of variation. This thesis research also evaluated accelerometer-derived measures and was the first to identify decreased FFT quartiles and ratio of even to odd harmonics (REOH) as indicators of increased gait variability under DT conditions. Decreased pelvis and shank acceleration standard deviations during DT gait were also identified for the first time, which could, along with decreased gait velocity and other associated temporal changes, represent compensatory gait strategies to counter increased gait variability and maintain stability.
3. <u>For the first time, accelerometer and pressure sensing-insole based measures were developed and evaluated concurrently for their ability to detect differences between prospective elderly fallers and non-fallers based on ST and DT gait.</u> Some statistical differences were identified between prospective elderly fallers and non-fallers based on ST and DT gait, primarily related to gait variability.
4. <u>Developed and evaluated new multi-sensor and single-sensor models for fall risk prediction based on accelerometer and pressure-sensing insole wearable-sensor-based measures</u>. This is the first study to compare features from multiple accelerometer sites and pressure-sensing insoles to determine the best single-sensor and multi-sensor combination, and the best measures for fall risk prediction. While multi-sensor-based

models outperformed single-sensor-based models, single-sensor-based models may be desirable to reduce cost and complexity for clinical and long-term assessment. This novel research used new measures, multiple sensor sites, and based the evaluation on prospective fall information. Furthermore, feature selection was employed to eliminate irrelevant features and improve fall risk predictive performance.

5. <u>Determined that wearable-sensor-based elderly fall risk classification can outperform clinical-assessment-based and posturography-based elderly fall risk classification</u>. Sensor-based models outperformed clinical-assessment-based models and posturography-based models for both retrospective and prospective fall classification. These results demonstrate the advantage of using wearable sensors when assessing fall risk compared to using clinical assessments or posturography assessments. Weiss et al., 2013 [36], van Schooten et al., 2015 [37], and Rispens et al., 2015 [38] also found that sensor-based predictive models, or a combination of sensor-based and clinical assessments, improved fall risk prediction compared to clinical assessment alone. However, this is the first study to compare wearable-sensor-based elderly fall risk classification directly to posturography-based elderly fall risk classification. This research provides important information to improve future clinical point-of-care assessments. Gait assessment may provide a more stability-challenging and thus more complete assessment of older adult fall risk than static posturography or clinical assessments. Therefore, the integration of wearable-sensors into point-of-care older adult fall risk assessments could improve fall risk identification.

Publications derived from this thesis research include:

- Howcroft J, Lemaire ED, Kofman J. Wearable-sensor-based prediction models for fall risk in older adults. PLOS One. 2016; 11(4): e0153240.
- Howcroft J, Kofman J, Lemaire ED, McIlroy WE. Analysis of dual-task elderly gait in fallers and non-fallers using wearable sensors. Journal of Biomechanics. 2016; 49(7): 992-1001.
- Howcroft J, Kofman J, Lemaire ED, McIlroy WE. Static posturography of elderly fallers and non-fallers with eyes open and closed. World Congress on Medical Physics and Biomedical Engineering. 7-12 June 2015; 51: 966-969.

- Howcroft J, Lemaire ED, Kofman J, McIlroy WE. Analysis of dual-task elderly gait using wearable plantar-pressure insoles and accelerometers. 36th Annual International Conference of the IEEE EMBS. 26-30 Aug 2014; 5003-5006.
- Howcroft J, Kofman J, Lemaire ED. Review of fall risk assessment in geriatric populations using inertial sensors. Journal of NeuroEngineering and Rehabilitation. 2013; 10: 91.

1.4 Thesis Outline

Chapter 1 provided an introduction with background information, rationale, objectives and contributions of this research. Chapter 2 provides a review of the relevant literature, focusing on an overview of fall risk and occurrence in older individuals, clinical fall risk assessment tools, and sensor-based fall risk assessment. Chapter 3 details the methodology used in this study; including, participant information, data collection protocol, and data processing. Chapter 4 presents the results and discussion of the static posturography analysis, detailing differences between and cut-off scores for prospective faller, multi-faller, and non-faller classifications, and differences between eyes open and eyes closed static posturography. Chapter 5 details the evaluation of single-task and dual-task gait in older adults. Chapter 6 presents the development, analysis, and discussion of fall prediction models based on full feature sets. In Chapter 6, a comparison between sensor site locations (single and multi-site) in terms of fall risk predictive performance and a comparison between wearable-sensor-based models, posturography-based models, and clinical-assessment-based models are presented. Chapter 7 details the inclusion of feature selection in model development and discusses the improvements in fall risk classification performance compared to classification without feature selection. Chapter 8 presents the thesis conclusions and provides direction for future work.

Chapter 2 Background and Literature Review

2.1 Older Adults

2.1.1 Fall Risk Factors

Older adults often have multiple, interdependent risk factors that increase their risk of falling, making fall risk a complex, multi-factorial issue. These factors can be internal factors that involve deterioration, disease, or failing of a biological function; gait factors that directly impact mobility; or lifestyle factors [39]. Specific risk factors are:

- Internal factors: muscle weakness [17,25,26,40], cognitive impairment [4,25,26,41], visual impairment [4,9,26,40,41], dizziness/vertigo [4,40], postural hypotension [26], neural system deterioration [4], neurological disorders [41], vestibular deficiencies [9], cardiopulmonary impairment [9,41], reduced proprioception [9,27], reduced orthostasis [27], urinary incontinence [13], arthritis [17,40], foot problems [40,42], and reduced flexibility [43];
- Gait factors: mobility limitations [26], gait deterioration during dual tasks [44], reduced reaction time [45], gait impairment [4,17,25,26,40,41], balance impairment [17,26,41], postural unsteadiness [46], and gait variability [47,48]; and
- Lifestyle factors: reduced activity [13,27], multiple medications [13,26,41], depression [13,17,25], alcohol use [41], fear of falling [13,26,40], history of falls [13,17,25,26], and environmental factors [4,40].

These fall risk factors often worsen or challenge an individual's stability, increasing the likelihood of a fall while performing activities of daily living [49].

2.1.2 Stability Issues

Dynamic stability is a property of a body that causes it when disturbed from a condition of equilibrium or steady motion to develop forces or moments that restore the original conditions [50]. During walking, an individual must control centre of mass displacements with respect to a changing base of support [51]. Dynamic stability is often worse in older individuals compared to their younger counterparts [52,53].

Risk factors for dynamic stability deterioration are similar to many fall risk factors; including, deterioration in musculoskeletal, neuromuscular, and somatosensory systems; lifestyle factors; and other factors [54]. Many studies have found poorer dynamic stability control in elderly fallers, suggesting that deteriorations in dynamic stability control may be a fall risk factor. A combination of poor dynamic balance, poor executive function, and low exercise levels was found to be a predictor of increased fall risk for older, community dwelling individuals [49]. Therefore, dynamic stability should be considered as a fall risk factor that may be representative of overall fall risk, given its associations with many of the internal and lifestyle fall risk factors.

2.1.3 Fall Occurrence

Between 25% and 35% of individuals aged 65 years and older fall per year [41,55-57]. In addition, approximately 12% of older adults aged 65 years and older will fall more than once per year [58]. The rate of falling increases to between 32% and 42% for people aged 75 years and older [2,59] and continues to increase with increasing age [60]. The rate of falling also increases for women on colder days and during winter [3], individuals in long-term care facilities such as nursing homes, and individuals receiving home care services compared to community-dwelling older adults [61]. A review of 12 nursing home fall occurrence studies found that 43% of older adults fall per year (range 16% to 75%) [62]. Luukinen et al., 1994 [63] reported higher fall rates for long-term-care-dwelling older adults (men: 2012 falls per 1,000 person years, female: 1423 falls per 1,000 person years) compared to community-dwelling older adults (men: 368 falls per 1,000 person years, female: 611 falls per 1,000 person years). Two studies that investigated 90-day fall occurrence in older adults receiving home care services reported fall occurrence rates of 27% [64] and 35.9% [65]. A study comparing 90-day fall rates in Canada, United States, Finland, United Kingdom, Belgium, Italy, and Hong Kong found higher fall rates for home care (8.4 to 41.8%) compared to nursing home (5.3 to 32.1%) populations, suggesting that older adults receiving home care may experience the highest fall rates [66].

2.1.4 Consequences of Falls

By 2020, the direct care costs of fall injuries for individuals aged 65 years and older is expected to reach $32.4 billion, with an additional $21.8 billion in indirect costs [7]. Falls are the leading cause of injury and death due to injury in the elderly, primarily due to the health impact of falls on individuals aged 85 years and older [41]. Between 40% and 60% of falls lead to injuries, with 30% to 50% of falls resulting in minor injuries, 5% causing fractures, and 5% leading to major injuries [3]. Major injuries include head trauma and severe soft tissue injuries

[27]. Injurious falls can have long-term consequences including admission to a long-term care institution, long-term disability, deconditioning, strength reduction, and functional decline [5,9,13,67]. Hip fracture is a serious fall injury that can result in high health care costs, long term care or nursing home admission, and reduced independence [67,68] with a mortality rate of 21% if surgical repair is required [69].

Injurious falls can also result in psychological consequences. The psychological combined with the physical effect of a fall can lead to reduced activity and mobility levels [5,13,17,67]. This can lead to reduced participation in events, reduced independence, and isolation [5,17]. Falls can also lead to feelings of helplessness, reduced self-confidence, depression, and reduced falls self-efficacy in older individuals [5,13,17]. Falls can also increase or result in fear of falling. Fear of falling can result in a negative cyclical pattern shown in Figure 2.1 that can lead to nursing home admission [70].

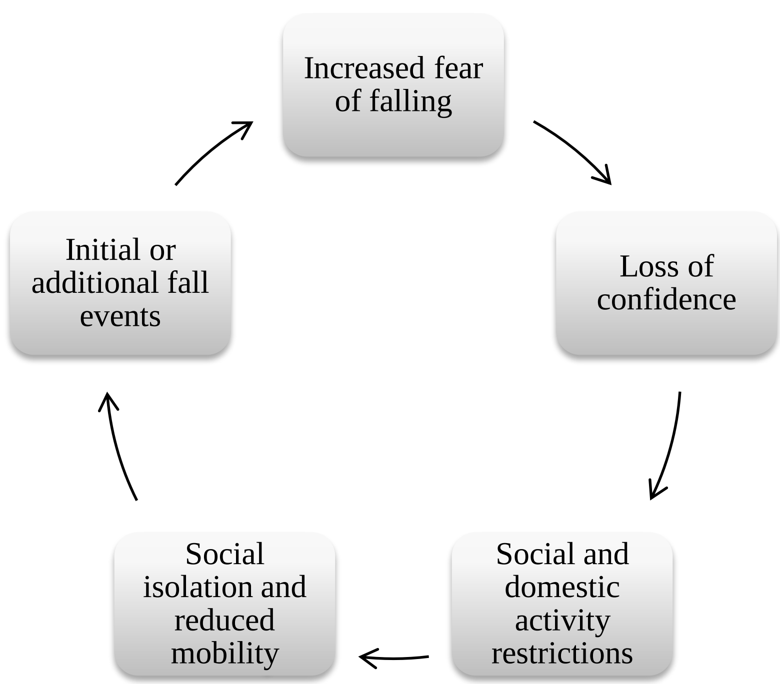

Figure 2.1. Negative cyclical events resulting from fear of falling [70].

2.2 Clinical Assessments Related to Fall Risk

2.2.1 Introduction

Clinical assessment tools measure a person’s ability to perform specific tasks or activities [18]. A properly designed clinical tool can provide a standardized, consistent, and accurate description of a person's functional abilities [18]. However, clinical assessment tools can have issues such as ceiling or floor effects, low resolution, and subjective elements that allow the rater's experience to affect results [19].

A wide variety of clinical assessment tools have been used to assess elderly populations for fall risk. Some key assessment tools are summarized in this section. Interested readers are directed to Tyson and Connell, 2009 [21] and Anemaet and Moffa-Trotter, 1999 [18] for more thorough reviews of clinical fall risk assessments.

2.2.2 Timed Walking Distance Tests

The two-minute, six-minute, ten-minute, and twelve-minute walk tests are all designed to assess functional capacity with the total distance walked during the test period measured [21]. For the six-minute walk test (6MWT), participants are asked to walk as far as they can during a six-minute period [71]. The 6MWT was first introduced by Guyatt et al., 1985 [71] as a measure of exercise capacity in patients with chronic heart failure. The 6MWT has demonstrated construct validity based on strong correlations between distances walked and peak oxygen consumption [72-74]. The 6MWT has been assessed as a mobility-related function test in older adults [75]. Harada et al., 1999 [75] reported a one-week test-retest reliability of 0.95 (Pearson's correlation coefficient) for 6MWT distances, and convergent validity between 6MWT distances and performance-based, clinical, and self-report measures of physical function and general health with a subset of measures explaining 69% of the variability in 6MWT distances. Lord and Menz, 2002 [76] also assessed convergent validity and found that strength, maximal balance range, medication use, and age explained 52.5% of the variability in 6MWT distances. The American Thoracic Society released practical guidelines for administering a standard 6MWT [77].

The 25 ft walk test is a subset of the Hauser Ambulation Index [78]. Different time intervals are provided to score 25 ft walk performance: less than or equal to 10 seconds, less than or equal to 20 seconds, greater than 20 seconds, and unable to complete a 25 ft walk [78]. The Hauser Ambulation Index was designed to assess individuals with multiple sclerosis [78]. Reference gait speed values for a range of ages at comfortable and maximum walking speed for a 25 ft distance were reported by Bohannon et al., 1997 [79]. For individuals in their 60s, the mean comfortable walking speed was 135.9 ± 20.5 cm/s for men (n = 18) and 129.6 ± 21.3 cm/s for women (n = 18). The mean maximum speed was 193.3 ± 36.4 cm/s for men and 177.4 ± 25.4

cm/s for women [79]. For individuals in their 70s, the mean comfortable walking speed was 133.0 ± 19.6 cm/s for men (n = 22) and 127.2 ± 21.1 cm/s for women (n = 20). The mean maximum speed was 207.9 ± 36.3 cm/s for men and 174.9 ± 28.1 cm/s for women [79].

Additional walking tests include 8 ft, 5 m, 10 m, and 30 m distances. These walking distances are primarily used for assessing stroke populations. Normative values for 8 ft walk times were provided by Guralnik et al., 1994 [80] for men and women aged 70 years and older. Eight foot walk time, in combination with other measures, was related to mortality risk and nursing home admission [80]. Walking speed over 5 m was sensitive to change for pre- and post-stroke assessments [81]. Flansbjer et al., 2005 [82] assessed a 10 m walking test for a post-stroke population and found high test-retest agreement (ICC [Intraclass Correlation Coefficient] > 0.90) and small standard error of measurement (< 7.9%). Green et al., 2002 [83] assessed speed test-retest reliability for a 10 m walking assessment with a 1 year post-stroke population and found high within-assessment reliability (ICC ≥ 0.95) and good between-assessment reliability (ICC ≥ 0.87). High reproducibility (ICC ≥ 0.97) was reported for 10 m and 30 m walking distances in a multiple sclerosis population [84]. A lack of consistency exists between these relatively short walking distance assessments in terms of walking pace (e.g., self-selected comfortable pace or maximum pace) and whether a 'rolling' start is used [21].

2.2.3 Activity Performance Tests

The Timed Up and Go (TUG) is commonly used to test elderly populations for fall risk, with longer completion times associated with impaired mobility and increased fall risk [85,86]. The TUG was first proposed by Podsiadlo and Richardson, 1991 [87] as a modification of the Get Up and Go test. The American Geriatrics Society, British Geriatrics Society, and Society of Nordic Geriatricians recommend the TUG as a screening test for fall risk [85,88]. The TUG requires the participant to get up from a chair, walk three meters, return to the chair, and sit down [85,87,89,90]. Participants are allowed to use walking aids [85]. Optimal thresholds to determine fall risk have been recommended, ranging from 10 to 33 s [91]. The TUG has demonstrated good to excellent inter-rater reliability, ICC between 0.80 and 0.99 [85,87,91], and moderate to excellent test-retest reliability [85,87,92]. TUG assessment results correlated well to moderately well with other clinical measures such as the Berg Balance Scale (r = -0.81), Barthel Index (r = -0.78, assesses ability to independently perform activities of daily living) [87], and gait speed (r = -0.61) and has achieved 87% sensitivity and 87% specificity in discriminating between elderly individuals with a six month history of multiple falls and elderly individuals with no six month fall history [93].

The Berg Balance Scale (BBS), developed by Berg et al., 1989 [94], uses 14 activities to assess balance for elderly populations, using a five-point ordinal scale with a maximum possible score of 56 [18,94,95]. These activities include: sit to stand, stand to sit, unsupported standing, unsupported sitting, transfers, turning 360°, and others [18]. Scores lower than 40 indicate a high risk of falls [18]. Berg et al., 1992 [96] found that BBS could predict the occurrence of multiple falls in the elderly, with a score less than 45 indicating a 2.7 times increased risk of multiple falls, and could discriminate between elderly mobility aid users and non-users. BBS has demonstrated excellent inter and intra-rater reliability, ICC of 0.98 and 0.99, respectively [94]. The BBS has achieved 77% sensitivity and 86% specificity in discriminating between elderly individuals with a six month history of multiple falls and elderly individuals with no six month fall history using a cut-off score of 49 [95].

The Clinical Test of Sensory Integration and Balance (CTSIB) is a clinical version of the Sensory Organization Test (SOT), originally developed by Nashner et al., 1990 [97]. The SOT, unlike the CTSIB, uses a force plate to measure centre of pressure excursions and will be discussed in 2.3.1. The CTSIB assesses participant balance for six conditions: eyes open on firm surface, eyes open on compliant, foam surface, eyes closed on firm surface, eyes closed on foam surface, visual conflict on firm surface, and visual conflict on foam surface [98]. The visual conflict is a dome, originally designed by Shumway-Cook and Horak, 1986 [99], placed over the participant's head with horizontal lines that follow head movement, reducing the meaning of the visual input. The time the participant can hold a static posture without moving the feet or upper limbs is recorded up to a maximum stance time of 30 seconds. The CTSIB has good test-retest reliability (r = 0.75) [100] and correlated well with TUG times (r = 0.47 to 0.67) [100]. Ricci et al., 2009 [98] performed the CTSIB on a group of 96 elderly individuals and obtained stance times for each of the six conditions for sub-groups of non-fallers, single-fallers, and multi-fallers, with multi-fallers tending to perform the worst of the three groups. Di Fabio and Anacker, 1996 [101] used the 95% confidence interval for the composite CTSIB score as a lower limit for a normal CTSIB score, which resulted in 44% sensitivity and 90% specificity when classifying 31 non-falling and 16 falling healthy elderly adults. When standing times for only foam conditions were averaged, a cut-off score of 81 s (mean stance duration) resulted in a sensitivity of 75% and a specificity of 65% [101]. Discriminant functions that include CTSIB scores and age correctly classified 77% of non-fallers and 63% of fallers [101].

The Community Balance and Mobility Scale (CBMS) was designed by Howe et al., 2006 [102] to identify postural instability, balance, and mobility issues in community dwelling adults with traumatic brain injury [21,102]. The CBMS uses a 6-point scale to assess high level tasks including hopping, crouching and walking, walking and looking, and running with a controlled stop [102]. Excellent intra-rater, inter-rater, and test-retest reliability (ICC > 0.95) and internal consistency (Cronbach's α= 0.96 to 0.97) were found [102,103]. Good construct validity was found for the CBMS when compared to maximal walking velocity (r = 0.64) [102]. Good construct validity was indicated by Innes et al., 2011 [104] who found significant correlations between CBMS and gait measures (e.g. walking velocity, step length, and step width), measures of dynamic stability (e.g. step length variability), and the Activities-specific Balance Confidence (ABC) scale. When assessing individuals with traumatic brain injury, CBMS is less susceptible to ceiling effects than BBS [104]. CBMS has also demonstrated good construct validity when assessing stroke populations with moderate to high convergent validities (Spearman correlation between 0.70 and 0.83) between CBMS, BBS and TUG [105]. CBMS was associated with stroke-induced functional limitations and muscle weakness and showed greater sensitivity to change than TUG or BBS [105]. The CBMS was able to discriminate between older adult multiple fallers and non-fallers with a sensitivity of 79% and a specificity of 76% using a cut-off value of 39 [103].

The Dynamic Gait Index [106] assesses dynamic postural control in older adults, particularly those with vestibular dysfunction, using a ranking score from 0 to 3 for various walking tasks ranging from self-selected speed walking to climbing stairs [107]. The Dynamic Gait Index has excellent inter-rater reliability (0.96) and test-retest reliability (0.98) [108]. A moderate, significant correlation was found between the BBS and Dynamic Gait Index, indicating concurrent validity [107]. Whitney et al., 2000 [109] found that a Dynamic Gait Index score of less than or equal to 19 indicated a 2.58 times increase in the likelihood of falling for individuals with vestibular dysfunction. Shumway-Cook et al., 1997 [95] used an identical threshold to predict fall risk in older individuals, which resulted in a sensitivity of 59% and a specificity of 64%.

The Elderly Mobility Scale was originally designed to assess mobility levels of frail elderly hospital patients [110]. This scale scores performance of seven mobility items; including, lying to sitting, sit to stand, walking, and functional reach. Concurrent validity with the Barthel score and functional independence measure were found in older adults (Spearman's $\rho \geq 0.787$) [110,111]. The Elderly Mobility Scale has excellent inter-rater reliability (Spearman's $\rho = 0.88$) [111] and has been used to make placement decisions in extended care settings [112].

The functional reach test assesses the maximum distance a person can reach forward beyond arm's length while maintaining a fixed, standing base of support [113]. In a population of elderly veterans, a logistic regression analysis indicated an increased risk of experiencing multiple falls if individuals were unable to reach (odds ratio = 8.07), reached less than or equal to 6 inches (odds ratio = 4.02), and reached greater than 6 inches but less than or equal to 10 inches (odds ratio = 2.00) [114]. Normative data for the functional reach test in women aged 20 to 80 was published by Isles et al., 2004 [115], showing a decrease in functional reach distance with increasing age. There is some disagreement in the literature as to whether functional reach distance relates to dynamic stability limits. Jonsson et al., 2002 [116] found a low correlation ($r = 0.38$) between reach distance and centre of pressure displacement and a moderate correlation ($r = 0.68$) between trunk forward rotation and reach distance. This result suggested that the functional reach test may relate to compensatory mechanisms more than stability limits [116]. Kage et al., 2009 [117] found moderate, but significant, correlations between the one-arm functional reach test distance and centre of pressure excursions ($r = 0.60$, $p < 0.001$) and that trunk rotation did not contribute significantly to reach distance.

The multi-directional reach test is similar to but more complex than the forward reach test. The multi-directional reach test asks the participant to reach their hands as far as possible in four directions: forward, backward, right, and left [118]. For the backwards direction, participants are asked to lean as far as possible [118]. The test demonstrated good internal consistency (Cronbach's alpha = 0.842), reliability (ICC = 0.942) and good construct validity with significant correlations to BBS and TUG [118]. An investigation of multi-directional reach in individuals aged 20 to 79 years old found a decrease in forward, left, and right but not backward stability limits with increasing age [119].

The Modified Gait Abnormality Rating Scale [120] ranks gait based on 7 items, with higher scores indicating greater abnormality and a total possible worst score of 21. This scale is based on the original 16 item Gait Abnormality Rating Scale developed by Wolfson et al., 1990 [121]. Concurrent validity of the modified Gait Abnormality Rating Scale was good, with relationships to stride length (r = -0.754) and walking speed (r = -0.679) [120]. Construct validity was demonstrated by finding significant differences between elderly fallers and non-fallers, with elderly fallers having a higher score on the scale [120]. When used to predict recurrent fall occurrence in an elderly population, the modified Gait Abnormality Rating Scale achieved a sensitivity of 62.3% and a specificity of 87.1%, with a cut-off score of 9 [122].

The One Legged Stance test requires the participant to balance on one foot with their hands on their hips [20]. Standing on one leg requires the participant to move their centre of mass over the stance leg and then maintain postural orientation and stability on the stance leg [123]. The one legged stance test has excellent inter-rater reliability (ICC $\geq$ 0.832) [124]. The one legged stance test appears within the BBS (maximal score at 10 s), Bohannon's ordinal balance scale (maximal score at 30 s), and Tinetti's Balance Subscale (maximal score at 5 s) [123]. A study by Jonsson et al., 2004 [123] identified the first five seconds as a critical assessment period, when force variability rapidly decreased. This decrease was more rapid in younger participants compared to older participants [123]. Normative one legged stance times for individuals aged 18 to 99 years old were reported by Springer et al., 2007 [124]. Older individuals, who could not balance on one leg for five seconds were at an increased risk of injurious falls, with a predictive sensitivity of 36%, specificity of 76%, and positive predictive value of 31% [125].

The Physiological Profile Assessment (PPA) was developed by Lord et al., 2003 [126] as a tool to evaluate fall risk. This assessment evaluates participant vision, peripheral sensation, muscle force, reaction time, and postural sway to obtain an overall indication of the ability to maintain postural stability [126]. PPA construct validity was determined by evaluating its ability to identify elderly individuals at risk of falls and achieved accuracy rates between 75 and 79% when compared to one year prospective fall occurrence [126]. The PPA sub-elements have moderate to excellent test-retest reliability ($0.50 \leq \text{ICC} \leq 0.97$), fair intra-rater reliability ($0.24 \leq \text{ICC} \leq 0.94$) and good inter-rater reliability ($0.54 \leq \text{ICC} \leq 0.95$) [126,127]. A comparison across age groups found greater variability in PPA sub-element scores in younger age groups, whereas older age groups exhibited an overall reduction in PPA scores across most, if not all elements [128].

The Sharpened Romberg test is a variation of the Romberg test with increased task difficulty to better identify balance issues. The Sharpened Romberg test requires a person to maintain balance during tandem stance (i.e. heel-to-toe position) and is often assessed with eyes open and eyes closed [129,130]. The Sharpened Romberg test has excellent inter-rater reliability (ICC = 0.99) and good to excellent test-retest reliability ($0.76 \leq ICC \leq 0.91$) [131]. Sharpened Romberg assessments of community dwelling elderly women found no significant differences between fallers and non-fallers but did find a significant deterioration in performance under eyes closed conditions compared to eyes open [130].

The Tinetti Assessment tool [20] is one of the oldest clinical balance assessment tools and is widely used to assess older populations [132]. The Tinetti Assessment tool contains a balance section with ten activities and a gait section with eight activities [18]. The performance of each activity is ranked by the assessor, providing a maximum score of 16 for the balance section and 12 for the gait section, giving an overall maximum score of 28 [18]. A score less than or equal to 18 indicates a high fall risk, 19 to 23 indicates a moderate fall risk, and greater than or equal to 24 indicates a low fall risk [133].

2.2.4 Questionnaire-Based Tests

The Activities-specific Balance Confidence scale (ABC) is a questionnaire designed to evaluate balance confidence across a range of activities of daily living [134] and has been identified as the most appropriate assessment of balance confidence for moderate to high functioning older adults [135]. The ABC has excellent test-retest reliability ($r = 0.92$), good consistency (Cronbach's $\alpha = 0.90$ to 0.95), and good construct validity demonstrated by an ability to discriminate between low and high mobility older adults [134,136,137]. Different critical cut-off values have been identified when assessing older individuals, with scores greater than 80% considered high functioning, 50-80% moderate functioning, and less than 50% low functioning in terms of physical abilities [138]. In addition, a score less than 67% was predictive of fall occurrence, with a sensitivity of 84.4% and specificity of 87.5% at predicting one year fall history [139]. In a study that evaluated fear of falling, as measured by ABC, Falls Efficacy Scale, and Survey of Activities and Fear of Falling in the Elderly (SAFE), only ABC was able to discriminate between fallers and non-fallers [136].

The Falls Efficacy Scale asks older adults to rank their confidence in their ability to not fall while performing a variety of activities of daily living with a maximum score of 100 [140]. A score greater than 70 indicates a fear of falling and a score greater than 80 indicates an increased risk of falling [140]. The questionnaire has good test-retest reliability (r = 0.71, ICC of 0.58 to 0.83), excellent internal reliability (Cronbach's α of 0.902 to 0.97), and excellent internal consistency (Cronbach's α = 0.91 to 0.94) [136,140-142]. Concurrent validity for evaluating older individuals has been demonstrated through correlations with ABC (r = 0.86) and the Survey of Activities and Fear of Falling in the Elderly (SAFE) questionnaires (r = 0.67) [143]. In a comparison between ABC and the Falls Efficacy Scale, the ABC had better test-retest reliability and was better able to discriminate between fallers and non-fallers [142].

The Community Healthy Activities Model Program for Seniors (CHAMPS) Activities Questionnaire measures participation in physical activities and activities of daily living and allows estimation of energy expenditure [144]. The questionnaire is designed such that older adults with memory and cognitive issues could still accurately identify activity participation [144]. CHAMPS can be used to calculate calories expended per week based on the duration of activity per week and the standard metabolic equivalent of task (MET) values for the different activities [145]. This tool has moderate test-retest reliability (ICC ≥ 0.58) and discriminated between low and high activity older individuals, demonstrating construct validity [145].

SAFE was developed by Lachman et al., 1998 [146] and asks the person to indicate their participation in eleven different activities, rank their fear of falling when performing that activity, and indicate whether their performance of that activity has changed over the past five years. For activities that participants do not do, the survey asks them to specify the reason for not participating [146]. Concurrent validity was demonstrated through correlations to the Falls Efficacy scale (r = -0.76) and a simple fear question (r = -0.59) [146]. SAFE has a good internal consistency (Cronbach's α = 0.82 to 0.86) [136,137]. SAFE was able to distinguish between fallers and non-fallers in elderly individuals [147].

2.2.5 Discussion of Clinical Fall-Risk Assessment Tools

Clinical assessment tools often involve a specific threshold that is used to classify individuals into high fall risk or no fall risk categories. This is a concerning aspect since a difference of one point for one activity can affect the fall risk diagnosis. Therefore, subjective influence from the rater, whether due to inexperience, incorrect application of instructions, or personal bias, can become critical for borderline participants. The chosen thresholds for timed tools are also a concern due to the wide range of thresholds that have been used and presented in the literature. For example, the TUG has been used with thresholds between 10 and 33 s [91]. Even for similar elderly populations (i.e., identical disease status, similar living environment, similar age ranges), 11 to 20 s thresholds have been used to determine fall risk [148-150].

2.3 Sensor-Based Assessment of Fall Risk

Assessments based on quantitative measurements from sensors are less vulnerable to subjective influences than clinical assessments. This section will summarize some of the important sensor-based assessments that have been applied to fall risk assessment.

2.3.1 Posturography

Posturography assesses a person’s ability to stand independently (static posture or spontaneous sway) and maintain or recover balance following a sensory or mechanical perturbation (dynamic posture or induced sway) [151]. Postural assessments typically employ a force platform or pressure platform to assess static and dynamic postural stability.

Force platforms measure tri-axially applied forces and moments using strain gauge, piezoelectric, or capacitive transducers [152]. Force platforms provide ground-reaction force and moment data and plantar centre of pressure (CoP) data [153] and are considered the gold standard for obtaining load information between the participant and flat ground [29]. The person stands on the force plate for static postural assessments and walks over the force plate for dynamic walking assessments. Force plates have high sensitivity, low crosstalk, repeatability, and signal measurement stability [154]. While a force platform can provide accurate loading data, it is typically limited to laboratory environments and one-step, level ground movements [29].

Pressure platforms can be used to detect peak pressures and pressure-time integrals during gait [155], centre of pressure progression during gait [156], areas of high pressure under the foot during static standing [157], and anatomical foot deformities [158]. The pedobarograph is an example of a pressure platform that consists of a glass plate that is illuminated along its edge by light [159]. The participant walks over the glass plate with applied pressure breaking the path of light, as shown in Figure 2.2 [157,159]. The applied pressure is proportional to the image grey scale intensity and can be used as a measure of pressure [157]. While pedobarographs provide useful pressure information, they have similar limitations to force platforms.

A commonly used posturography assessment is the Sensory Organization Test (SOT). The SOT is similar to the CTSIB (Section 2.2.3), except that the six stance conditions (eyes open, eyes closed, and visual conflict, for firm and foam surfaces) are performed on a force plate to measure postural sway through CoP movements. A modified version of this test only assesses the eyes open and eyes closed conditions. The SOT has demonstrated good overall test-retest reliability (ICC of 0.66) with individual components having ICCs ranging from 0.26 to 0.68 [160].

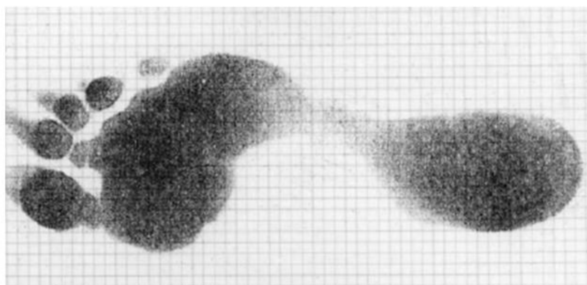

Figure 2.2. Static foot image from a pedobarograph [159].

Posturography assessments can measure declines in postural balance that occur with increasing age. A large study by Era et al., 2006 [161] of 7,979 adults aged 30 years and older found that deteriorations in postural balance started as early as 30 years of age and this deterioration accelerated after 60 years of age. Another study of 96 adults by Cohen et al., 1996 [162] found that postural balance deteriorations begin in mid-life, 45 to 69 years old, and become more pronounced with increasing age. Maki et al., 1994 [163] found that the speed and mean frequency of CoP displacements increased with age, except for medial-lateral (ML) spontaneous sway. In addition to a general deterioration with age, differences between young and elderly adults have been identified [12,164,165]; such as, speed, range, and power-spectrum-derived centroidal frequency of CoP displacements [164]. Cross-spectral, least squares, and maximum likelihood analyses of CoP displacements were also able to identify differences between young and elderly adults [12]. Prieto et al., 1996 [165] found differences between young and elderly adults for range, sway area, mean frequency, fractal dimension, total power, and centroidal frequency of CoP displacements.

Eyes open and eyes closed conditions are the two most commonly assessed static posturography conditions and differences in postural balance have been identified between these conditions. Eyes open and closed static posturography revealed that adults of any age increased sway path length with eyes closed [166]. Differences between eyes open and eyes closed conditions were greater for elderly than younger adults [165,167]. For elderly adults, differences between eyes open and eyes closed conditions were found for sway area, mean frequency, fractal dimension, total power, 50% power frequency, 95% power frequency, and centroidal frequency parameters of CoP displacements [165]. Furthermore, Perrin et al., 1997 [167] reported increased path length and area, particularly in the anterior-posterior (AP) direction, during eyes closed posturography tests, compared to eyes open, for elderly adults. The study with 7,979 participants (2730 over 60 years) found increased AP CoP speed and velocity moment (mean area covered by the CoP movement per unit time) for eyes closed static posturography tests compared to eyes open [161]; however, no statistical analysis was reported. These studies have shown that postural control worsens under eyes closed conditions compared to eyes open and that this worsening of postural control is more pronounced in older adults.

For older adults, poor postural balance can be predictive of future falls [161,168] and indicates an impaired ability to recover from small postural perturbations [164]. Static posturography assessments can be used to detect these postural balance differences and distinguish between fallers and non-fallers. A review of static posturography studies identified four differences in posturography measures between fallers and non-fallers [168]. Fallers exhibited higher ML sway amplitude under eyes closed and eyes open conditions, higher AP speeds under eyes open conditions, higher ML CoP root mean square distance from mean (RMS) under eyes closed conditions, and higher mean CoP speed under eyes closed conditions compared to non-fallers [168]. A need was identified for additional studies based on prospective fall occurrence to better understand the predictive value of static posturography for fall risk [168]. Topper et al., 1993 [169] used posturography to identify fallers and non-fallers and achieved an accuracy of 65%, sensitivity of 78%, and specificity of 46%.

Few studies have examined posturography measures for multi-fallers [170-172]. Stel et al., 2003 [170] found that increased ML sway was predictive of recurrent fallers, based on one year prospective fall history. Buatois et al., 2006 [171] found increased sway in multi-fallers, based on 16 month prospective fall occurrence, compared to non-fallers under eyes closed conditions. Merlo et al., 2012 [172] found increased AP and ML RMS for multi-fallers, based on one year retrospective fall occurrence, compared to single-fallers and non-fallers on a compliant surface, eyes open only, and increased 95% confidence ellipse area for multi-fallers compared to non-fallers on a firm surface.

Posturography can also be assessed after a sensory or mechanical perturbation occurs, which evaluates the ability of the participant to maintain or recover balance in a dynamic setting [151]. Most dynamic posturography assessments use a moving platform that elicits a relative acceleration between the feet and the upper body [173]. During a dynamic posturography assessment, fallers had greater ML sway amplitudes compared to non-fallers [163]. Maki et al., 1990 [164] compared a static posturography assessment to a dynamic posturography assessment with a random AP platform acceleration. The static posturography assessment successfully identified elderly fallers based on speed, range, and power-spectrum-derived centroidal frequency of CoP displacements, but the dynamic posturography assessment could not identify elderly fallers [164]. However, in a separate study, Maki et al., 1987 [12] identified fallers based on deviations from normative dynamic posturography data with a false positive rate of 25% when positive prediction was 100%.

2.3.2 Laboratory-based Gait Assessment Sensors

Laboratory-based, quantitative gait analysis is considered the gold standard for walking assessment [28] and can involve a wide variety of sensors including video systems, optoelectronic systems, force plates, electromyography, and electronic walkways [151,174]. This allows three-dimensional reconstruction of the person's walking pattern and quantitative analysis of kinematic, kinetic, and spatiotemporal parameters [28]. Gait analysis can identify subtle gait impairments and abnormal postural control strategies, but due to the expensive equipment and time consuming data collection and analysis for systems that use cameras and force plates, this method has a limited role in clinical practice [28]. However, instrumented walkways can be used in gait assessment to efficiently measure temporal parameters, foot placement, and plantar loading patterns for multiple sequential steps.

The 4.6 m long GAITRite® instrumented level walkway contains a grid of 13,824 pressure sensors in the middle 3.6 m [175]. Spatiotemporal parameters include stride length, stride width, cadence, gait velocity, and gait symmetry [175-178]. For assessing elderly walking, this walkway has excellent reliability for walking speed, cadence, step length, and left toe in/out angle with ICC values between 0.82 and 0.91 and fair to good reliability for base of support and right toe in/out angle with ICC between 0.49 and 0.71 [175].

Gait assessments were reviewed in the studies by: Hamacher et al., 2011 [179] and Judge et al., 1996 [180]. The Hamacher et al., 2011 [179] systematic review identified 29 studies that assessed gait stability via biomechanical measures of foot kinematics in elderly individuals. Swing and stance time variability and Floquet multipliers (measures of orbital stability) were identified as useful measures for distinguishing between elderly fallers and non-fallers. Step width, stride velocity, and local stability measures were identified as useful measures for distinguishing between younger and older adults.

Judge et al., 1996 [180] summarized kinematic and kinetic gait changes that occur in older individuals, compared with younger individuals, and identified changes that continue to occur with advancing age. Decreased gait velocity and increased double support and stance time were identified as temporal gait changes as age increases beyond 70 years. Shortened step length, upright torso without a forward lean, greater thoracic curvature, increased forward pelvis tilt, reduced frontal and transverse plane pelvis range of motion, greater hip flexion and hip abduction, greater knee hyperextension during midstance, reduced peak knee flexion during swing phase, reduced ankle plantarflexion during terminal stance, and greater external foot rotation were identified as kinematic gait changes in older adults compared to younger adults. In terms of kinetic gait changes, older adults generated less power at the ankle compared to younger adults, which may be compensated for by greater power generation in the hip flexors.

2.3.3 Wearable Gait Assessment Sensors

Pedometers are simple wearable sensors that measure the number of steps that occur during gait [181]. Some pedometers count steps using a spring-loaded mass or similar switch mechanism that detects impact associated with each step [181]. Step data can be used to estimate walking distance and energy expenditure but lacks accuracy [181].

Foot switches can detect gait events from pressure on the foot's plantar surface [182,183]. The applied pressure produces a proportional voltage [182]. These sensors are typically slim with a fast dynamic response [182]. However, some foot switch sensors, such as force sensitive resistors (Figure 2.3), lack pressure measurement accuracy and therefore should be limited to detecting on and off foot contact information [182,183]. Wearable sensors that provide better accuracy than pedometers and footswitches include inertial sensors and pressure-sensing insoles, which will be described in greater detail in Sections 2.3.3.1 and 2.3.3.2.

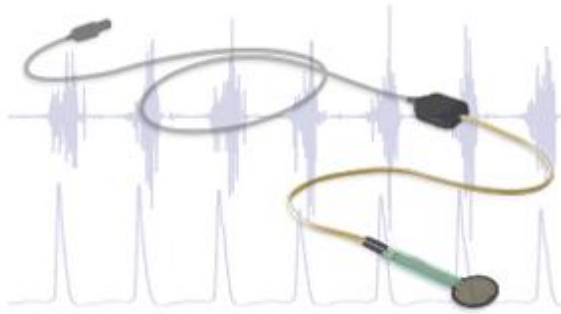

Figure 2.3. Delsys force sensitive resistor foot switch [183].

2.3.3.1 Inertial Sensors

As part of this thesis research, a literature review of inertial sensor use for geriatric fall risk was published in the *Journal of NeuroEngineering and Rehabilitation* [184]. This section summarizes the key findings from this review and was updated to include relevant papers published since the original literature review was performed.

Sixty-four studies met the search criteria: investigated elderly fall risk using inertial sensors, mean participant age greater than or equal to 60 years, and published in English. Accelerometers were the sole inertial sensor in 68.8% of the studies, whereas gyroscopes were the sole inertial sensor in only 3.1% of studies. Both accelerometers and gyroscopes were used in 28.1% of the studies. Accelerometers measure linear acceleration, and the signal can be integrated to determine linear velocity. Gyroscopes measure angular velocity, and the signal can be integrated to determine angular displacement.

To assess the accuracy of inertial sensor-based fall risk classification, inertial sensor classifications were compared to three criterion classification methods: retrospective fall history (32.8%), prospective fall occurrence (17.2%), and scores on clinical assessments (29.7%). A combination of retrospective fall history and clinical assessment tools were used to establish fall risk in 15.6% of the studies and a combination of retrospective and prospective fall occurrence were used in 4.7%. Table 2.1 lists the fall risk criterion classification methods used in the literature. Brief descriptions of the clinical assessment tools are provided in Table 2.2. The majority of studies used retrospective fall history or clinical assessments as a criterion classification method. These methods are not as accurate as prospective fall occurrence. Retrospective fall history is less accurate compared to prospective fall occurrence due to participant fall recollection issues with retrospective assessment. Furthermore, retrospective fall assessment means that a fall would have occurred before the study assessment, and participants may have adjusted their walking and mobility pattern to be more conservative, stable and safe after the fall but before the study assessment. The use of clinical assessments as a criterion classification method is also less accurate compared to prospective fall occurrence. Clinical assessments include errors (i.e. false positives and false negatives) and could introduce inaccuracies when evaluating sensor-based systems. This is in addition to the limitations already discussed in Chapter 2.2. Therefore, prospective fall occurrence should be the criterion classification method of choice in sensor-based fall-risk assessment studies.

Table 2.1. Criterion classification methods used to establish fall risk for comparison with inertial-sensor-based fall-risk measures. Assessment-tool thresholds indicate levels that designated a high fall risk category.

	Retrospective History	**Prospective Occurrence**	**Assessment Tools**
Auvinet et al., 2003 [185]	1 year		
Bautmans et al., 2011 [148]	6 months		TUG > 15 s or Tinetti score ≤ 24
Brodie et al., 2014 [186]	1 year		
Brodie et al., 2015 [187]	1 year		
Brodie et al., 2015 [188]	1 year		
Brodie et al., 2015 [189]		1 year	
Caby et al., 2011 [190]	1 year		25 m walking, Mini Motor test, Tinetti test, TUG, Physical Performance Scale, Fukuda test, One Legged Stance test
Cho and Kamen, 1998 [191]	1 year		Self-reported frequent fallers
Doheny et al., 2011 [192]	5 years		Self-reported fear of falling or presence of cardiovascular risk factors
Doheny et al., 2012 [193]	5 years		
Doheny et al., 2013 [194]	1 year		
Doi et al., 2013 [195]		1 year	
Galan-Mercant et al., 2013, 2015 [196,197]			Fried's criteria for frailty

Ganea et al., 2011 [198]			Fried’s criteria for frailty
Giansanti et al., 2006, 2008 [199-201]	Unspecified		Tinetti test level 3
Gietzelt et al., 2009 [22]			STRATIFY score (includes 2 month fall history) ≥ 2
Gietzelt et al., 2014 [202]		2, 4, and 6 months	
Greene et al., 2010 [203]	5 years		
Greene et al., 2014 [204]	1 year		Fried's criteria for frailty
Ihlen et al., 2015 [205]	1 year		
Ishigaki et al., 2011 [149]			One Legged Stance test (eyes open) ≤ 15 s and/or TUG ≥ 11 s
Isho et al., 2015 [206]	1 year		
Kojima et al., 2008 [207]	1 year		
Laessoe et al., 2007 [208]		1 year (fall diary with contact at 6 months)	
Latt et al., 2009 [209]	1 year		
Liu et al., 2008 [210]	Unspecified		Falling during gait perturbation assessment, medical history, self-identification as frequent faller
Liu et al., 2011 [211]			Physiological Profile Assessment (PPA)
Liu et al., 2011 [212]	1 year		
Liu et al., 2014 [213]		1 year	
Mancini et al., 2016 [214]	1 year	6 months	
Marschollek et al., 2008 [150]			TUG>20 s, STRATIFY score > 2, Barthel Index: Mobility score < 10
Marschollek et al., 2009 [23]	In-hospital history		
Marschollek et al., 2011 [215,216]		1 year	
Martinez-Ramirez et al., 2011 [217]			Body mass loss ≥ 4.5 kg, low energy, low physical activity, weakness, slowness
Menz et al., 2003 [218]			Overall fall risk score (low, moderate, high risk) based on vision, peripheral sensation, strength, reaction time, balance tests
Mignardot et al., 2014 [219]		2 years	
Moe-Nilssen et al., 2005 [220]	1 year		
Najafi et al., 2002 [221]			Fall risk score ≥ 5 based on balance, gait, visual, cognitive and depressive disorders,

			history of falls.
Najafi et al., 2013 [222]			Tinetti score < 21
Narayanan et al., 2008, 2009, 2010 [223-225]			PPA
O’Sullivan et al., 2009 [1]	1 year		
Paterson et al., 2011 [226]		1 year	
Redmond et al., 2010 [227]			PPA
Rispens et al., 2015 [228]	1 year		
Rispens et al., 2015 [38]		6 months	
Riva et al., 2013 [229]	1 year		
Schwesig et al., 2013 [230]		1 year	
Senden et al., 2012 [231]			Tinetti test ≤ 24 (Low risk 19-24, High risk < 19)
Tanaka et al., 2014 [232]			TUG > 13.5 s
Toebes et al., 2012 [233]	1 year		
Toebes et al., 2015 [234]	1 year		
van Schooten et al., 2015 [37]	6 months	6 months	
Wang et al., 2014 [235]			PPA
Weiss et al., 2011 [236]	1 year		
Weiss et al., 2013 [36]	1 year	6 months	
Wu et al., 2013 [237]	1 year		
Yack and Berger, 1993 [238]	1 year		Self report of unsteady or unstable walking and/or standing
Zakaria et al., 2015 [239]			TUG ≥ 13.5 s

Table 2.2. Clinical assessment tools

Assessment tool	Description
Barthel Index [240]	Ordinal scale from 0 (total dependence) to 100 (total independence) based on 8 self-care and 2 mobility activities of daily living.
Fried's Frailty Criteria [241]	Presence of 3 or more of 5 frailty indicators: substantial and unintentional weight loss, grip weakness, poor endurance and energy, slow walking speed, low physical activity level.
Fukuda Test [242]	The person is blindfolded, extends both arms, and marches in place for 50 to 100 steps. Maximum body rotation greater than 30° indicates vestibular deficits.
Mini Motor Test [243]	20 item test that assesses bed positions (2 items), sitting position (3 items), standing position (9 items), and gait (6 items).
One Legged Stance Test [244]	Time standing on one leg without upper extremity support and without bracing the suspended leg against the stance leg. Greater than 30 s indicates low fall risk and less than 5 s indicates high fall risk.
Physical Performance Scale [80]	Ability to stand with feet together side-by-side, semi-tandem, and tandem; walk 8 feet; and rise from a chair and return to seated position.
Physiological Profile Assessment [126]	Assessment of vision, peripheral sensation, muscle force, reaction time, and postural sway. Score of 0-1 = mild, 1-2 = moderate, and > 2 = high risk of falling.
STRATIFY Score [245]	Assessment of 2-month fall history, mental alteration, frequent toileting, visual impairment, psychotropic medication use, and mobility issues. Score of < 2 indicates increased fall risk.
Timed Up and Go (TUG) [87]	Time to stand up from an armchair, walk 3 m, turn, walk back to the chair, and sit down again. Times that exceed 14 s indicate increased fall risk for community dwelling elderly without neurological disorders.
Tinetti Assessment Tool [133]	Dynamic balance and gait evaluation with 10 balance components and 8 gait components. Overall scores < 19 = high, 19-23 = moderate, > 23 = low fall risk. Maximum score = 40.

Accelerometers and gyroscopes are small enough to be attached to a body part, belt, or headband for measurement during activity. The lower back, including the pelvis, sacrum, and spinal vertebrae between L3 and L5, is the most common single-sensor location (54.7%). This site approximates the centre of mass location [22,23,199,215,236] and is acceptable for long-term at-home use [22,215]. Other sensor locations include the head [186,191,209,246], upper back [229,233,234,238], sternum [188,189,192,194,196-198,204,221,222,237], shoulder [190], elbow [190], wrist [190,235], hip [191,210], thigh [192,194,204], knee [190,210], shank [203,204], ankle [190,210,235,237], and foot [214,226]. To date, there has been no objective evaluation to determine which sensor site, or combination of sites, provide the most appropriate and reliable fall-risk data. Careful investigation of optimal variables should be included in this assessment, because optimal sites will likely be variable specific. Likewise, investigation of variables should consider that optimal variables may be site specific.

Various activities have been used for inertial-sensor-based fall-risk assessment. The most frequently assessed activity was level ground walking (42.2%), followed by TUG (31.2%), sit-stand transitions (STS, 21.9%), free-living walking (14.1%), standing postural sway assessment (12.5%), left-right alternating step test on level ground (AST, 10.9%), and uneven-ground walking (1.6%). Many studies used a combination of activities (20.3%).

While gait is often assessed under single-task (ST) conditions, where the participant is only asked to walk, gait can also be assessed under dual-task (DT) conditions. DT gait involves walking while performing an attention-demanding task, often verbal or mathematical. In older adults, DT gait can result in:

- **Reduced**: walking speed [30,31,33-35,247-251], stride frequency [33];
- **Increased** percentage of missteps [252], step duration, stride time [33], stance time [251];
- **Increased** [251] or **decreased** [30,31] swing time;
- **Increased variability**: swing time [30,31], stride-to-stride gait velocity [248], stride time [33,250], stride length [250], and phase variability index [33];
- **Decreased**: root mean square and peak anterior-posterior (AP) and medial-lateral (ML) trunk accelerations [33];
- **Increased**: local stability exponent for AP and ML trunk accelerations [33], sample entropy for AP trunk accelerations [33].

Opinions are mixed regarding DT potential for predicting future falls or diagnosing underlying problems [253,254]. Some DT measures for differentiating elderly fallers from non-fallers are lower gait speed [255-257]; greater swing [31,32,258] and stride [259] time variability; and greater dual task cost for mean step width, mean step time, and mean step length variability [260]; and faster walking speed for older adults with speeds above the 50th percentile [261]. However, other studies found no fall prediction improvement after adding a second task [262,263].

In the literature, 180 distinct variables were derived from accelerometer and gyroscope data and can be categorized as: position and angle (4.2%), angular velocity (17.8%), linear acceleration (30.5%), spatial (1.7%), temporal (20.3%), other (25.4%). From the review published in the *Journal of NeuroEngineering and Rehabilitation* [184], nine variables from more than one study were significant each time they were assessed:

1) ratio of mean squared modulus for postural sway [199-201];
2) standard deviation of anterior-posterior acceleration [191,236];
3) gait speed [148,209,218,236];
4) sit/stand transition duration [198,221];
5) dominant Fast Fourier Transform (FFT) peak parameters derived from lower-back linear acceleration signals [150,215,216];
6) ratio of even to odd harmonic magnitudes derived from head, upper back, and lower-back linear acceleration signals [209,211,212,238,246];
7) area under the first six harmonics divided by the remaining area for lower-back linear acceleration signals [211,212];
8) ratio of the first four harmonics to the magnitude of the first six harmonics for lower-back linear acceleration signals [211,212];
9) discrete wavelet transform parameters from lower-back angular velocity and linear acceleration signals and sternum linear acceleration signals [198,217].

Two of these multi-study variables (variables 3 and 6) were from different research groups, while seven variables (variables 1,2,4,5, and 7-9) were from a single research group. Additional research is needed to corroborate these initial, relatively isolated findings and identify a larger set of inertial-sensor-based variables that could be used to predict fall risk.

While identifying variables that correlate with fall risk is an important first step, the next step should be to use these variables to develop a predictive fall risk model. Just over half of the studies (51.6%) have taken this step. Regression models, mathematical classifiers, decision trees, support vector machines, neural networks, and cluster analysis were employed to predict fall risk. The accuracy, specificity, and sensitivity of these models are shown in Table 2.3.

Table 2.3. Model type, validation method, accuracy, specificity, and sensitivity listed by research article

Author	**Model**	**Model Validation**	**Accuracy (%)**	**Specificity (%)**	**Sensitivity (%)**
Bautmans et al., 2011† [148]	Logistic regression, ROC curve	Not specified	77	78	78
Caby et al., 2011* [190]	Radial basis function neural network, support vector, k-nearest neighbour, and naive Bayesian classifiers	Leave-one-out cross-validation	75-100	40-100	93-100
Doheny et al., 2013† [194]	Logistic regression, ROC curve	Leave-one-out cross-validation	59.0-74.4	75.0-80.0	42.1-68.7
Doi et al., 2013‡ [195]	Logistic regression, ROC curve	Not specified		84.2	68.8
Ganea et al., 2011* [198]	Logistic regression, ROC curve	Not specified		35-88	55-92
Giansanti et al., 2006*† [199]	Mahalanobis cluster analysis	47:53 split (Train:Test)	93.5-94.5	93-94	93.9-94.9
Giansanti et al., 2008*† [201]	Multi-layer perceptron neural network	47:53 split (Train:Test)	88-91	88-92	88-91
Giansanti et al., 2008*† [200]	Multi-layer perceptron neural network	47:53 split (Train:Test)	97	97	98
Gietzelt et al., 2009* [22]	Decision tree	Not specified	90.5	91.0	89.4
Gietzelt et al., 2014‡ [202]	Decision tree	Ten-fold cross validation	74.8-88.5	28.0-96.8	33.6-98.3
Greene et al., 2010† [203]	Logistic regression	80:20 split (Train:Test)	76.8	75.9	77.3
Greene et al., 2012† [203]	Support vector machine	Ten-fold cross validation	71.5	68.4	65.4
Greene et al., 2014*† [204]	Support vector machine	Ten-fold cross validation	56.6-87.6		
Ihlen et al., 2015† [205]	Partial Linear Square Discriminant Analysis, ROC curve	Cross validation	AUC: 0.83-0.93	79-87	69-72
Isho et al., 2015† [206]	Regression, ROC curve	Not specified	AUC: 0.745	84.6	72.7
Kojima et al., 2008† [207]	Regression, canonical discriminant classifier	Not specified	62.1	68.2	61.1
Liu et al., 2011* [212]	Linear regression, linear discriminant classifier	Leave-one-out cross-validation	71	98.3	88.9

Liu et al., 2014‡ [213]	Logistic regression	50:50 split (Train:Test)	47-83	42-100	0-71
Marschollek et al., 2008* [150]	Logistic regression, classifier	Stratified ten-times ten-fold cross validation	65.5-89.1	15.4-60.4	78.5-99.0
Marschollek et al., 2009† [23]	Decision tree	Not possible due to limited sample size	90	100	57.7
Marschollek et al., 2011‡ [215]	Logistic regression, decision tree	Stratified ten-times ten-fold cross validation	78-80	82-96	58-74
Marschollek et al., 2011‡ [216]	Logistic regression, classifier	Stratified ten-times ten-fold cross validation	70	78	58
Mignardot et al., 2014‡ [219]	Principal component analysis, ROC curve	Not specified	AUC: 0.67-0.70		
Moe-Nilssen et al., 2005† [220]	Linear regression, ROC curve	Not specified	80	85	75
Rispens et al., 2015‡ [38]	Logistic regression, ROC curve	Not specified	AUC: 0.68-0.81		
Riva et al., 2013† [229]	Factor analysis, Logistic regression	Not specified	71.0-72.5	96.6	16.7-21.4
Schwesig et al., 2012‡ [230]	Binary logistic regression, ROC curve	Not specified		42-61	63-100
Senden et al., 2012* [231]	Linear regression, ROC curve	Not specified	AUC: 0.67-0.85		
van Schooten et al., 2015‡ [37]	Logistic regression, ROC curve	Not specified	AUC: 0.71-0.82	66.3-80.9	67.9-70.0
Weiss et al., 2011† [236]	Logistic regression	Not specified	63.4-87.8	50.0-83.3	65.2-91.3
Weiss et al., 2013‡ [36]	Logistic regression	Not specified	71.6-94.7	78.9-100	33.5-75.0
Wu et al., 2013† [237]	Logistic regression	Not specified		86.7	80.0
Zakaria et al., 2015†	k-nearest neighbour	76:24 split (Train:Test)			

AUC: Area under curve, ROC: receiver operating characteristic, Criterion classification method: *Clinical assessment, †Retrospective fall history, ‡Prospective fall history

Inertial sensors have demonstrated potential as tools to provide quantitative, objective, and reliable indications of older adult fall risk. Fall risk prediction models based on inertial sensor data have achieved high levels of accuracy, specificity, and sensitivity. However, these early fall risk prediction models could be improved by identifying fallers prospectively and comparing the effectiveness of different promising sensor site(s) and variables directly instead of comparing results between different studies.

2.3.3.2 Pressure-Sensing Insoles

Pressure-sensing (PS) insoles can give a visual and quantitative depiction of the temporal patterns of forces acting on the plantar foot surface during weight-bearing activities [264]. Unlike force platforms, which are typically restricted to laboratory environments [265], PS insoles can measure foot pressure during a variety of functional activities [266] and in various environments such as ramps, stairs, and uneven surfaces. Furthermore, PS insoles provide the pressure distribution over the whole plantar surface rather than just the CoP, as with force plates. An insole can also detect metatarsal length, arch information, bony prominences, and the presence of claw and hammer toes [267]. This plantar pressure information can be useful in diagnosing and assessing those with diabetic peripheral neuropathy or musculoskeletal, integumentary, and neurological disorders [265]. While PS insoles are useful, they are limited to measuring perpendicularly applied forces and cannot measure shear forces [265].

Three commercially available PS insoles are predominant in the literature: F-Scan, Pedar, and Parotec (Table 2.4). F-Scan (Figure 2.4) has the largest number of sensors, better spatial resolution, and it is the thinnest sensor, making it the least likely to affect gait. The F-Scan insole consists of two polymer sheets with electrical circuits separated by semi-conductive ink [268]. The application of pressure decreases the sensor's electrical resistance, allowing the measurement of applied pressure [268]. A mylar substrate insulates the electronic components from moisture [269].

Table 2.4. Commercially available pressure-sensing insole specifications

	F-Scan Insole	**Pedar Insole**	**Parotec System**
Sensor Type [265,268,270,271]	Force sensitive resistor	Capacitance Transducer	Microsenor mounted beneath a hydrocell
Number of Sensors [268,269,272,273]	960	99	24
Spatial Resolution (sensors/cm^2) [268,270]	4	2	
Sensor thickness (mm) [270-273]	0.18	2.6	3
Sensor Range (kPa) [269-271]	56-868	40-600	0-625

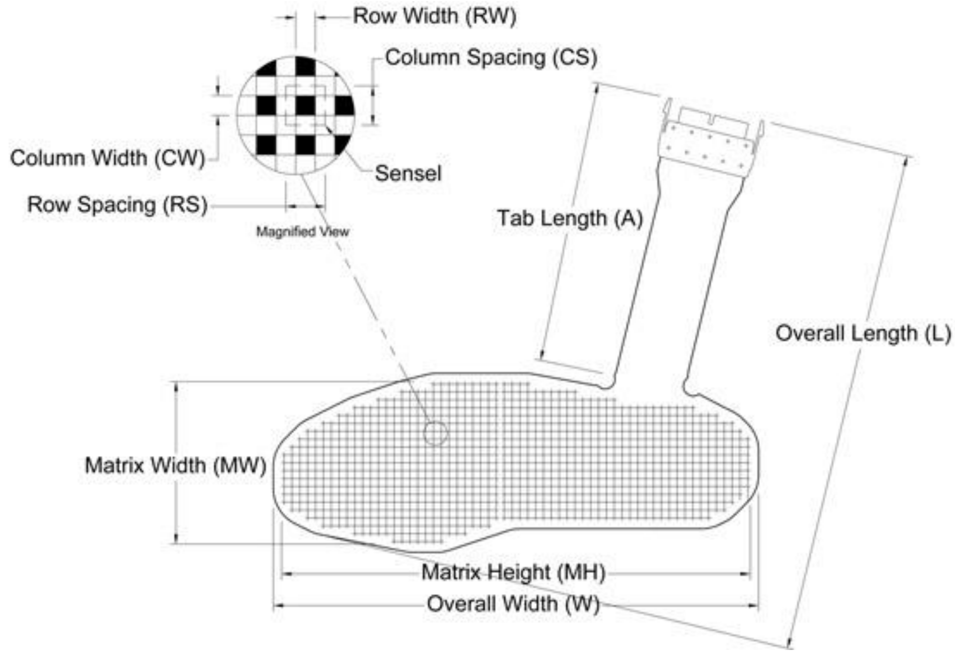

Figure 2.4. F-Scan Sensor [274].

F-Scan sensors have been studied in depth to determine their accuracy, reliability, and other characteristics. A wide range of error levels have been reported in the literature and are shown in Table 2.5. Furthermore, Hsiao et al., 2002 [268] found that error was dependent on the calibration pressure. When the calibration pressure was similar to the applied pressure, the error was low (1.3 to 5.8%) and when the calibration pressure was dissimilar, the error was high (-26.4% to 33.9%) [268]. Studies have also reported pressures decrease after numerous trials [269,275]. This led to the recommendation that an F-Scan sensor should only be used for up to 30 gait cycles, because the pressure decline is limited to 3.5% at 30 cycles, but declines more rapidly due to wear after 30 gait cycles, decreasing to 20.5% after approximately 70 cycles [269]. The F-Scan sensor has good reliability [269,275,276] although material creep has resulted in increasing pressure values between 2.3 and 19.0% over time in static loading scenarios [272,273,277]. Hysteresis tests showed typical preconditioning effects, leading to the recommendation that sensor warm up should occur before use [272]. Sensor warm up also decreases the inter-person coefficient of variation [275]. Further increase in sensor temperature after sensor warm up has been shown to decrease total force measurements but did not appear to impact CoP measurements with good consistency in AP ($r > 0.90$) and ML ($r > 0.717$) CoP trajectories over time [278].

Table 2.5. Percent errors for F-Scan sensors

	Percent Error	**Tested Sensor Range**
Woodburn and Helliwell (1996) [273] (Woodburn301)	<14%	735-880 N
McPoil et al. 1995 [277] (McPoil95)	4%	50 kPa
McPoil et al. 1995 [277] (McPoil95)	<24%	500 kPa
Luo et al. 1998 [279] (Luo186)	<20%	
Nicolopoulos et al. 2000 [272] (Nicolopoulos124)	3-24%	413-757 kPa

Studies utilizing the F-Scan insoles have assessed plantar pressure over several foot areas such as the forefoot, midfoot, metatarsals, and hindfoot [280-282]. Kim et al., 2013 [282] identified differences in toe, first metatarsal, and heel region contact surface areas but not peak plantar pressure between dominant and non-dominant feet in older woman fallers. Mueller and Strube, 1996 [266] used F-Scan sensors to compare people with diabetic peripheral neuropathy to a control population and determined that foot deformities in those with peripheral neuropathy accounted for increases in plantar pressure. While this sensor has not yet been used to assess elderly fall risk, it has been successfully used to develop the Dynamic Stability Index, which was evaluated with healthy people and simulated instability [283] and with transtibial amputees [284]. The variables that make up the Dynamic Stability Index are shown in Table 2.6. The Dynamic Stability Index represents an important step in applying F-Scan insoles to the field of fall risk. However, no studies to date have assessed the potential of F-Scan insoles, or other PS insoles, to determine fall risk in older adults. The important fall risk variables for older adults will likely be different from a simulated-instability or transtibial-amputee population, although some overlap is expected. Furthermore, even for variables that do overlap and predict fall risk in multiple populations, their relative importance will likely vary between specific populations. Therefore, it is important that a new fall risk prediction model be developed, independent of the Dynamic Stability Index, for an older adult population.

Table 2.6. Dynamic Stability Index variables [284]

Variable	Description
Shifts in anterior-posterior (AP) centre of pressure (CoP)	Number of times the first derivative of the AP CoP crossed a threshold of ± 0.5 mm/frame.
Shifts in medial-lateral (ML) CoP	Number of times the first derivative of the ML CoP crossed a threshold of ± 0.5 mm/frame.
Maximum lateral placement of force	Maximum activated lateral sensor cell position of the foot CoP during a stride as a percentage of the insole width. Higher values would be linked with increased instability.
Cell triggering	Maximum number of times a sensor cell is triggered (turned on after being off) during a stride divided by the number of frames during the stride. Cells should only be triggered once per stride.
Stride time	Time (s) from foot strike to the following foot strike of the same foot.
Double support time	Time (s) spent with both feet in contact with the ground within a single stance phase.

2.4 Summary

Approximately one third of adults aged 65 years and older will experience a fall each year [1,2], with the fall rate increasing with age [3,4]. These falls can have negative physical and psychological consequences. Fall risk assessments are performed to identify older adults at increased fall risk. Clinical assessments based on observational assessments or questionnaires have been used to identify individuals at increased fall risk; however, clinical tools are limited by ceiling or floor effects, low resolution, and subjective elements [18,19]. Sensor-based fall risk assessments provide a quantitative assessment, typically of standing balance or gait, and are less vulnerable to subjective influences than clinical assessments. Laboratory-based equipment (e.g., force platforms, pressure platforms, instrumented walkways) can provide a complete, quantitative assessment of body kinematics and dynamics. Unfortunately, this equipment is expensive and time consuming for data collection and analysis [28], and not suitable for assessment on uneven-terrain. Wearable sensors also provide quantitative information and allow measurement in a variety of environments. Inertial sensors, primarily accelerometers, have been used for older adult fall risk prediction with high levels of accuracy (47-100%), sensitivity (0-100%), and specificity (15-100%). However, only 30% of these models classified prospective fall occurrence. There is a need to evaluate different promising sensor sites and sensor-derived variables for fall risk prediction directly, instead of comparing results between studies in the literature. Furthermore, F-Scan pressure-sensing insoles have been used to assess amputee stability and may provide useful gait data relevant to older adult fall risk assessment. A concurrent evaluation of accelerometers and pressure-sensing insoles can determine if insole data provides features relevant to fall risk and if insole-derived features provide different fall risk information than accelerometers. There is a need to develop fall risk classification models based on accelerometer-derived and pressure-sensing insole-derived features and evaluate their predictive accuracy in older adult faller classification. Feature selection should also be employed to eliminate irrelevant features and identify a set of fall risk relevant features for fall risk classification model development. Finally, there is a need to directly compare wearable-sensor-based fall risk classification models to models based on other fall risk relevant information, such as posturography assessments and clinical assessments.

Chapter 3 Methodology

3.1 Overview

Chapter 3 details the data collection and data processing methodology common to all analyses. Methods specific to different analyses are detailed in Chapters 4-7, with the associated results and discussion.

To evaluate wearable sensors as an older adult fall risk assessment tool and accomplish the objectives outlined in Section 1.2, gait, posturography, fall occurrence, and participant data were collected on a sample of older adults (Section 3.2). Participants completed the Activities-specific Balance Confidence scale, Community Health Activities Model Program for Seniors questionnaire, static posturography with eyes open and closed, six minute walk test, and 25 ft walk under ST and DT conditions, and ranked their fear of falling (Sections 3.3 and 3.4). Accelerometer and pressure-sensing insole data were collected for the ST and DT conditions and vertical force data were collected for the static posturography assessments. Data were processed and relevant features computed (Section 3.5) to evaluate differences between conditions, differences between faller and non-faller groups, and for input into fall risk models.

For the static posturography assessment, statistical techniques were used to identify significant differences between eyes open and closed static posturography conditions and between faller and non-faller groups. Three methods for determining cut-off scores (clinical cut-off scores, receiver-operator characteristic curves, discriminant functions) were used to classify fallers and non-fallers (Section 4.2). For the ST and DT gait assessment, statistical techniques were used to identify significant differences between ST and DT walking conditions and between faller and non-faller groups (Section 5.2). For fall risk model development, three classifier models (multi-layer perceptron neural network, naïve Bayesian, support vector machine) were used to assess fall risk predictive capability for all wearable-sensor data, posturography data, and clinical assessment data (Section 6.2). Multi-site accelerometer data and pressure-sensing insole data were used for wearable-sensor-based fall risk model development, involving all sensor combinations. Finally, feature selection algorithms (CFS, FCBF, Relief-F) were used to eliminate irrelevant features for all sensor combinations to determine whether feature selection improved fall risk predictive performance (Section 7.3).

3.2 Participants

A convenience sample of 100 people, 65 years or older, were recruited from the community. Of the 100 participants, 61 were recruited from local churches (United Church of Canada), 38 were recruited from the University of Waterloo Retirees Association, and one was recruited directly from a retirement home (Chartwell Bankside Terrace Retirement Residence). Four participants used a cane and two used a walker during everyday life; however, they did not use their assistive device during walking assessments. Potential participants were excluded if they had a cognitive disorder (self-reported) or were unable to walk for six minutes without an assistive device. The University of Waterloo, Office of Research Ethics approved the study and all participants gave informed written consent.

Falls were defined as “an event which results in a person coming to rest unintentionally on the ground or other lower level, not as a result of a major intrinsic event (such as a stroke) or overwhelming hazard” [2]. The 100 participants were divided into five falling categories:

- **Retrospective non-fallers (RNF)**, N=76: did not fall in the six-month period before data collection. 67 (88%) lived residentially and 9 (12%) lived in retirement homes. 75 RNF completed the six month fall follow-up period.
- **Retrospective fallers (RF)**, N=24: fell in the six-month period before data collection. 23 (96%) lived residentially and 1 (4%) lived in a retirement home.
- **Prospective faller (PF)**, N=28: fell during the six month follow-up period, but did not fall in the six-month period before data collection (i.e., subset of RNF). 22 (79%) lived residentially and 6 (21%) lived in a retirement home.
- **Prospective multi-fallers (PMF)**, N=6: PF who fell more than once during the six month follow-up period. 5 (83%) lived residentially and 1 (17%) lived in a retirement home.
- **Prospective non-faller (PNF)**, N=47: did not fall during the six month follow-up period. 44 (94%) lived residentially and 3 (6%) lived in a retirement home.

For the 28 PF, the mean number of falls during the six month follow-up was 1.3 (range: one to four falls).

Table 3.1 reports anthropometric, demographic, and baseline data for the participant sub-populations. The participants were a high-functioning, high balance confidence subset of the general older adult population, based on CHAMPS calories expended per week, 6MWT distances, and ABC scores. The CHAMPS calories expended per week were higher than those reported by Stewart et al., 2001 [145] of 2420 ± 1831 kcal/week (n = 249, aged 65 to 90 years) but similar to those reported for an active subset with 3386 ± 219 kcal/week (n = 76, aged 65 to 85 years). Similarly, CHAMPS calories expended per week were higher than those reported by Harada et al., 2001 [285] for a retirement home population of 1548 ± 1767 kcal/week (n = 36, aged 65 to 89 years) but similar to those reported for community-dwelling older adults of 3484 ± 2042 kcal/week (n = 51, aged 65 to 86 years). Therefore, the CHAMPS calories expended per week for this thesis (3491 ± 2671 kcal/week) indicated an active population. The average 6MWT distance (453.6 ± 101.7 m) was similar to those reported by Lord et al., 2002 [76] of 442 ± 142 m for men and 400 ± 125 m for women (n = 515, aged 62 to 95 years, retirement-home-dwelling); Harada et al., 1999 [75] of 497 ± 95 m (n = 51, aged 65 to 86 years, community-dwelling); and Steffen et al., 2002 [286] of mean distances of 392 m to 572 m for various age and gender groupings (n = 96, age groups: 60-69, 70-79, 80-89 years, community-dwelling). However, the 6MWT distance was greater than the distance from retirement-home-dwelling older adult reported by Harada et al., 1999 [75] of 275 ± 107 m (n = 35, aged 65 to 89 years). ABC scores (88.9 ± 9.8) were higher than those reported by Myers et al., 1996 [135] for community-dwelling older adults (aged 65 to 95 years) of 74.0 ± 20.9 for a non-fearful subset (n = 26), 68.7 ± 23.4 for a fearful but not avoiding activities subset (n = 16), and 30.8 ± 16.2 for a fearful and avoiding activities subset (n = 18); by Moore et al., 2011 [136] of 74.7 (confidence interval: 71.3 to 78.1, n = 133, aged 51 to 95 years); and by Talley et al., 2008 [137] of 78.2 ± 16.7 (n = 272, aged 70 to 98 years, female). This suggests that participants in this thesis research had higher balance confidence than other older adult populations. However, ABC results were similar to those reported by Myers et al., 1998 [138] for older adults, who were mostly involved in exercised-oriented research projects and programs, with ABC scores of 89.8 ± 27 for men and 84.4 ± 17 for women. Therefore, this thesis study's population was active, based on CHAMPS calories expended per week, and had equivalent or higher balance confidence, based on ABC scores, compared to other older adult populations. In addition, fear of falling scores were low (1.8 out of 10, averaged across all participants, where 10 is high fear of falling).

Separate analyses were performed for retrospective (RNF, RF) and prospective groups (PNF, PF, PMF) because a pre-assessment fall may cause a participant to develop fear of falling and change gait patterns [287]. Furthermore, RF would already be identified as being at increased risk of future falls due to their fall history [17].

Table 3.1. Participant characteristics by fall group (mean ± standard deviation)

	RF	**RNF**	**PNF**	**PF**	**PMF**	**All**
n	24	76	47	28	6	100
Male/Female	13/11	31/45	17/30	14/14	3/3	44 / 56
Age (years)	76.3 ± 7.0	75.2 ± 6.6	75.3 ± 5.5	75.0 ± 8.2	71.8 ± 8.1	75.5 ± 6.7
Height (cm)	165.2 ± 10.3	165.1 ± 10.0	164.8 ± 10.5	165.7 ± 9.3	168.7 ± 10.9	165.1 ± 10.0
Weight (kg)	71.9 ± 14.3	73.3 ± 13.4	73.3 ± 13.6	73.4 ± 13.2	86.2 ± 13.2	72.8 ± 13.5
ABC	87.5 ± 10.9	89.3 ± 9.4	89.6 ± 10.2	88.4 ± 8.0	89.0 ± 6.6	88.9 ± 9.8
CHAMPS Calories Expended (kcal/week)	4671 ± 3631	3118 ± 2189	3005 ± 2368	3314 ± 1921	3368 ± 1091	3491 ± 2671
Fear of Falling (0 to 10)	1.9 ± 2.1	1.8 ± 2.0	1.8 ± 2.0	2.0 ± 2.2	1.5 ± 2.0	1.8 ± 2.0
6MWT distance (m)	446.6 ± 101.4	455.8 ± 102.4	462.1 ± 110.0	444.7 ± 91.1	440.7 ± 81.0	453.6 ± 101.7

3.3 Protocol

Participants reported six month retrospective fall occurrence, age, and sex. Body weight and height were measured. Participants completed the Activities-specific Balance Confidence (ABC) [134] and Community Health Activities Model Program for Seniors (CHAMPS) [144] questionnaires. They also rated their fear of falling from 0 (no fear) to 10 (high level of fear).

All participants completed a static posturography assessment. Two Wii Balance Boards (WBB) were placed such that their long axes were oriented parallel to the AP axis (Figure 3.1). Recent WBB studies reported good correspondence with force platform measures [288,289], excellent test-retest reliability [288,290], and good to excellent concurrent validity [288,290] for CoP displacement measures.

Figure 3.1. WBB orientation and foot position.

Participants stood in a comfortable stance on two WBBs, with one foot on each board. Participants stood quietly for 30 seconds with eyes open and then 30 seconds with eyes closed while WBB data were collected at 100Hz [291].

After the posturography assessment, PS insoles (I) (F-Scan 3000E, Tekscan, Boston, MA) were equilibrated using multi-point calibration (137.9, 275.8, 413.7 kPa), fit to the shoes, and calibrated. Accelerometers (X16-1C, Gulf Coast Data Concepts, Waveland, MS) were attached to the posterior head with a band (H), posterior pelvis with a belt (P), and left and right lateral shank (LS and RS, respectively), just above the ankle, with a band. Plantar pressure data were collected at 120 Hz and accelerometer data at 50 Hz. Participants completed a 25 ft (7.62 m) walk with and without a cognitive load with completion times recorded via a stopwatch. Participants started walking approximately 1 m before the start of the 25 ft course and stopped walking approximately 1 m after the end of the course. These 1 m distances allowed for participant acceleration and deceleration and were excluded from analysis. The cognitive load was a verbal word fluency task requiring the participants to say words starting with letters A, F, or S [292]. Participants also completed the six minute walk test (6MWT) [71]. The starting letter and order of walking activities were randomized.

3.4 Clinical Assessments

Three clinical assessments were evaluated: 6MWT, ABC questionnaire, and CHAMPS activities questionnaire. These assessment methods, described in detail in Section 2.2.2 (6MWT) and 2.2.4 (ABC, CHAMPS), were used in this research because they provided information on important functional abilities as listed in Table 3.2 and because of their high reliability and validity.

The 6MWT assesses walking capacity, with participants instructed to walk as far and as fast as possible for six minutes, with the distance (6MWD) recorded [71]. The 6MWT has good test-retest reliability ($0.88 < r < 0.94$), good convergent validity when compared to treadmill performance ($0.71 < r < 0.82$), and moderate construct validity by discriminating between age groups and between low and high activity older individuals [293].

ABC is a situation-specific measure of balance confidence over a wide range of activity difficulty [134] with excellent test-retest reliability ($r = 0.92$), good consistency (Cronbach's $\alpha = 0.90$), and good construct validity for discriminating between low and high mobility older adults

[134]. Furthermore, as described in Section 2.2.4, ABC was able to discriminate between older adult fallers and non-fallers while two other fear of falling questionnaire tools could not (Falls Efficacy Scale and SAFE) [128].

The CHAMPS activities questionnaire was designed for accurate completion by older adults who may have memory and cognitive issues that make accurate recall difficult. CHAMPS can be used to calculate calories expended per week (CalExp) [145] and has moderate test-retest reliability (ICC ≥ 0.58) and construct validity by discriminating between low and high activity older individuals [145].

Table 3.2. Clinical assessments and related functional abilities

Clinical Assessment	Functional Correlates
6MWT [76]	Physical performance and mobility
ABC [134,135]	Balance confidence, fear of falling
CHAMPS [144]	Physical activity level

3.5 Data Processing

3.5.1 Posturography Data Processing

Vertical force data from the WBB were filtered using a 15 point moving average filter and plantar CoP were computed using purpose-built software (NiMBaL Balance Assessment, University of Waterloo). Outcome variables were AP and ML absolute CoP motion range (Range); AP and ML CoP RMS distance from mean; mean AP and ML CoP total excursion velocities; and AP and ML mean resultant CoP velocity vector sum magnitude (VSM) [165]. For all values, the Romberg Quotient (RQ) was calculated as eyes closed divided by eyes open [294].

3.5.2 Wearable Sensors Data Processing

Gait velocities for ST and DT trials were calculated as 7.62 m divided by the stopwatch recorded time. Plantar-pressure and accelerometer data were exported to Matlab v2010a to calculate outcome variables.

Plantar pressure features:

- **CoP path** (Figure 3.2):
    - Number, length, and duration of posterior deviations per stance phase. Since the CoP path should advance monotonically and anteriorly, posterior CoP path movements were identified as irregular.

    - Number, length, and duration of ML path deviations per stance: first derivative of the CoP ML signal exceeding a dual threshold of ± 0.5 mm/frame [283]. Smooth medial and lateral movements were expected.
    - Minimum, maximum, mean, and median CoP path velocities, normalized by stance time.
    - AP and ML coefficients of variation (CoV) for the stance phase CoP path: Mean and standard deviation (SD) of CoP path positions calculated at 1% intervals, determined using ensemble averaging [295], for the entire stance phase and used to calculate the overall CoP path stance phase CoV as in Winter, 1991 [296].
- **Temporal**: Cadence, stride time, stance time, swing time, percent stance time, percent double support time, stride time symmetry index [297] between the left and right limbs, and CoV for stride time, stance time, and swing time, were calculated.
- **Impulse**: Impulse from the total force-time curve (sum of forces from all insole sensors, Figure 3.3), calculated using the area under the force-time curve normalized by body mass (Ns/kg) for: I1 (foot-strike to first peak), I2 (first peak to minimum), I3 (minimum to second peak), I4 (second peak to foot-off), I5 (foot-strike to minimum), I6 (minimum to foot-off), and I7 (foot-strike to foot-off).

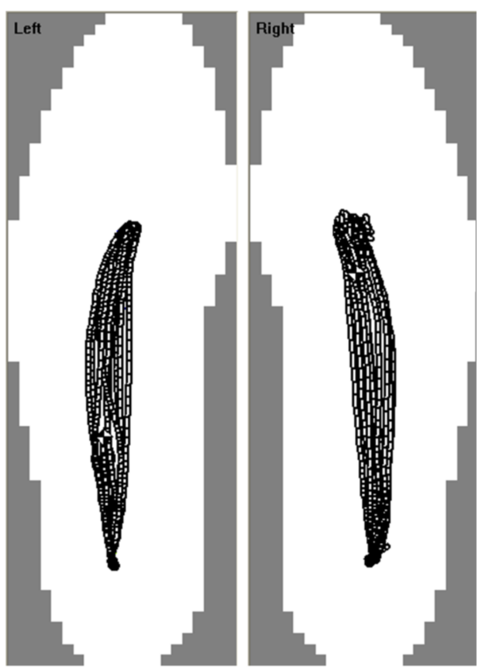

Figure 3.2. Typical plantar pressure derived CoP path for 10 ST gait strides.

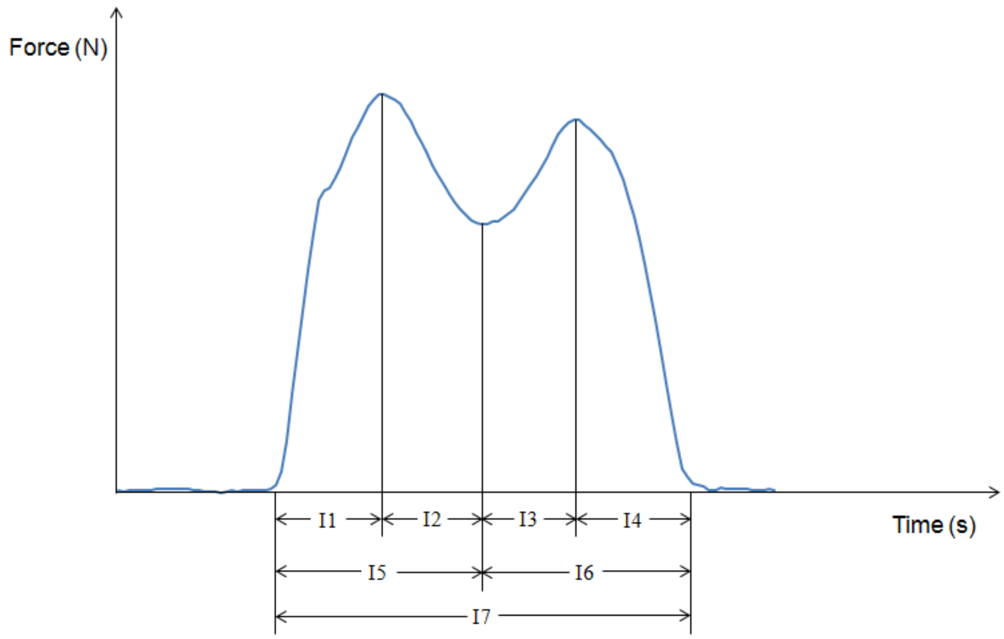

Figure 3.3. Typical total ground reaction force curve with impulse phases indicated. I1: foot-strike to first peak, I2: first peak to minimum, I3: minimum to second peak, I4: second peak to foot-off, I5: foot-strike to minimum, I6: minimum to foot-off, I7: stance phase.

For accelerometer data, the positive vertical axis was upwards, positive AP axis was anterior, and positive ML axis was toward the participant's right. Accelerometer features:

- **Temporal**: Cadence, stride time.
- **Descriptive statistics**: Maximum, mean, and SD of acceleration for the superior, inferior, anterior, posterior, right, and left axes by stride.
- **Fast Fourier Transform (FFT) First Quartile:** Percentage of acceleration frequencies in the first quartile (i.e., frequencies < 12.5 Hz) of an FFT frequency plot for vertical, AP, and ML axes over the entire walking trial.
- **Ratio of even to odd harmonics (REOH):** Proportion of the acceleration signal in phase with stride frequency. The harmonic ratio is used to measure irregular accelerations and overall gait pattern stability [209,218,238].The harmonic ratio was calculated for vertical, AP, and ML axes over the entire walking trial [298].
- **Maximum Lyapunov exponent (MLE):** Average rate of expansion or contraction of the original trajectory in response to perturbations [210], calculated for vertical, AP, and ML accelerations over the entire walking trial [299]. The number of dimensions was

determined using the global false nearest neighbours method [300] and a time delay based on the first minimum of the average mutual information [301].

For descriptive statistics, temporal, and MLE parameters, acceleration data were filtered using a fifth order, low pass Butterworth filter with a 12.5 Hz cut-off frequency. Unfiltered acceleration data were used to calculate the FFT quartile and REOH. Pelvis accelerometer data were missing for two non-fallers (RNF and PNF) and left shank accelerometer data were missing for one non-faller (RNF and PNF) due to sensor power failure.

Chapter 4 Static Posturography Assessment of Older Adults

4.1 Objectives

The objectives of the static posturography assessment research were to identify differences between retrospective and prospective fallers and non-fallers. Appropriate outcome measure cut-off scores for prospective faller, multi-faller, and non-faller classifications were then determined to assess whether this information could be used as a viable screening tool for older people at risk of falling. The data was also examined to determine if differences could be detected between eyes open and eyes closed static posturography conditions.

Outcomes from this static posturography research were published in [302]:

- Howcroft JD, Kofman J, Lemaire ED, McIlroy WE. Static posturography of elderly fallers and non-fallers with eyes open and closed. IFMBE Proceedings of the World Congress on Medical Physics and Biomedical Engineering. Toronto, Ontario. 7-12 June 2015; 51: 966-969.

4.2 Data Analysis

Normality was assessed for each variable using the Shapiro-Wilk test ($\alpha = 0.05$). For eyes open and eyes closed comparisons, a paired *t*-test was used for normal variables and a Wilcoxon Signed-Rank Test was used for non-normal variables. For faller versus non-faller comparisons, a Mann-Whitney U Test was used for non-normal variables and a Levene Test for equality of variance was used for normal variables. An independent *t*-test was used for equal variance and a Welch's *t*-test was used for unequal variance. Significance was tested at $p < 0.05$.

For variables that were significantly different between PF and PNF, or PMF and PNF, cut-off scores for faller classification were determined using the Clinical Cut-off Score [303], Receiver-Operator Characteristic (ROC) curves, and discriminant functions.

The clinical cut-off score C, was calculated by:

$$C = \frac{\sigma_n \mu_c + \sigma_c \mu_n}{\sigma_n + \sigma_c} \tag{4.1}$$

where σ_n and σ_c are the variable standard deviation for the normal non-faller group and clinical faller group, respectively; and μ_n and μ_c are the variable mean for the normal non-faller group and clinical faller group, respectively [303].

For Receiver-Operator Characteristic (ROC) curves, the predictive value was based on area-under-curve, accuracy, sensitivity, and specificity. A cut-off score with at least 80% sensitivity was selected because correctly identifying fallers in a clinical setting would be more important than minimizing false positives.

A discriminant function was based on all variables that showed a significant difference between PNF and PF, and between PNF and PMF. The cut-off score was the mean value between the discriminant function group centroid values.

4.3 Results

4.3.1 Eyes Open and Closed

Eyes closed results were significantly greater than eyes open for both PNF and PF groups, for AP range of CoP motion, AP RMS, AP and ML CoP velocities, and CoP velocity VSM (Table 4.1). For PNF, the largest percent increase (eyes open to eyes closed) was 101% for AP velocity, followed by VSM (78%), AP range (76%), AP RMS (68%), and ML velocity (28%). PF percent increases were AP velocity (120%), VSM (99%), AP range (49%), ML velocity (46%), and AP RMS (40%). For PMF, all variables were significantly greater for eyes closed than eyes open (Table 4.1). The largest percent increase was 188% for AP velocity, followed by VSM (164%), AP RMS (89%), AP range (86%), ML velocity (58%), ML RMS (48%), and ML range (44%).

Table 4.1. Mean, standard deviation, ($\mu \pm \sigma$) and p-value between eyes open and eyes closed static posturography trials for prospective fallers

Measures	**Eyes Open**	**Eyes Closed**	***p* value**
Prospective Non-Faller			
CoP Range, AP (mm)	21.42 ± 7.24	37.72 ± 12.99	**<0.001**
CoP Range, ML (mm)	14.98 ± 9.70	15.58 ± 7.09	0.662
CoP RMS, AP (mm)	4.12 ± 1.22	6.91 ± 2.35	**<0.001**
CoP RMS, ML (mm)	2.80 ± 1.80	2.86 ± 1.20	0.810
CoP Velocity, AP (mm/s)	7.53 ± 1.93	15.11 ± 5.59	**<0.001**
CoP Velocity, ML (mm/s)	4.57 ± 1.57	5.83 ± 2.01	**<0.001**
CoP Velocity, VSM (mm/s)	9.70 ± 2.34	17.26 ± 6.04	**<0.001**
Prospective Faller			
CoP Range, AP (mm)	22.86 ± 5.47	34.00 ± 12.37	**<0.001**
CoP Range, ML (mm)	13.43 ± 9.97	14.32 ± 5.77	0.665
CoP RMS, AP (mm)	4.65 ± 1.25	6.51 ± 2.03	**<0.001**
CoP RMS, ML (mm)	2.65 ± 1.94	2.72 ± 1.41	0.864
CoP Velocity, AP (mm/s)	7.75 ± 1.66	17.03 ± 8.39	**<0.001**
CoP Velocity, ML (mm/s)	4.63 ± 1.67	6.74 ± 4.53	**0.007**
CoP Velocity, VSM (mm/s)	9.84 ± 2.32	19.58 ± 9.82	**<0.001**
Prospective Multi-Faller			
CoP Range, AP (mm)	22.48 ± 7.52	41.91 ± 14.55	**0.046**
CoP Range, ML (mm)	10.49 ± 1.22	15.09 ± 3.25	**0.046**
CoP RMS, AP (mm)	4.44 ± 0.96	8.38 ± 2.12	**0.028**
CoP RMS, ML (mm)	2.08 ± 0.41	3.07 ± 0.99	**0.028**
CoP Velocity, AP (mm/s)	7.67 ± 1.43	22.06 ± 11.31	**0.028**
CoP Velocity, ML (mm/s)	4.28 ± 0.86	6.77 ± 1.89	**0.046**
CoP Velocity, VSM (mm/s)	9.21 ± 2.12	24.27 ± 11.31	**0.046**

For RNF and RF, AP range of CoP motion, AP RMS, AP CoP velocity, and CoP VSM were significantly greater for eyes closed compared to eyes open (Table 4.2). For RF, ML CoP velocity was also significantly greater for eyes closed compared to eyes open. For RNF, the largest percent increase for eyes closed was 107% for AP CoP velocity, followed by CoP VSM (86%), AP range of CoP (66%), and AP RMS (57%). For RF, the largest percent increase for eyes closed was 136% for AP CoP velocity, followed by VSM (112%), AP range of CoP motion (71%), ML CoP velocity (55%), and AP RMS (54%).

Table 4.2. Mean, standard deviation, ($\mu \pm \sigma$) and *p*-value between eyes open and eyes closed static posturography trials for retrospective fallers

Measures	Eyes Open	Eyes Closed	*p* value
Retrospective Non-Faller			
CoP Range, AP (mm)	21.84 ± 6.67	36.31 ± 12.72	**<0.001**
CoP Range, ML (mm)	14.39 ± 9.70	15.13 ± 6.58	0.509
CoP RMS, AP (mm)	4.30 ± 1.26	6.75 ± 2.22	**<0.001**
CoP RMS, ML (mm)	2.74 ± 1.83	2.82 ± 1.27	0.717
CoP Velocity, AP (mm/s)	7.65 ± 1.84	15.86 ± 6.74	**<0.001**
CoP Velocity, ML (mm/s)	5.07 ± 4.34	6.19 ± 3.18	0.500
CoP Velocity, VSM (mm/s)	9.79 ± 2.32	18.17 ± 7.65	**<0.001**
Retrospective Faller			
CoP Range, AP (mm)	20.54 ± 6.25	35.06 ± 18.27	**<0.001**
CoP Range, ML (mm)	12.64 ± 5.60	15.51 ± 12.20	0.391
CoP RMS, AP (mm)	4.19 ± 1.29	6.47 ± 3.11	**<0.001**
CoP RMS, ML (mm)	2.38 ± 1.20	2.94 ± 2.33	0.106
CoP Velocity, AP (mm/s)	7.34 ± 2.47	17.34 ± 16.03	**0.002**
CoP Velocity, ML (mm/s)	4.45 ± 1.43	6.88 ± 5.85	**0.019**
CoP Velocity, VSM (mm/s)	9.43 ± 2.95	19.98 ± 17.85	**0.003**

4.3.2 Fallers, Non-Fallers, and Predictive Capabilities

RQ for AP range and AP RMS were significantly greater for PNF than PF (Table 4.3). No other differences between PNF and PF were found. RQ cut-off scores based on RQ AP range and RQ AP RMS achieved 56.0-62.7% accuracy, 60.7-82.1% sensitivity, and 40.4-57.4% specificity (Table 4.4). The RQ for AP range clinical cut-off score achieved the best accuracy and specificity results and ROC cut-off score achieved the best sensitivity results for discriminating between PF and PNF (Table 4.4).

Table 4.3. Romberg Quotient mean, standard deviation, ($\mu \pm \sigma$) and *p*-values for comparisons between prospective faller (PF) and prospective non-faller (PNF) groups

Variables	PNF	PF	*p* value
CoP Range, AP	1.90 ± 0.79	1.53 ± 0.54	**0.028**
CoP Range, ML	1.25 ± 0.61	1.22 ± 0.48	0.827
CoP RMS, AP	1.77 ± 0.65	1.46 ± 0.48	**0.021**
CoP RMS, ML	1.20 ± 0.55	1.18 ± 0.57	0.892
CoP Velocity, AP	2.04 ± 0.65	2.18 ± 0.97	0.510
CoP Velocity, ML	1.34 ± 0.45	1.43 ± 0.57	0.467
CoP Velocity, VSM	1.81 ± 0.57	2.02 ± 1.07	0.360

Table 4.4. Prospective fall group clinical, ROC, and discriminant function cut-off scores (classified as faller for scores less than cut-off score)

Method	Measure	Cut-Off	Accuracy (%)	Sensitivity (%)	Specificity (%)
Clinical	RQ CoP Range, AP	1.68	62.7	71.4	57.4
	RQ CoP RMS, AP	1.59	57.3	60.7	55.3
ROC	RQ CoP Range, AP (AUC=0.633)	1.96	57.3	82.1	42.6
	RQ CoP RMS, AP (AUC=0.640)	1.81	56.0	82.1	40.4
Discriminant Function	-2.779 + 0.812 x RQAPRange + 0.817 x RQAPRMS	-0.071	57.3	67.9	51.1

RQAPRange: RQ CoP Range, AP; RQAPRMS: RQ CoP RMS, AP

PMF eyes closed AP velocity (p = 0.015) and eyes closed VSM (p = 0.020) were significantly greater than PNF. The Romberg Quotients for AP velocity and VSM were also significantly greater for PMF compared to PNF (Table 4.5). Cut-off scores for eyes closed AP velocity, eyes closed VSM, RQ for AP velocity, and RQ for VSM velocity achieved 45.3-84.9% accuracy, 50-83.3% sensitivity, and 40.4-89.4% specificity (Table 4.6). Discriminant function achieved the best accuracy and specificity results (Table 4.6). ROC cut-off score for eyes closed AP velocity achieved the best sensitivity results for discriminating between PMF and PNF (Table 4.6).

Table 4.5. Romberg Quotient mean, standard deviation, ($\mu \pm \sigma$) and p-values for comparisons between prospective multi-faller (PMF) and prospective non-faller (PNF) groups

Ratio Variables	PNF	PMF	*p* value
CoP Range, AP	1.90 ± 0.79	1.98 ± 0.65	0.651
CoP Range, ML	1.25 ± 0.61	1.45 ± 0.30	0.213
CoP RMS, AP	1.77 ± 0.65	1.95 ± 0.54	0.401
CoP RMS, ML	1.20 ± 0.55	1.49 ± 0.46	0.197
CoP Velocity, AP	2.04 ± 0.65	2.86 ± 1.51	**0.019**
CoP Velocity, ML	1.34 ± 0.45	1.59 ± 0.39	0.187
CoP Velocity, VSM	1.81 ± 0.57	2.80 ± 1.83	**0.006**

Table 4.6. Prospective multiple fall group clinical, ROC, and discriminant function cut-off scores (classified as faller for scores greater than the cut-off score)

Method	Measure	Cut-Off	Accuracy (%)	Sensitivity (%)	Specificity (%)
Clinical	CoP Velocity, AP, Eyes Closed (mm/s)	17.41	69.8	50.0	72.3
	CoP Velocity, VSM, Eyes Closed (mm/s)	19.70	67.9	50.0	70.2
	RQ CoP Velocity, AP	2.29	71.7	50.0	74.5
	RQ CoP Velocity, VSM	2.05	69.8	50.0	72.3
ROC	CoP Velocity, AP, Eyes Closed (mm/s) (AUC = 0.688)	13.78	49.1	83.3	44.7
	CoP Velocity, VSM, Eyes Closed (mm/s) (AUC = 0.691)	15.34	47.2	83.3	42.6
	RQ CoP Velocity, AP (AUC = 0.660)	1.83	45.3	83.3	40.4
	RQ CoP Velocity, VSM (AUC = 0.670)	1.69	45.3	83.3	40.4
Discriminant Function	-1.481 + 0.146 x APVelEC - 0.114 x VSMVelEC - 2.027 x RQAPVel + 2.877 x RQVSMVel	0.541	84.9	50.0	89.4

APVelEC: CoP velocity, AP, eyes closed; VSMVelEC: CoP velocity, VSM, eyes closed; RQAPVel: RQ CoP velocity, AP; RQVSMVel: RQ CoP velocity, VSM

No significant differences were found between RF and RNF for eyes open, eyes closed, and RQ (Table 4.7) posturography values.

Table 4.7. Romberg Quotient mean, standard deviation, ($\mu \pm \sigma$) and *p*-values for comparisons between retrospective fallers (RF) and retrospective non-fallers (RNF) groups

Ratio Variables	RNF	RF	*p* value
CoP Range, AP	1.77 ± 0.73	1.68 ± 0.52	0.494
CoP Range, ML	1.24 ± 0.55	1.26 ± 0.63	0.894
CoP RMS, AP	1.66 ± 0.60	1.57 ± 0.55	0.502
CoP RMS, ML	1.20 ± 0.55	1.27 ± 0.57	0.608
CoP Velocity, AP	2.09 ± 0.78	2.16 ± 0.91	0.731
CoP Velocity, ML	1.35 ± 0.51	1.44 ± 0.65	0.543
CoP Velocity, VSM	1.89 ± 0.79	1.94 ± 0.81	0.759

Based on these results, the recommended cut off score for classifying fallers and non-fallers based on a static posturography assessment was 1.68 for RQ of AP CoP range. The cut off scores for classifying multi-fallers was 0.541 based on a discriminant function that includes eyes closed AP velocity, eyes closed VSM velocity, RQ of AP velocity, and RQ of VSM velocity: (-1.481 + 0.146 x APVelEC - 0.114 x VSMVelEC - 2.027 x RQAPVel + 2.877 x RQVSMVel).

4.4 Discussion

Static posturography measures discriminated between elderly fallers and non-fallers, with RQ and AP measures being particularly relevant for fall risk classification. Since cut-off score classifications achieved up to 84% accuracy (Table 4.6), an "eyes open : eyes closed" static posturography assessment can be considered as a screening tool for older people at risk of falling.

For all participants, measures sensitive to AP motion increased when visual input was removed, with the largest percent increases for PMF. This suggests that older adults have an increased reliance on visual input for postural control, particularly older adults at increased risk of multiple falls. For PF and PNF, percent increases from eyes open to eyes closed were inconsistent, with PF having greater percent increases in AP velocity (PF: 120%, PNF: 101%) but smaller percent increases in AP range (PF: 49%, PNF: 76%) and RMS (PF: 40%, PNF: 68%). These differences in distance (range, RMS) and velocity may be because PNF might be able to tolerate a larger range of CoP movements, allowing them to better withstand potentially fall-inducing perturbations [12]. Conversely, PF may have a lower tolerance, to compensate for poorer postural control, requiring increased AP velocities compared to PNF to maintain CoP within a smaller area of stability. PMF may be unable to maintain a smaller range of CoP movements because of postural control issues that result in greater increases in range, RMS, and velocity. Greater AP CoP movement with eyes closed was also found within RF and RNF groups, but AP CoP measures could not discriminate between RF and RNF.

For ML measures, CoP velocity increased with eyes closed for PNF and PF. However, all ML measures for PMF increased with eyes closed. These results further support the premise that PMF have poorer postural control than PNF and PF. Since significant increases in ML range and RMS only occurred for PMF, ML balance control assessment with eyes closed may only be important for evaluating the risk of multiple falls (i.e., people at higher fall risk).

Romberg Quotient was the best measure for differentiating between PF and PNF, with significant differences for RQ AP range and RQ AP RMS. This is in contrast to retrospective falls, where static posturography results were not significantly different between RF and RNF. PMF had greater RQ AP velocity and RQ VSM velocity than PNF. These results highlighted the importance of testing postural balance with and without visual input and calculating RQ to give the clearest indication of fall risk, for both single and multi-fallers, in an older adult population.

The clinical cut-off score achieved the best results for PF classification and the discriminant function cut-off score achieved the best results for PMF classification, in terms of accuracy and specificity. For PF, a clinical cut-off score of 1.68 for RQ AP range produced moderate faller classification results that were comparable to the literature (i.e., 62.7% accuracy, 71.4% sensitivity, 57.4% specificity versus Topper et al., 1993 [169] with 65% accuracy, 78% sensitivity, 46% specificity). For PMF, a discriminant function with AP velocity EC, VSM velocity EC, RQ AP velocity, RQ VSM velocity and a cut-off score of 0.541 achieved good fall risk classification results with 84.9% accuracy, 50% sensitivity, and 89.4% specificity. The PMF cut-off score classification outperformed the PF cut-off score classification in terms of accuracy and specificity. Identifying and classifying PF can be challenging because some one-time fallers may have fallen, in part, due to environmental causes (e.g., unexpected obstacle, icy conditions, etc.), and may have relatively good balance compared to other fallers.

While clinical and discriminant function cut-off scores achieved the best overall results, the ROC cut-off score achieved the best sensitivity results because a preferred sensitivity level can be set with the ROC method. Therefore, it is important to consider the classification goals when choosing a cut-off score method. ROC would be preferable when avoiding misclassifying fallers as non-fallers is a priority.

Discriminant function cut-off scores could be determined using the clinical cut-off score (Equation 4.1) instead of the mean value between the discriminant function group centroid values. This would include variance within the faller and non-faller calculations and could improve predictive results.

With only six multi-fallers, the multi-faller sensitivity results for the determined cut-off scores were limited to one of seven levels (0%, 17%, 33%, 50%, 67%, 83%, and 100%). More precise determination of predictive sensitivity could be determined with a larger sample of multi-fallers.

Static posturography was evaluated for its ability to identify elderly people who are at risk of falling but had not previously fallen. The best faller classification measures were RQ AP range and RQ AP RMS for all prospective fallers and eyes closed AP velocity, eyes closed VSM velocity, RQ AP velocity, and RQ VSM velocity for multi-fallers, suggesting that RQ calculations are particularly relevant for elderly fall risk assessments. Cut-off scores based on posturography measures achieved good results for multi-faller classification and achieved reasonable results when including prospective fallers who had only fallen once. PMF classification with a discriminant function: (-1.481 + 0.146 x *Eyes Closed AP Velocity* - 0.114 x *Eyes Closed Vector Sum Magnitude Velocity* - 2.027 x *RQ AP Velocity* + 2.877 x *RQ Vector Sum Magnitude Velocity*) and cut-off score of 0.541 could be used as a screening tool for older people at risk of multiple falls.

Chapter 5 Evaluation of Single-Task and Dual-Task Gait in Older Adults based on Wearable Sensor Data

5.1 Objectives

The objectives of this part of the research were to determine whether pressure-sensing insole and accelerometer wearable sensors can detect biomechanical differences in gait that occur with a secondary cognitive task and whether ST or DT gait data from pressure-sensing insole and accelerometer wearable sensors can differentiate between elderly fallers and non-fallers. Specifically, wearable accelerometers and pressure-sensing insoles were used to: detect gait differences between fallers and non-fallers for ST walking, detect gait differences between fallers and non-fallers for DT walking, detect differences between ST and DT walking for fallers, and detect differences between ST and DT walking for non-fallers.

Outcomes from this research were published in the Journal of Biomechanics [304].

- Howcroft J, Kofman J, Lemaire ED, and McIlroy WE. Analysis of Dual-Task Elderly Gait in Fallers and Non-Fallers using Wearable Sensors. Journal of Biomechanics. 2016; 49(7): 992-1001.

5.2 Data Analysis

For each variable, a mixed-design ANOVA test was performed with a 2-factor within-subject walking condition (ST, DT) and a 2-factor between-subject faller status condition (faller, non-faller). A post-hoc assessment was performed for variables with a significant ($p < 0.05$) main effect for walking condition or faller condition or significant interaction effect (retrospective fall occurrence: Appendix A, Tables A.1-A.5; prospective fall occurrence: Appendix A, Tables A.6-A.10). For the post-hoc assessment, normality was assessed using the Shapiro-Wilk Test ($\alpha = 0.05$). Wilcoxon Signed-Rank Tests were used to compare ST and DT walking conditions, with faller and non-faller data analyzed separately, for non-normal data sets. A paired *t*-test was used for normal data sets. For faller versus non-faller comparisons, a Mann-Whitney U Test was used for non-normal data sets, with DT and ST gait data analyzed separately. A Levene Test for equality of variance was performed for normal data sets. For equal variance, an independent *t*-test was used. Welch's *t*-test was used for unequal variance. The critical *p*-value for all comparisons was 0.05. Corrections for multiple tests were applied [305];

thus, not all variables with $p < 0.05$ were significantly different. R^2 categories for correlations between gait velocity and wearable-sensor-derived measures were negligible (0-0.3), low (0.3-0.5), moderate (0.5-0.7), high (0.7-0.9), and very high (0.9-1.0) [306].

5.3 Results

5.3.1 Single-Task and Dual-Task Gait in Older Adults

5.3.1.1 Retrospective Fallers

5.3.1.1.1 Pressure-sensing insole measures

For RF, DT parameters were significantly greater than ST for PD per stride, ML deviation duration, stride time, stance time, swing time, stride time CoV, swing time CoV, percent stance time, percent double-support time, stride time symmetry index, CoV AP, I1, I4 to I7 (Table 5.1). DT was significantly lower than ST for minimum, mean, and median CoP velocity; and cadence.

For RNF, DT was significantly greater than ST for PD per stride, medial deviation duration, stride time, stance time, swing time, stride time CoV, stride time symmetry index, CoV (AP and ML), I1, and I4 to I7 (Table 5.1). DT was significantly lower than ST for minimum, mean, and median CoP velocity; and cadence.

Table 5.1. Mean and SD of pressure-sensing insole variables with a significant ($p < 0.05$) ANOVA result for retrospective fallers and non-fallers. Bold *p*-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			Non-Fallers		
	ST	**DT**	***p***	**ST**	**DT**	***p***
CoP Path						
PD per Stride	1.2 ± 0.9	2.3 ± 2.6	**0.022**	1.6 ± 2.3	2.5 ± 2.5	**<0.001**
ML Deviation Duration (s)	0.034 ± 0.012	0.042 ± 0.015	**0.007**	0.031 ± 0.014	0.037 ± 0.016	**0.004**
Min CoP Vel (m/s)	0.033 ± 0.016	0.025 ± 0.015	**<0.001**	0.029 ± 0.011	0.022 ± 0.009	**<0.001**
Mean CoP Vel (m/s)	0.297 ± 0.050	0.248 ± 0.046	**<0.001**	0.290 ± 0.044	0.250 ± 0.047	**<0.001**
Median CoP Vel (m/s)	0.263 ± 0.048	0.218 ± 0.050	**<0.001**	0.249 ± 0.038	0.211 ± 0.043	**<0.001**
Temporal						
Cadence (steps/minute)	112.1 ± 12.3	97.1 ± 14.9	**<0.001**	111.1 ± 10.2	97.4 ± 14.3	**<0.001**
Stride Time (s)	1.09 ± 0.13	1.27 ± 0.23	**<0.001**	1.09 ± 0.11	1.26 ± 0.20	**<0.001**
Stance Time (s)	0.71 ± 0.09	0.85 ± 0.20	**<0.001**	0.72 ± 0.08	0.83 ± 0.14	**<0.001**
Swing Time (s)	0.38 ± 0.05	0.42 ± 0.07	**0.002**	0.38 ± 0.05	0.43 ± 0.07	**<0.001**
Stride Time CoV	0.03 ± 0.02	0.05 ± 0.04	**0.023**	0.03 ± 0.02	0.04 ± 0.02	**<0.001**
Stance Time CoV	0.05 ± 0.04	0.07 ± 0.04	0.088	0.06 ± 0.04	0.06 ± 0.03	0.513
Swing Time CoV	0.08 ± 0.05	0.11 ± 0.08	**0.022**	0.11 ± 0.08	0.10 ± 0.05	0.692
Percent Stance Time (%)	64.62 ± 3.05	66.81 ± 4.93	**0.001**	65.86 ± 3.49	65.93 ± 2.93	0.248
Percent Double-Support Time (%)	14.64 ± 3.01	16.87 ± 4.93	**<0.001**	15.91 ± 3.48	15.93 ± 2.90	0.328
Stride Time Symmetry Index	1.92 ± 0.79	3.07 ± 2.56	**0.005**	2.14 ± 1.31	2.89 ± 1.59	**0.001**
CoP Path Stance Phase CoV						
CoV AP	4.95 ± 1.41	6.05 ± 2.46	**0.012**	4.63 ± 1.57	5.81 ± 1.98	**<0.001**
CoV ML	6.47 ± 2.36	6.83 ± 2.54	0.376	6.66 ± 2.36	7.60 ± 2.80	**0.001**
Impulse (Ns/kg)						
Foot-strike to first peak (I1)	1.20 ± 0.43	1.54 ± 0.70	**<0.001**	1.20 ± 0.46	1.45 ± 0.61	**<0.001**
Min to second peak (I3)	1.47 ± 0.58	1.58 ± 0.56	0.047	1.67 ± 0.64	1.76 ± 0.71	0.057
Second peak to foot-off (I4)	0.97 ± 0.30	1.39 ± 0.58	**<0.001**	1.08 ± 0.46	1.41 ± 0.80	**<0.001**
Foot-strike to min (I5)	2.35 ± 0.65	2.67 ± 0.88	**0.007**	2.40 ± 0.91	2.56 ± 0.88	**0.007**
Min to foot-off (I6)	2.36 ± 0.76	2.89 ± 0.90	**<0.001**	2.67 ± 0.99	3.10 ± 1.28	**<0.001**
Foot-strike to foot-off (I7)	4.65 ± 1.27	5.50 ± 1.58	**<0.001**	4.99 ± 1.68	5.60 ± 1.96	**<0.001**

5.3.1.1.2 Accelerometer measures

For RF and RNF, significant differences were found between DT and ST gait conditions (Table 5.2 to Table 5.5). These differences are summarized in Table 5.6 for RF and Table 5.7 for RNF.

Table 5.2. Mean and SD of head accelerometer variables with a significant ($p < 0.05$) ANOVA result for retrospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	43.7 ± 12.7	36.6 ± 13.1	**0.004**	43.8 ± 13.3	38.6 ± 11.7	**<0.001**
AP	50.9 ± 10.7	44.9 ± 10.9	0.034	52.4 ± 10.2	47.3 ± 9.6	**<0.001**
ML	50.5 ± 12.9	47.1 ± 12.6	0.304	55.1 ± 11.5	50.4 ± 10.9	**0.004**
Ratio of Even to Odd Harmonics						
Vertical	2.55 ± 1.12	1.60 ± 0.67	**0.002**	2.17 ± 0.94	1.86 ± 0.94	**0.022**
AP	1.75 ± 0.68	1.37 ± 0.55	0.021	1.71 ± 0.81	1.49 ± 0.61	**0.022**
ML	0.61 ± 0.29	0.45 ± 0.18	0.086	0.52 ± 0.26	0.48 ± 0.21	0.366
Maximum Lyapunov Exponent						
ML	0.23 ± 0.10	0.27 ± 0.11	0.179	0.25 ± 0.09	0.28 ± 0.11	0.112
Acceleration Descriptive Statistics (g)						
Superior Max	0.26 ± 0.13	0.31 ± 0.09	0.030	0.25 ± 0.08	0.31 ± 0.09	**<0.001**
Superior Mean	0.11 ± 0.05	0.13 ± 0.05	0.086	0.10 ± 0.04	0.12 ± 0.03	**<0.001**
Superior SD	0.07 ± 0.04	0.08 ± 0.02	0.241	0.06 ± 0.02	0.08 ± 0.02	**<0.001**
Anterior Mean	0.13 ± 0.06	0.11 ± 0.05	0.732	0.15 ± 0.06	0.12 ± 0.06	**0.003**
Posterior Max	0.42 ± 0.17	0.33 ± 0.14	**0.009**	0.34 ± 0.12	0.34 ± 0.14	0.679
Posterior Mean	0.17 ± 0.08	0.13 ± 0.06	**0.007**	0.13 ± 0.04	0.13 ± 0.05	0.376
Posterior SD	0.12 ± 0.05	0.09 ± 0.04	**0.004**	0.09 ± 0.03	0.09 ± 0.03	0.649
Right Max	0.28 ± 0.08	0.29 ± 0.09	0.475	0.25 ± 0.11	0.30 ± 0.11	**0.001**
Right Mean	0.12 ± 0.04	0.13 ± 0.05	0.305	0.11 ± 0.05	0.13 ± 0.05	**<0.001**
Right SD	0.07 ± 0.02	0.08 ± 0.02	0.424	0.07 ± 0.03	0.08 ± 0.03	**<0.001**

Table 5.3. Mean and SD of posterior pelvis accelerometer variables with a significant ($p < 0.05$) ANOVA result for retrospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	34.0 ± 9.6	27.0 ± 8.1	**0.002**	34.2 ± 10.2	26.6 ± 9.3	**<0.001**
ML	32.0 ± 10.4	28.6 ± 9.8	0.253	33.8 ± 10.9	29.6 ± 10.1	**<0.001**
Ratio of Even to Odd Harmonics						
Vertical	2.09 ± 0.84	1.82 ± 0.66	0.568	2.23 ± 0.84	1.96 ± 0.76	**0.029**
AP	1.81 ± 0.64	1.64 ± 0.64	0.648	2.18 ± 0.81	1.88 ± 0.70	**0.006**
Maximum Lyapunov Exponent						
Vertical	0.32 ± 0.12	0.36 ± 0.11	0.081	0.34 ± 0.11	0.30 ± 0.09	0.053
Acceleration Descriptive Statistics (g)						
Superior Max	0.32 ± 0.12	0.27 ± 0.10	**0.012**	0.31 ± 0.09	0.29 ± 0.10	**0.011**
Superior Mean	0.10 ± 0.03	0.08 ± 0.02	**0.002**	0.11 ± 0.03	0.09 ± 0.03	**<0.001**
Superior SD	0.08 ± 0.03	0.06 ± 0.02	**0.007**	0.08 ± 0.02	0.07 ± 0.02	**<0.001**
Inferior Max	0.47 ± 0.18	0.35 ± 0.12	**<0.001**	0.44 ± 0.11	0.38 ± 0.14	**<0.001**
Inferior Mean	0.17 ± 0.07	0.12 ± 0.05	**<0.001**	0.15 ± 0.05	0.13 ± 0.04	**<0.001**
Inferior SD	0.12 ± 0.05	0.09 ± 0.03	**<0.001**	0.12 ± 0.03	0.10 ± 0.04	**<0.001**
Anterior Max	0.47 ± 0.16	0.34 ± 0.11	**<0.001**	0.46 ± 0.16	0.37 ± 0.13	**<0.001**
Anterior Mean	0.17 ± 0.06	0.13 ± 0.04	**0.004**	0.16 ± 0.06	0.14 ± 0.04	**<0.001**
Anterior SD	0.13 ± 0.05	0.09 ± 0.03	**<0.001**	0.13 ± 0.05	0.10 ± 0.04	**<0.001**
Posterior Max	0.29 ± 0.11	0.24 ± 0.09	**0.004**	0.29 ± 0.11	0.26 ± 0.10	**<0.001**
Posterior Mean	0.12 ± 0.04	0.09 ± 0.03	**0.004**	0.11 ± 0.04	0.10 ± 0.04	**0.002**
Posterior SD	0.08 ± 0.03	0.06 ± 0.02	**0.001**	0.08 ± 0.03	0.07 ± 0.02	**<0.001**
Right Max	0.42 ± 0.15	0.32 ± 0.12	**0.001**	0.39 ± 0.12	0.34 ± 0.14	**<0.001**
Right Mean	0.14 ± 0.05	0.10 ± 0.03	**<0.001**	0.13 ± 0.04	0.11 ± 0.04	**<0.001**
Right SD	0.11 ± 0.04	0.08 ± 0.03	**0.001**	0.10 ± 0.03	0.09 ± 0.04	**<0.001**
Left Max	0.41 ± 0.18	0.31 ± 0.11	**<0.001**	0.39 ± 0.11	0.34 ± 0.12	**<0.001**
Left Mean	0.13 ± 0.06	0.10 ± 0.04	**0.002**	0.13 ± 0.03	0.11 ± 0.04	**<0.001**
Left SD	0.11 ± 0.05	0.08 ± 0.03	**<0.001**	0.10 ± 0.03	0.09 ± 0.03	**<0.001**

Table 5.4. Mean and SD of right shank accelerometer variables with a significant ($p < 0.05$) ANOVA result for retrospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			Non-Fallers		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	36.2 ± 11.7	29.4 ± 9.5	**0.022**	39.1 ± 12.1	30.2 ± 10.6	**<0.001**
AP	27.5 ± 8.6	20.5 ± 6.7	**0.002**	29.0 ± 8.6	21.8 ± 7.2	**<0.001**
ML	24.8 ± 8.6	19.5 ± 6.1	**0.012**	27.5 ± 8.0	21.0 ± 6.5	**<0.001**
Maximum Lyapunov Exponent						
Vertical	0.50 ± 0.19	0.60 ± 0.13	0.067	0.56 ± 0.13	0.56 ± 0.11	0.664
Acceleration Descriptive Statistics (g)						
Superior Max	0.51 ± 0.16	0.44 ± 0.15	**0.029**	0.52 ± 0.19	0.47 ± 0.17	**0.001**
Superior Mean	0.16 ± 0.05	0.13 ± 0.04	**0.006**	0.17 ± 0.06	0.15 ± 0.05	**0.005**
Superior SD	0.14 ± 0.04	0.11 ± 0.04	**0.004**	0.14 ± 0.05	0.12 ± 0.04	**<0.001**
Inferior Max	0.77 ± 0.24	0.66 ± 0.24	**0.003**	0.79 ± 0.31	0.65 ± 0.25	**<0.001**
Inferior Mean	0.23 ± 0.08	0.18 ± 0.06	**<0.001**	0.22 ± 0.07	0.18 ± 0.07	**<0.001**
Inferior SD	0.21 ± 0.07	0.17 ± 0.06	**0.001**	0.21 ± 0.08	0.17 ± 0.07	**<0.001**
Anterior Max	1.73 ± 0.73	1.32 ± 0.56	**<0.001**	1.66 ± 0.53	1.29 ± 0.54	**<0.001**
Anterior Mean	0.45 ± 0.19	0.33 ± 0.12	**0.001**	0.42 ± 0.12	0.33 ± 0.12	**<0.001**
Anterior SD	0.50 ± 0.22	0.35 ± 0.16	**0.001**	0.47 ± 0.17	0.34 ± 0.16	**<0.001**
Posterior Max	1.18 ± 0.41	1.10 ± 0.38	0.101	1.15 ± 0.36	1.13 ± 0.35	0.528
Posterior Mean	0.31 ± 0.08	0.28 ± 0.07	**0.021**	0.31 ± 0.08	0.28 ± 0.07	**<0.001**
Right Max	0.63 ± 0.21	0.50 ± 0.19	**0.001**	0.59 ± 0.20	0.50 ± 0.18	**<0.001**
Right Mean	0.18 ± 0.06	0.14 ± 0.05	**<0.001**	0.18 ± 0.06	0.15 ± 0.06	**<0.001**
Right SD	0.17 ± 0.06	0.12 ± 0.05	**<0.001**	0.15 ± 0.05	0.12 ± 0.05	**<0.001**
Left Max	0.72 ± 0.26	0.65 ± 0.23	**0.021**	0.75 ± 0.32	0.63 ± 0.25	**<0.001**
Left Mean	0.24 ± 0.08	0.20 ± 0.07	**0.001**	0.24 ± 0.11	0.20 ± 0.08	**<0.001**
Left SD	0.22 ± 0.09	0.19 ± 0.08	**0.001**	0.23 ± 0.10	0.18 ± 0.08	**<0.001**

Table 5.5. Mean and SD of left shank accelerometer variables with a significant (p < 0.05) ANOVA result for retrospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	39.9 ± 14.5	30.0 ± 11.6	**0.001**	36.9 ± 12.7	29.6 ± 10.9	**<0.001**
AP	30.4 ± 11.3	22.4 ± 8.2	**0.004**	27.8 ± 8.4	21.6 ± 7.4	**<0.001**
ML	26.9 ± 11.6	19.4 ± 7.6	**0.005**	24.0 ± 8.4	18.8 ± 6.9	**<0.001**
Maximum Lyapunov Exponent						
ML	0.32 ± 0.17	0.33 ± 0.16	0.932	0.38 ± 0.16	0.29 ± 0.14	**<0.001**
Acceleration Descriptive Statistics (g)						
Superior Max	0.68 ± 0.26	0.52 ± 0.18	**0.002**	0.71 ± 0.32	0.58 ± 0.26	**<0.001**
Superior Mean	0.20 ± 0.05	0.15 ± 0.04	**<0.001**	0.21 ± 0.07	0.17 ± 0.06	**<0.001**
Superior SD	0.19 ± 0.07	0.13 ± 0.05	**<0.001**	0.20 ± 0.09	0.15 ± 0.08	**<0.001**
Inferior Max	0.85 ± 0.25	0.72 ± 0.24	**0.001**	0.84 ± 0.28	0.76 ± 0.24	**<0.001**
Inferior Mean	0.23 ± 0.06	0.18 ± 0.07	**0.001**	0.22 ± 0.07	0.18 ± 0.06	**<0.001**
Inferior SD	0.22 ± 0.07	0.18 ± 0.07	**<0.001**	0.22 ± 0.08	0.18 ± 0.06	**<0.001**
Anterior Max	1.69 ± 0.66	1.19 ± 0.43	**<0.001**	1.55 ± 0.42	1.25 ± 0.43	**<0.001**
Anterior Mean	0.48 ± 0.23	0.32 ± 0.14	**<0.001**	0.44 ± 0.13	0.33 ± 0.11	**<0.001**
Anterior SD	0.51 ± 0.23	0.33 ± 0.14	**<0.001**	0.46 ± 0.13	0.34 ± 0.13	**<0.001**
Posterior Max	1.02 ± 0.36	0.87 ± 0.26	**0.016**	1.00 ± 0.29	0.99 ± 0.34	0.347
Posterior Mean	0.29 ± 0.10	0.22 ± 0.07	**<0.001**	0.28 ± 0.07	0.25 ± 0.08	**<0.001**
Posterior SD	0.28 ± 0.09	0.23 ± 0.07	**<0.001**	0.27 ± 0.08	0.26 ± 0.09	0.044
Right Max	0.71 ± 0.23	0.64 ± 0.21	0.037	0.71 ± 0.23	0.67 ± 0.23	0.039
Right Mean	0.21 ± 0.06	0.18 ± 0.05	**0.007**	0.20 ± 0.06	0.18 ± 0.05	**<0.001**
Right SD	0.22 ± 0.07	0.19 ± 0.07	**0.019**	0.21 ± 0.07	0.19 ± 0.07	**0.005**
Left Max	0.79 ± 0.31	0.64 ± 0.28	**<0.001**	0.80 ± 0.33	0.66 ± 0.28	**<0.001**
Left Mean	0.23 ± 0.07	0.17 ± 0.06	**<0.001**	0.22 ± 0.08	0.18 ± 0.06	**<0.001**
Left SD	0.21 ± 0.09	0.15 ± 0.08	**<0.001**	0.21 ± 0.09	0.16 ± 0.08	**<0.001**

Table 5.6. Summary of accelerometer variables with significant differences between ST and DT gait conditions for retrospective fallers

Locations	Variables with Significant Differences	DT versus ST
Head Pelvis Left Shank Right Shank	Vertical FFT quartiles Posterior mean	DT < ST
Head Pelvis Left Shank	Posterior maximum, SD	DT < ST
Pelvis Left Shank Right Shank	Superior maximum, mean, SD Inferior maximum, mean, SD Anterior maximum, mean, SD Right mean, SD Left maximum, mean, SD	DT < ST
Pelvis Right Shank	Right maximum	DT < ST
Left Shank Right Shank	AP FFT quartiles ML FFT quartiles	DT < ST
Head	Vertical Ratio of even to odd harmonics (REOH)	DT < ST

Table 5.7. Summary of accelerometer variables with significant differences between ST and DT gait conditions for retrospective non-fallers

Locations	Variables with Significant Differences	DT versus ST
Head Pelvis Left Shank Right Shank	Vertical FFT quartiles ML FFT quartiles Anterior mean	DT < ST
Head Left Shank Right Shank	AP FFT quartiles	DT < ST
Pelvis Left Shank Right Shank	Superior maximum, mean, SD Inferior maximum, mean, SD Anterior maximum, SD Posterior mean Right mean, SD Left maximum, mean, SD	DT < ST
Head Pelvis	Vertical Ratio of even to odd harmonics (REOH) AP Ratio of even to odd harmonics (REOH)	DT < ST
Pelvis Right Shank	Right maximum	DT < ST
Head	Superior maximum, mean, SD Right maximum, mean, SD	DT > ST
Pelvis	Posterior maximum, SD	DT < ST
Left Shank	ML Maximum Lyapunov exponents (MLEs)	DT < ST

5.3.1.2 Prospective Fall Occurrence

5.3.1.2.1 Pressure-sensing insole measures

For PF, DT parameters were significantly greater than ST for PD per stride, ML deviation duration, stride time, stance time, swing time, stride time CoV, stride time symmetry index, I1, I4, I6, and I7 (Table 5.8). DT parameters were significantly lower than ST for minimum, mean, and median CoP velocity; cadence; and I2.

For PNF, DT parameters were significantly greater than ST for PD per stride, ML deviation duration, stride time, stance time, swing time, stride time CoV, stride time symmetry index, CoV AP, CoV ML, I1, I4, I5, I6, and I7 (Table 5.8). DT parameters were significantly lower than ST for minimum, mean, and median CoP velocity; and cadence.

Table 5.8. Mean and SD of pressure-sensing insole variables with a significant (p < 0.05) ANOVA result for prospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
CoP Path						
PD per Stride	1.8 ± 2.7	2.6 ± 3.1	**<0.001**	1.5 ± 2.0	2.5 ± 2.1	**<0.001**
Lateral Deviation Length (mm)	0.9 ± 0.6	1.1 ± 0.7	0.165	1.0 ± 1.2	1.4 ± 1.4	0.051
ML Deviation Duration (s)	0.029 ± 0.013	0.038 ± 0.014	**0.029**	0.031 ± 0.015	0.037 ± 0.017	**0.019**
Min CoP Vel (m/s)	0.028 ± 0.010	0.021 ± 0.009	**0.001**	0.031 ± 0.012	0.023 ± 0.010	**<0.001**
Mean CoP Vel (m/s)	0.284 ± 0.038	0.249 ± 0.044	**<0.001**	0.293 ± 0.048	0.250 ± 0.049	**<0.001**
Median CoP Vel (m/s)	0.247 ± 0.034	0.208 ± 0.035	**<0.001**	0.250 ± 0.041	0.213 ± 0.047	**<0.001**
Temporal						
Cadence (steps/minute)	109.6 ± 10.0	98.4 ± 12.9	**<0.001**	111.9 ± 10.5	96.4 ± 14.9	**<0.001**
Stride Time (s)	1.11 ± 0.10	1.24 ± 0.18	**<0.001**	1.09 ± 0.11	1.28 ± 0.21	**<0.001**
Stance Time (s)	0.73 ± 0.09	0.83 ± 0.13	**<0.001**	0.72 ± 0.09	0.84 ± 0.15	**<0.001**
Swing Time (s)	0.38 ± 0.05	0.42 ± 0.07	**<0.001**	0.37 ± 0.06	0.44 ± 0.07	**<0.001**
Stride Time CoV	0.03 ± 0.03	0.04 ± 0.02	**0.031**	0.03 ± 0.01	0.04 ± 0.02	**<0.001**
Stride Time Symmetry Index	2.13 ± 1.14	2.95 ± 1.79	**0.005**	2.18 ± 1.41	2.86 ± 1.50	**0.026**
CoP Path Stance Phase CoV						
CoV AP	4.90 ± 1.63	5.22 ± 1.42	0.248	4.48 ± 1.54	6.17 ± 2.21	**<0.001**
CoV ML	6.57 ± 2.44	7.39 ± 2.60	0.059	6.66 ± 2.33	7.70 ± 2.96	**0.007**
Impulse (Ns/kg)						
Foot-strike to first peak (I1)	1.22 ± 0.41	1.40 ± 0.52	**0.009**	1.20 ± 0.50	1.50 ± 0.66	**<0.001**
First peak to min (I2)	1.22 ± 0.48	1.10 ± 0.49	**0.004**	1.27 ± 0.49	1.24 ± 0.51	0.435
Min to second peak (I3)	1.83 ± 0.66	1.95 ± 0.79	0.219	1.58 ± 0.61	1.68 ± 0.63	0.111
Second peak to foot-off (I4)	1.14 ± 0.41	1.43 ± 0.71	**0.014**	1.05 ± 0.49	1.41 ± 0.85	**<0.001**
Foot-strike to min (I5)	2.36 ± 0.79	2.42 ± 0.86	0.554	2.44 ± 0.99	2.66 ± 0.90	**0.001**
Min to foot-off (I6)	2.89 ± 1.00	3.30 ± 1.24	**0.009**	2.56 ± 0.98	3.01 ± 1.30	**<0.001**
Foot-strike to foot-off (I7)	5.19 ± 1.62	5.66 ± 1.89	**0.026**	4.89 ± 1.74	5.61 ± 2.01	**<0.001**

5.3.1.2.2 Accelerometer measures

For PF and PNF, significant differences were found between DT and ST gait conditions (Table 5.9 to Table 5.12). These differences are summarized in Table 5.13 for fallers and Table 5.14 for non-fallers.

Table 5.9. Mean and SD of head accelerometer variables with a significant ($p < 0.05$) ANOVA result for prospective fallers and non-fallers. Bold *p*-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	45.0 ± 13.0	37.6 ± 10.0	**0.009**	46.4 ± 13.7	39.3 ± 12.9	**<0.001**
AP	50.4 ± 9.9	44.0 ± 7.3	**0.011**	53.5 ± 10.5	49.3 ± 10.4	**<0.001**
ML	56.3 ± 10.1	50.5 ± 10.8	0.065	54.7 ± 12.4	50.6 ± 11.1	0.033
Ratio of Even to Odd Harmonics						
Vertical	2.17 ± 0.58	1.99 ± 0.94	0.210	2.17 ± 1.12	1.77 ± 0.92	0.033
AP	1.90 ± 0.78	1.45 ± 0.63	0.033	1.60 ± 0.83	1.50 ± 0.61	0.420
Maximum Lyapunov Exponent						
ML	0.24 ± 0.09	0.30 ± 0.10	0.088	0.25 ± 0.09	0.27 ± 0.12	0.391
Acceleration Descriptive Statistics (g)						
Superior Max	0.27 ± 0.08	0.33 ± 0.08	**0.001**	0.23 ± 0.07	0.29 ± 0.09	**0.001**
Superior Mean	0.11 ± 0.04	0.13 ± 0.03	**0.002**	0.10 ± 0.03	0.12 ± 0.03	**0.005**
Superior SD	0.07 ± 0.02	0.08 ± 0.02	**0.006**	0.06 ± 0.02	0.08 ± 0.02	**0.005**
Anterior Mean	0.14 ± 0.07	0.11 ± 0.05	0.106	0.15 ± 0.06	0.12 ± 0.06	**0.014**
Right Max	0.27 ± 0.10	0.29 ± 0.10	0.179	0.25 ± 0.12	0.30 ± 0.12	**0.003**
Right Mean	0.11 ± 0.05	0.13 ± 0.05	0.084	0.11 ± 0.05	0.13 ± 0.05	**0.004**
Right SD	0.07 ± 0.02	0.08 ± 0.03	0.151	0.07 ± 0.03	0.08 ± 0.03	**0.002**

Table 5.10. Mean and SD of posterior pelvis accelerometer variables with a significant ($p < 0.05$) ANOVA result for prospective fallers and non-fallers. Bold *p*-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			Non-Fallers		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	32.9 ± 10.6	26.3 ± 9.4	0.014	34.8 ± 10.0	26.5 ± 9.1	**<0.001**
AP	40.7 ± 8.5	37.4 ± 7.8	0.076	43.0 ± 9.8	40.0 ± 7.9	0.072
ML	32.7 ± 11.4	29.5 ± 9.6	0.072	34.1 ± 10.6	29.3 ± 10.3	**0.003**
Ratio of Even to Odd Harmonics						
Vertical	2.20 ± 0.84	2.00 ± 0.74	0.151	2.25 ± 0.85	1.94 ± 0.79	0.071
AP	2.11 ± 0.76	1.86 ± 0.77	0.088	2.23 ± 0.86	1.90 ± 0.67	**0.037**
Maximum Lyapunov Exponent						
ML	0.28 ± 0.12	0.24 ± 0.10	0.295	0.25 ± 0.11	0.21 ± 0.10	**0.037**
Acceleration Descriptive Statistics (g)						
Superior Max	0.32 ± 0.08	0.30 ± 0.09	0.569	0.31 ± 0.10	0.28 ± 0.10	**0.011**
Superior Mean	0.11 ± 0.03	0.09 ± 0.03	**0.013**	0.11 ± 0.03	0.09 ± 0.03	**0.001**
Superior SD	0.08 ± 0.02	0.07 ± 0.02	0.045	0.08 ± 0.02	0.07 ± 0.02	**<0.001**
Inferior Max	0.45 ± 0.09	0.41 ± 0.14	0.029	0.44 ± 0.13	0.37 ± 0.15	**<0.001**
Inferior Mean	0.15 ± 0.03	0.14 ± 0.04	**0.023**	0.16 ± 0.05	0.13 ± 0.05	**<0.001**
Inferior SD	0.12 ± 0.02	0.11 ± 0.03	0.032	0.12 ± 0.03	0.10 ± 0.04	**<0.001**
Anterior Max	0.42 ± 0.12	0.37 ± 0.12	**0.004**	0.48 ± 0.17	0.38 ± 0.14	**<0.001**
Anterior Mean	0.15 ± 0.04	0.13 ± 0.04	**0.020**	0.17 ± 0.06	0.14 ± 0.04	**<0.001**
Anterior SD	0.12 ± 0.03	0.10 ± 0.03	**0.001**	0.13 ± 0.05	0.10 ± 0.04	**<0.001**
Posterior Max	0.31 ± 0.10	0.27 ± 0.08	**0.018**	0.28 ± 0.12	0.25 ± 0.11	**0.028**
Posterior Mean	0.12 ± 0.03	0.10 ± 0.03	**0.004**	0.11 ± 0.05	0.10 ± 0.04	**0.011**
Posterior SD	0.08 ± 0.02	0.07 ± 0.02	**0.015**	0.07 ± 0.03	0.06 ± 0.03	**0.005**
Right Max	0.40 ± 0.11	0.37 ± 0.15	0.053	0.38 ± 0.13	0.31 ± 0.12	**<0.001**
Right Mean	0.13 ± 0.03	0.12 ± 0.04	0.050	0.13 ± 0.04	0.10 ± 0.03	**<0.001**
Right SD	0.11 ± 0.03	0.10 ± 0.05	**0.021**	0.10 ± 0.03	0.08 ± 0.03	**<0.001**
Left Max	0.40 ± 0.08	0.36 ± 0.09	0.068	0.39 ± 0.13	0.33 ± 0.14	**<0.001**
Left Mean	0.13 ± 0.03	0.11 ± 0.03	**0.005**	0.13 ± 0.04	0.10 ± 0.04	**<0.001**
Left SD	0.10 ± 0.02	0.09 ± 0.02	**0.020**	0.10 ± 0.03	0.08 ± 0.03	**<0.001**

Table 5.11. Mean and SD of right shank accelerometer variables with a significant ($p < 0.05$) ANOVA result for prospective fallers and non-fallers. Bold p-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	38.6 ± 11.4	29.9 ± 10.2	**0.006**	39.3 ± 12.7	30.2 ± 10.9	**<0.001**
AP	27.3 ± 8.1	20.7 ± 6.0	**0.005**	29.9 ± 8.8	22.1 ± 7.6	**<0.001**
ML	25.9 ± 7.6	20.0 ± 6.3	**0.002**	28.2 ± 8.0	21.3 ± 6.4	**<0.001**
Maximum Lyapunov Exponent						
AP	0.50 ± 0.15	0.43 ± 0.13	0.059	0.48 ± 0.15	0.43 ± 0.15	0.058
Acceleration Descriptive Statistics (g)						
Superior Max	0.47 ± 0.18	0.46 ± 0.16	0.762	0.56 ± 0.19	0.48 ± 0.17	**<0.001**
Superior Mean	0.15 ± 0.04	0.14 ± 0.04	0.600	0.18 ± 0.06	0.15 ± 0.05	**0.010**
Superior SD	0.12 ± 0.04	0.12 ± 0.04	0.189	0.15 ± 0.05	0.12 ± 0.05	**<0.001**
Inferior Max	0.74 ± 0.32	0.65 ± 0.27	**0.014**	0.82 ± 0.31	0.65 ± 0.24	**<0.001**
Inferior Mean	0.21 ± 0.08	0.18 ± 0.07	**0.001**	0.22 ± 0.07	0.18 ± 0.07	**<0.001**
Inferior SD	0.20 ± 0.09	0.16 ± 0.07	**0.001**	0.22 ± 0.08	0.17 ± 0.07	**<0.001**
Anterior Max	1.58 ± 0.44	1.32 ± 0.40	**0.004**	1.71 ± 0.58	1.26 ± 0.60	**<0.001**
Anterior Mean	0.40 ± 0.08	0.33 ± 0.08	**0.001**	0.44 ± 0.14	0.32 ± 0.13	**<0.001**
Anterior SD	0.44 ± 0.13	0.34 ± 0.12	**0.001**	0.49 ± 0.18	0.34 ± 0.18	**<0.001**
Posterior Mean	0.29 ± 0.07	0.28 ± 0.06	0.412	0.31 ± 0.09	0.28 ± 0.08	**<0.001**
Right Max	0.57 ± 0.20	0.47 ± 0.16	**0.007**	0.61 ± 0.21	0.51 ± 0.19	**<0.001**
Right Mean	0.17 ± 0.05	0.14 ± 0.05	**0.011**	0.18 ± 0.06	0.15 ± 0.06	**0.001**
Right SD	0.15 ± 0.05	0.12 ± 0.04	**0.002**	0.16 ± 0.06	0.13 ± 0.05	**<0.001**
Left Max	0.71 ± 0.33	0.64 ± 0.27	0.068	0.77 ± 0.31	0.62 ± 0.24	**<0.001**
Left Mean	0.23 ± 0.11	0.20 ± 0.09	**0.019**	0.25 ± 0.10	0.19 ± 0.07	**<0.001**
Left SD	0.22 ± 0.12	0.18 ± 0.09	**0.002**	0.24 ± 0.10	0.18 ± 0.08	**<0.001**

Table 5.12. Mean and SD of left shank accelerometer variables with a significant ($p < 0.05$) ANOVA result for prospective fallers and non-fallers. Bold *p*-values indicate a significant difference between ST and DT conditions after correction for multiple comparisons.

	Fallers			**Non-Fallers**		
	ST	**DT**	***p***	**ST**	**DT**	***p***
FFT Quartile (%)						
Vertical	34.8 ± 12.9	28.9 ± 11.7	0.046	37.9 ± 12.7	29.6 ± 10.3	**<0.001**
AP	26.4 ± 8.3	20.8 ± 7.0	**0.005**	28.4 ± 8.3	21.6 ± 7.1	**<0.001**
ML	21.5 ± 7.4	17.3 ± 4.9	0.056	25.3 ± 8.6	19.5 ± 7.6	**<0.001**
Ratio of Even to Odd Harmonics						
Vertical	1.27 ± 0.43	1.11 ± 0.25	0.056	1.17 ± 0.31	1.22 ± 0.40	0.482
Maximum Lyapunov Exponent						
AP	0.48 ± 0.16	0.38 ± 0.16	**0.011**	0.45 ± 0.13	0.43 ± 0.15	0.544
ML	0.38 ± 0.17	0.27 ± 0.14	**0.003**	0.37 ± 0.16	0.30 ± 0.15	**0.010**
Acceleration Descriptive Statistics (g)						
Superior Max	0.70 ± 0.34	0.60 ± 0.26	**0.015**	0.71 ± 0.31	0.56 ± 0.26	**<0.001**
Superior Mean	0.20 ± 0.06	0.17 ± 0.05	**0.004**	0.21 ± 0.08	0.17 ± 0.06	**<0.001**
Superior SD	0.19 ± 0.09	0.16 ± 0.07	**0.005**	0.20 ± 0.09	0.15 ± 0.08	**<0.001**
Inferior Max	0.82 ± 0.28	0.75 ± 0.23	**0.027**	0.85 ± 0.28	0.76 ± 0.26	**0.001**
Inferior Mean	0.20 ± 0.06	0.18 ± 0.05	**0.003**	0.22 ± 0.07	0.18 ± 0.06	**<0.001**
Inferior SD	0.21 ± 0.07	0.18 ± 0.06	**0.003**	0.23 ± 0.08	0.18 ± 0.07	**<0.001**
Anterior Max	1.49 ± 0.45	1.22 ± 0.40	**0.001**	1.58 ± 0.41	1.25 ± 0.45	**<0.001**
Anterior Mean	0.42 ± 0.11	0.32 ± 0.10	**<0.001**	0.45 ± 0.14	0.33 ± 0.12	**<0.001**
Anterior SD	0.44 ± 0.15	0.34 ± 0.13	**<0.001**	0.47 ± 0.13	0.34 ± 0.14	**<0.001**
Posterior Mean	0.28 ± 0.06	0.24 ± 0.06	**<0.001**	0.28 ± 0.08	0.26 ± 0.09	**0.008**
Posterior SD	0.27 ± 0.08	0.25 ± 0.07	**0.011**	0.27 ± 0.08	0.27 ± 0.10	0.516
Right Mean	0.21 ± 0.07	0.19 ± 0.05	0.068	0.20 ± 0.05	0.18 ± 0.05	**<0.001**
Right SD	0.22 ± 0.09	0.20 ± 0.07	0.065	0.21 ± 0.06	0.19 ± 0.07	**0.039**
Left Max	0.78 ± 0.33	0.67 ± 0.25	**0.010**	0.82 ± 0.33	0.65 ± 0.29	**<0.001**
Left Mean	0.20 ± 0.07	0.17 ± 0.06	**0.005**	0.23 ± 0.09	0.18 ± 0.07	**<0.001**
Left SD	0.20 ± 0.08	0.16 ± 0.07	**0.004**	0.22 ± 0.10	0.16 ± 0.08	**<0.001**

Table 5.13. Summary of accelerometer variables with significant differences between ST and DT gait conditions for prospective fallers

Locations	**Variables with Significant Differences**	**DT versus ST**
Head Left Shank Right Shank	AP FFT Quartile	DT < ST
Pelvis Left Shank Right Shank	Inferior mean Anterior maximum, mean, SD Left mean, SD	DT < ST
Head Right Shank	Vertical FFT Quartile	DT < ST
Pelvis Left Shank	Superior mean Posterior mean, SD	DT < ST
Pelvis Right Shank	Right SD	DT < ST
Left Shank Right Shank	Inferior maximum, SD	DT < ST
Head	Superior maximum, mean, SD	DT > ST
Pelvis	Posterior maximum	DT < ST
Right Shank	ML FFT Quartile Right maximum, mean Left maximum	DT < ST
Left Shank	AP Maximum Lyapunov exponents (MLEs) ML Maximum Lyapunov exponents (MLEs) Superior maximum, SD	DT < ST

Table 5.14. Summary of accelerometer variables with significant differences between ST and DT gait conditions for prospective non-fallers

Locations	Variables with Significant Differences	DT versus ST
Head Pelvis Left Shank Right Shank	Vertical FFT Quartile Anterior mean	DT < ST
Head Left Shank Right Shank	AP FFT Quartile	DT < ST
Pelvis Left Shank Right Shank	ML FFT Quartile Superior maximum, mean, SD Inferior maximum, mean, SD Anterior maximum, SD Posterior mean Right mean, SD Left maximum, mean, SD	DT < ST
Pelvis Left Shank	ML Maximum Lyapunov exponents (MLEs)	DT < ST
Pelvis Right Shank	Right maximum	DT < ST
Head	Superior maximum, mean, SD Right maximum, mean, SD	DT > ST
Pelvis	AP Ratio of even to odd harmonics (REOH) Posterior maximum, SD	DT < ST

5.3.2 Gait Differences between Fallers and Non-Fallers under Single-Task and Dual-Task Conditions

5.3.2.1 Retrospective Fall Occurrence

Significant differences were found between fallers and non-fallers for the head and posterior pelvis accelerometers. No other accelerometer locations had significant differences between fallers and non-fallers. Fallers had significantly greater head posterior standard deviation (p = 0.025) for ST gait. Fallers also had significantly decreased posterior pelvis AP REOH (p = 0.023) for ST gait and significantly greater posterior pelvis vertical MLE (p = 0.017) for DT gait.

For pressure-sensing insole measures, no significant differences were found between RF and RNF for both DT and ST gait data.

5.3.2.2 Prospective Fall Occurrence

Significant differences were found in accelerometer measures between fallers and non-fallers. For the head accelerometer, AP FFT quartile was significantly lower (p = 0.011) for fallers than non-fallers for DT gait. For the left shank accelerometer, ML FFT quartile was significantly lower (p = 0.045) for fallers than non-fallers for ST gait. For the right shank accelerometer, superior maximum was significantly lower (p = 0.041) for fallers than non-fallers for ST gait.

For pressure-sensing insoles, fallers had significantly lower CoV AP (p = 0.046) than non-fallers for DT gait. No significant differences were found between fallers and non-fallers for ST gait.

5.3.3 Correlations between Wearable Sensor-derived Parameters and Gait Velocity

For all participant groups (PF, PNF, RF, RNF), DT gait velocity was significantly lower ($p \leq 0.001$) than ST gait velocity. For PF, DT gait velocity (0.95 ± 0.21 m/s) was significantly lower ($p < 0.001$) than ST (1.17 ± 0.16 m/s). For PNF, DT gait velocity (0.95 ± 0.23 m/s) was also significantly lower ($p < 0.001$) than ST (1.22 ± 0.23 m/s). For RF, DT gait velocity (0.95 ± 0.28 m/s) was significantly lower (p = 0.001) than ST (1.24 ± 0.28 m/s). For RNF, DT gait velocity (0.95 ± 0.23 m/s) was also significantly lower ($p < 0.001$) than ST (1.20 ± 0.21 m/s). No significant differences were found between RF and RNF or between PF and PNF for ST or DT gait velocity ($p \geq 0.261$). Table 5.15 reports correlations between gait velocity and pressure-sensing insole and accelerometer measures.

Table 5.15. Correlations (R^2) between wearable sensor measures and gait velocity for ST and DT gait for all (n = 100) participants. Negligible (≤ 0.3), low (0.3 – 0.5), moderate (0.5 - 0.7), and high (0.7 – 0.9) correlation levels were determined [306]. * indicates a negative correlation to gait velocity.

Wearable Sensor	ST	DT
Pressure-Sensing Insole	**Low** Mean CoP Velocity (0.496) Median CoP Velocity (0.355) Cadence (0.354) **Negligible** I4 (0.250)* I1 (0.244)* I6 (0.133)* I7 (0.119)* Maximum CoP Velocity (0.065) Minimum CoP Velocity (0.054)	**Moderate** Cadence (0.581) Median CoP Velocity (0.531) Mean CoP Velocity (0.526) I4 (0.418)* I1 (0.416)* **Negligible** I7 (0.276)* I6 (0.244)* Minimum CoP Velocity (0.221) I5 (0.202)*

	I5 (0.053)* I3 (0.046)* ML CoV (0.036) ML Deviation Duration (0.016)* Posterior Deviations per Stride (0.016)* ML Deviations per Stride (0.014) AP CoV (0.004)* Lateral Deviation Length (0.003)* Posterior Deviation Duration (0.003)* Posterior Deviation Length (0.001) Medial Deviation Length (0.001) I2 (<0.001)	Posterior Deviations per Stride (0.143)* ML Deviation Duration (0.137)* AP CoV (0.115)* I3 (0.028)* Lateral Deviation Length (0.022)* Medial Deviation Length (0.012)* Posterior Deviation Length (0.001) Posterior Deviation Duration (0.001)* I2 (<0.001) ML Deviations per Stride (<0.001)* ML CoV (<0.001) Maximum CoP Velocity (<0.001)
Head Accelerometer	**Moderate** Vertical FFT Quartile (0.552) **Negligible** ML FFT Quartile (0.267) AP FFT Quartile (0.265) Anterior Standard Deviation (0.258) Inferior Maximum (0.236) Inferior Standard Deviation (0.236) Posterior Mean (0.227) Inferior Mean (0.214) Anterior Maximum (0.176) Left Standard Deviation (0.167) Posterior Standard Deviation (0.165) Anterior Mean (0.144) Left Maximum (0.116) Posterior Maximum (0.115) Right Standard Deviation (0.088) Right Maximum (0.073) Left Mean (0.069) Superior Standard Deviation (0.039) Superior Maximum (0.032) Right Mean (0.028) Superior Mean (0.015) Vertical MLE (0.009) AP Harmonic Ratio (0.009)* AP MLE (0.008)* ML Harmonic Ratio (0.005) ML MLE (0.005) Vertical Harmonic Ratio (<0.001)	**Low** Posterior Standard Deviation (0.335) Vertical FFT Quartile (0.333) **Negligible** Left Standard Deviation (0.284) Posterior Mean (0.270) Inferior Mean (0.247) Posterior Maximum (0.245) Inferior Standard Deviation (0.223) Inferior Maximum (0.213) Left Maximum (0.209) Anterior Standard Deviation (0.147) Left Mean (0.137) Vertical Harmonic Ratio (0.114) Right Standard Deviation (0.106) AP FFT Quartile (0.099) Anterior Mean (0.091) Superior Maximum (0.074) Anterior Maximum (0.073) Right Maximum (0.070) ML FFT Quartile (0.059) ML MLE (0.059)* Superior Standard Deviation (0.057) AP Harmonic Ratio (0.054) Vertical MLE (0.039) AP MLE (0.017)* Right Mean (0.015) Superior Mean (0.009) ML Harmonic Ratio (0.002)*
Pelvis Accelerometer	**Low** Vertical FFT Quartile (0.457) Left Mean (0.403) Inferior Mean (0.399) Anterior Mean (0.374) Right Mean (0.360) Anterior Standard Deviation (0.357) Anterior Maximum (0.345) **Negligible** Inferior Maximum (0.291) Inferior Standard Deviation (0.285) Left Standard Deviation (0.276) Posterior Standard Deviation (0.252) Right Standard Deviation (0.249) Posterior Maximum (0.243)	**Moderate** Anterior Standard Deviation (0.565) Anterior Mean (0.536) Anterior Maximum (0.503) **Low** Left Mean (0.456) Left Standard Deviation (0.435) Inferior Mean (0.393) Inferior Standard Deviation (0.384) Superior Standard Deviation (0.374) Left Maximum (0.370) Inferior Maximum (0.357) Vertical FFT Quartile (0.353) Right Mean (0.319) Right Standard Deviation (0.315)

	Superior Mean (0.234) Left Maximum (0.232) Right Maximum (0.219) Posterior Mean (0.208) Superior Standard Deviation (0.188) Superior Maximum (0.186) AP FFT Quartile (0.067) ML FFT Quartile (0.039) AP MLE (0.018)* Vertical MLE (0.009) ML MLE (0.007) Vertical Harmonic Ratio (0.007) ML Harmonic Ratio (0.005) AP Harmonic Ratio (0.003)	**Negligible** Superior Maximum (0.295) Superior Mean (0.272) Posterior Standard Deviation (0.269) Posterior Maximum (0.254) Right Maximum (0.230) Posterior Mean (0.202) Vertical Harmonic Ratio (0.140) AP Harmonic Ratio (0.106) ML MLE (0.030) ML Harmonic Ratio (0.023)* ML FFT Quartile (0.015)* Vertical MLE (0.008) AP FFT Quartile (0.001) AP MLE (<0.001)
Right Shank Accelerometer	**Moderate** Anterior Mean (0.609) Anterior Standard Deviation (0.504) **Low** Right Standard Deviation (0.449) Anterior Maximum (0.442) Vertical FFT Quartile (0.425) Right Mean (0.380) ML FFT Quartile (0.355) AP FFT Quartile (0.316) Inferior Mean (0.305) Right Maximum (0.302) **Negligible** Inferior Standard Deviation (0.237) Posterior Mean (0.216) Inferior Maximum (0.173) Superior Standard Deviation (0.158) Posterior Maximum (0.150) Left Mean (0.118) Left Maximum (0.117) Superior Maximum (0.116) Posterior Standard Deviation (0.110) Left Standard Deviation (0.104) Superior Mean (0.101) AP Harmonic Ratio (0.070) ML Harmonic Ratio (0.068) ML MLE (0.027) Vertical Harmonic Ratio (0.025) Vertical MLE (0.020)* AP MLE (0.005)	**Moderate** Anterior Mean (0.650) Anterior Standard Deviation (0.550) Anterior Maximum (0.504) **Low** Right Standard Deviation (0.487) Inferior Mean (0.442) Right Mean (0.436) AP FFT Quartile (0.412) Inferior Standard Deviation (0.403) Vertical FFT Quartile (0.391) Right Maximum (0.373) Superior Standard Deviation (0.372) ML FFT Quartile (0.358) Inferior Maximum (0.355) Left Standard Deviation (0.354) Left Maximum (0.330) Left Mean (0.306) Superior Maximum (0.306) **Negligible** Posterior Mean (0.251) Superior Mean (0.207) Posterior Standard Deviation (0.129) Posterior Maximum (0.121) AP MLE (0.114) ML MLE (0.107) ML Harmonic Ratio (0.042) Vertical Harmonic Ratio (0.026) AP Harmonic Ratio (0.007) Vertical MLE (0.001)*
Left Shank Accelerometer	**Moderate** Anterior Standard Deviation (0.503) Anterior Mean (0.501) **Low** Anterior Maximum (0.486) Inferior Mean (0.456) Left Mean (0.450) Inferior Standard Deviation (0.422) Left Standard Deviation (0.403) Posterior Mean (0.398) Left Maximum (0.347)	**High** Anterior Mean (0.711) **Moderate** Anterior Standard Deviation (0.669) Anterior Maximum (0.566) Left Mean (0.528) Inferior Mean (0.515) **Low** Left Standard Deviation (0.464) Inferior Standard Deviation (0.449) Left Maximum (0.420)

	Inferior Maximum (0.333) Vertical FFT Quartile (0.306) **Negligible** AP FFT Quartile (0.250) Superior Standard Deviation (0.232) ML FFT Quartile (0.214) Superior Mean (0.214) Posterior Standard Deviation (0.191) Superior Maximum (0.191) Right Standard Deviation (0.163) Right Maximum (0.158) Right Mean (0.151) Posterior Maximum (0.142) Vertical MLE (0.017)* AP MLE (0.005)* AP Harmonic Ratio (0.005)* ML Harmonic Ratio (0.005) Vertical Harmonic Ratio (0.005) ML MLE (0.002)	Posterior Mean (0.307) Inferior Maximum (0.300) **Negligible** Superior Mean (0.269) Superior Standard Deviation (0.268) Vertical FFT Quartile (0.240) Superior Maximum (0.233) AP FFT Quartile (0.231) Right Standard Deviation (0.218) Right Mean (0.214) ML FFT Quartile (0.148) Posterior Standard Deviation (0.147) Right Maximum (0.128) Posterior Maximum (0.097) AP MLE (0.090) ML MLE (0.047) Vertical Harmonic Ratio (0.036) ML Harmonic Ratio (0.005) Vertical MLE (0.004)* AP Harmonic Ratio (<0.001)

5.4 Discussion of Wearable Sensor-based Single-Task and Dual-Task Gait Assessment

Wearable tri-axial accelerometers and pressure-sensing insoles could detect some differences between ST and DT gait in older adults. These differences included temporal and non-temporal parameters associated with impulse, movement frequency, abnormal foot movements, and body segment accelerations. For some measures, adding a cognitive load resulted in more variable and less stable gait, while other DT-related differences may represent elements of a conservative, compensatory gait strategy aimed at minimizing the impact of DT-induced dynamic stability alterations. Differences between fallers and non-fallers were related to gait variability and dynamic stability.

Wearable sensors detected some differences between prospective fallers and non-fallers. Prospective fallers had significantly smaller AP first quartile frequencies at the head during DT, and smaller ML first quartile frequencies at the left shank during ST compared to prospective non-fallers. Since there was less low frequency content, fallers likely had more numerous higher-frequency gait perturbations. These findings suggest that fallers exhibit dynamic stability issues related to high frequency gait perturbations that may increase their fall risk compared to non-fallers. However, CoV AP during DT was significantly lower for fallers than non-fallers, suggesting decreased faller CoP path variability at the foot-shoe interface. This suggests that fallers exhibit greater variability in body movements, such as at the pelvis and trunk, but lower variability at the foot-shoe interface, compared to non-fallers. Fallers also had lower maximum superior acceleration at the right shank during ST compared to non-fallers, which could also indicate reduced acceleration magnitude near the foot-shoe interface. Interestingly, gait speed, stride time CoV, and swing time CoV did not differ between fallers and non-fallers, while other studies used these measures to discriminate between fallers and non-fallers [31,32,255-259,307]. This could be due to differences between studies in the secondary task (physical vs. cognitive load, type of cognitive load) or older adult populations (community-dwelling, nursing home, disease population), which could also explain, in part, the lack of consensus on the usefulness of DT gait as a fall risk assessment tool. As suggested by Muir-Hunter and Wittwer, 2015 [253], differences in results and methodology between studies highlight the need to standardize DT assessment research, in part, by identifying the most appropriate secondary task [253].

Significant differences between older adult retrospective fallers and non-fallers did not coincide with the significant differences between prospective fallers and non-fallers. In particular, retrospective fallers exhibited significantly greater head posterior SD during ST, less posterior pelvis AP REOH during ST, and greater posterior pelvis vertical MLE during DT compared to retrospective non-fallers. All of these differences are indicative of greater variability and less stability in retrospective faller gait compared to non-faller gait. In the prospective analysis, greater variability and less stability were indicated in faller gait by lower AP FFT (head accelerometer, DT) and lower ML FFT (left shank accelerometer, ST) compared to non-faller gait. Differences between retrospective and prospective faller analyses could be due to the limitations of using retrospective fall occurrence: inaccurate recall of falls and changes to gait patterns that occur between the fall and assessment either in an attempt to increase stability or as a result of fear of falling. This difference between retrospective and prospective analyses could also be because the sub-group of participants in the prospective analysis did not have a recent history of falls (i.e., were RNF only). Detecting fallers without a recent history of falls could require a different subset of fall-risk sensitive variables, because this population is less likely to have a fear of falling and is more likely to be relatively healthy and fit compared to a population with a fall history (RF).

Greater gait variability and CoP path deviations during DT gait compared to ST, detected by the wearable sensor-derived measures, indicated that DT gait challenged walking stability.

The number of posterior CoP stance phase path deviations (retrospective and prospective analyses) and duration of ML CoP stance phase path deviations (retrospective and prospective analyses) were significantly greater during DT walking, for both fallers and non-fallers. Although CoP path length deviations from the expected path were relatively short, these deviations represented potential instabilities and could increase the risk of falls. For retrospective analysis, greater DT variability was also expressed by greater stride time symmetry index; and greater stance path, stride time, and swing time CoV; except for ML stance path CoV for fallers and swing time CoV for non-fallers. For prospective analysis, greater DT variability was expressed by greater stride time CoV, greater AP and ML stance path CoV (non-fallers only), and greater stride time symmetry index. Greater stride time variability [33,250] and swing time variability [30,31] have been reported previously. Stride and swing time variability under DT conditions have been linked to impaired executive function in Parkinsonian populations [308]. Stance path CoV may also be an appropriate DT gait variability indicator, with the advantage of separating AP and ML variability. Greater CoP path CoV was more pronounced in the AP than ML direction, suggesting greater AP than sideways instability. FFT first quartile frequency was lower during DT gait for both retrospective and prospective analyses, indicating less low frequency content with a cognitive load. REOH (proportion of acceleration in-phase with stride frequency) also was lower with a cognitive load, indicating greater gait variability. REOH was significantly lower in the retrospective analysis for fallers in the vertical direction at the head and non-fallers in the AP and vertical direction for the head and posterior pelvis. For prospective analysis, REOH was significantly lower with a cognitive load for non-fallers in the AP direction for the posterior pelvis. Thus, novel parameters derived from wearable pressure-sensing insoles and accelerometers can detect greater variability during DT walking.

Gait velocity, cadence, and all CoP stance velocity measures, except maximum CoP stance velocity, were lower under DT conditions for both retrospective and prospective analyses. Stride time, stance time, and swing time were greater for retrospective and prospective analyses. These temporal results agree with the literature [30,31,33-35,247-251]. The swing time results of the research in this thesis were similar to Wild et al., 2013 [251] but not Hausdorff et al., 2008 [30] and Springer et al., 2006 [31]. Body-weight normalized impulse increased with a cognitive load, for retrospective and prospective analyses, for all phases except I2 (first peak to minimum) and I3 (minimum to second peak). Since stance time increased (retrospective analysis: RF: 21%, RNF 15%; prospective analysis: PF: 14%, PNF: 17%) to a greater extent than overall impulse (I7, retrospective analysis: RF: 18%, RNF 12%; prospective analysis: PF: 9%, PNF: 15%), greater stance time was likely the main contributor to greater impulse during DT. These temporal and impulse changes with DT gait may be part of a compensatory, conservative gait strategy aimed at maintaining dynamic stability.

DT acceleration maximum, mean, and SD decreases occurred along all axes for all accelerometer locations, compared to ST, with only the head having instances of greater acceleration for DT compared to ST for both retrospective and prospective analyses (Table 5.6, Table 5.7, Table 5.13, and Table 5.14). During DT gait, greater head accelerations during DT gait may be due to non-gait related movements that accompany the cognitive task during particularly attention demanding periods (e.g., struggling to think of another word that starts with the desired letter, researcher prompts to continue with cognitive task). Lower SDs at the pelvis and shanks indicated less variability with a cognitive load. Lower acceleration variability may indicate the adoption of a conservative stiffening strategy, where body motions are reduced to minimize centre of mass deviations [309], as part of a DT compensatory strategy. In the prospective analysis, lower SDs occurred more consistently for non-fallers compared to fallers, with smaller SD measured at the pelvis, left shank, and right shank for all axes except posterior. This may indicate that non-fallers are better than fallers at compensating for the increased DT demands by reducing acceleration variability.

Since lower walking velocity is widely reported for DT gait, wearable-sensor-derived measures should be independent of lower gait velocity. One left shank measure (anterior mean acceleration, $R^2 = 0.711$) correlated highly to gait velocity. Five pressure sensing insole measures, one head accelerometer measure, three posterior pelvis measures, three right shank accelerometer measures, and five left shank accelerometer measures correlated moderately to gait velocity. Most measures had negligible correlations to gait velocity, indicating that most of the variability in these measures cannot be explained by gait velocity changes. Even for the few variables with non-negligible correlations to gait velocity, at least 29% of the variability cannot be explained by gait velocity changes. Since the wearable-sensor-derived measures provided information independent of lower gait velocity, these measures increase the understanding of DT-induced gait changes.

Cognitive task performance was not measured during DT performance. Therefore, participant prioritization of the cognitive or gait task could not be assessed and any inconsistencies in prioritization may have increased inter-individual variability. However, participants were encouraged to continue with the cognitive task when they visibly struggled or stopped listing words, preventing cognitive task abandonment. Individuals tend to prioritize motor tasks over cognitive tasks in DT scenarios [249,251], but prioritization across participants can vary, masking gait differences between fallers and non-fallers [310], and negatively affect fall risk prediction. Therefore, future studies should ensure that cognitive task performance is assessed during DT assessments. In addition to assessing single-task gait, single-task cognitive performance should also be evaluated to determine the dual task cost of the cognitive task.

The ST and DT gait assessment revealed potentially useful measures of DT gait changes, highlighting the necessity of investigating measures related to movement frequency and abnormal body segment movements. Greater gait variability under DT conditions was evident from greater posterior and ML CoP stance path deviations and CoV, and decreased FFT quartiles and REOH. Lower gait velocity and lower pelvis and shank acceleration SDs could represent compensatory gait strategies aimed at countering this greater gait variability and thus maintaining stability. Differences between PF and PNF related to movement frequency and variability were identified. New measures acquired from wearable sensors could be used in DT gait assessment in point-of-care environments to evaluate gait deficits related to executive function, particularly attention allocation.

Chapter 6 Fall Prediction Models based on Full Feature Sets derived from Wearable Sensor Gait Data

6.1 Objectives

The objectives of the research on fall-risk prediction modelling were to: identify the best wearable sensor type, location, and combination to be included in fall-risk classification and prediction models; determine whether ST or DT gait data provided the best data for faller/non-faller classification and prediction; evaluate naïve Bayesian classifiers, support vector machines, and neural networks as fall risk classifiers; and evaluate whether models based on wearable-sensor gait data outperform models based on clinical assessment data or posturography data for older adult fall-risk classification and prediction.

Outcomes from this research were published in PLOS One [311].

- Howcroft J, Lemaire ED, and Kofman J. Wearable-Sensor-Based Classification Models of Faller Status in Older Adults. PLOS One. 2016; 11(4): e0153240.

6.2 Methods

Three classifier models were assessed for fall risk predictive capability: multi-layer perceptron neural network (NN), naïve Bayesian (NB), and support vector machine (SVM). Retrospective and prospective fall occurrences were used separately as the classification criterion. For retrospective fall occurrence models, 75% of participant data (18 fallers, 57 non-fallers) were used for training and 25% were used for testing (6 fallers, 19 non-fallers). For prospective fall occurrence models, 75% of participant data (21 fallers, 35 non-fallers) were used for training and 25% were used for testing (7 fallers, 12 non-fallers). A holdout validation method was selected instead of a cross validation, because holdout validation may be more appropriate when predicting elderly fall risk with relatively small sample sizes and ensures that training data is completely independent from testing data [312].

All models were developed with the Matlab R2010a standard model algorithms. The Neural Network Pattern Recognition Toolbox was used for NN development and supervised backpropagation training was performed using the Neural Network Training tool. NN with 5, 10, 15, 20, and 25 nodes in a single hidden layer were evaluated. Neural networks between the best NN and the best of the two neighbouring NN were also evaluated. For example, if the 15-node

NN provided the best classification and the 20-node NN outperformed the 10-node NN, NN with 16, 17, 18, and 19 nodes were also evaluated. Other models included linear and quadratic discriminant NB models, and SVM with polynomial kernels with degrees one to seven.

In this section, fall prediction models were based on all gait variables derived from the wearable sensors, separately for ST and DT gait data. All possible sensor combinations (Table 6.1) were evaluated using all 146 parameters (30 pressure insole parameters, 29 accelerometer parameters at 4 body locations). In addition, models were developed with static posturography data (see Chapter 4.0) and clinical assessment data: ABC score, CHAMPS derived activity frequency and calorie expenditure, 6MWT distance, ST and DT walk times, fear of falling levels.

Model evaluation parameters included accuracy, specificity, sensitivity, positive predictive value (PPV), negative predictive value (NPV) [313], F1 score (harmonic mean of precision and sensitivity) [314], and Matthew's Correlation Coefficient (MCC) [315]. F1 score was calculated as:

$$F1 = \frac{2PPV \cdot sensitivity}{PPV + sensitivity} = \frac{2TP}{2TP + FP + FN} \quad , \qquad (6.1)$$

and MCC was calculated as:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad , \qquad (6.2)$$

where TP = true positive, TN = true negative, FP = false positive, and FN = false negative. A ranking method similar to Kendell et al., 2012 [316] was used to determine the best models. Each model evaluation parameter was ranked from best (1) to worst (n), and ranks for all model evaluation parameters were summed to identify the overall best model (lowest summed rank) (Figure 6.1).

Table 6.1. Summary of sensor combinations and total number of input parameters

Sensor Combination	Sensor Description	Total parameters
I	pressure insole	30
H	accelerometer (head)	29
P	accelerometer (pelvis)	29
LS	accelerometer (left shank)	29
RS	accelerometer (right shank)	29
H-P	accelerometer (head, pelvis)	58
H-LS	accelerometer (head, left shank)	58
H-RS	accelerometer (head, right shank)	58
P-LS	accelerometer (pelvis, left shank)	58
P-RS	accelerometer (pelvis, right shank)	58
LS-RS	accelerometer (left shank, right shank)	58
H-P-LS	accelerometer (head, pelvis, left shank)	87
H-P-RS	accelerometer (head, pelvis, right shank)	87
H-LS-RS	accelerometer (head, left shank, right shank)	87
P-LS-RS	accelerometer (pelvis, left shank, right shank)	87
H-P-LS-RS	accelerometer (head, pelvis, left shank, right shank)	116
I-H	pressure insole; accelerometer (head)	59
I-P	pressure insole; accelerometer (pelvis)	59
I-LS	pressure insole; accelerometer (left shank)	59
I-RS	pressure insole; accelerometer (right shank)	59
I-H-P	pressure insole; accelerometer (head, pelvis)	88
I-H-LS	pressure insole; accelerometer (head, left shank)	88
I-H-RS	pressure insole; accelerometer (head, right shank)	88
I-P-LS	pressure insole; accelerometer (pelvis, left shank)	88
I-P-RS	pressure insole; accelerometer (pelvis, right shank)	88
I-LS-RS	pressure insole; accelerometer (left shank, right shank)	88
I-H-P-LS	pressure insole; accelerometer (head, pelvis, left shank)	117
I-H-P-RS	pressure insole; accelerometer (head, pelvis, right shank)	117
I-H-LS-RS	pressure insole; accelerometer (head, left shank, right shank)	117
I-P-LS-RS	pressure insole; accelerometer (pelvis, left shank, right shank)	117
I-H-P-LS-RS	pressure insole; accelerometer (head, pelvis, left shank, right shank)	146

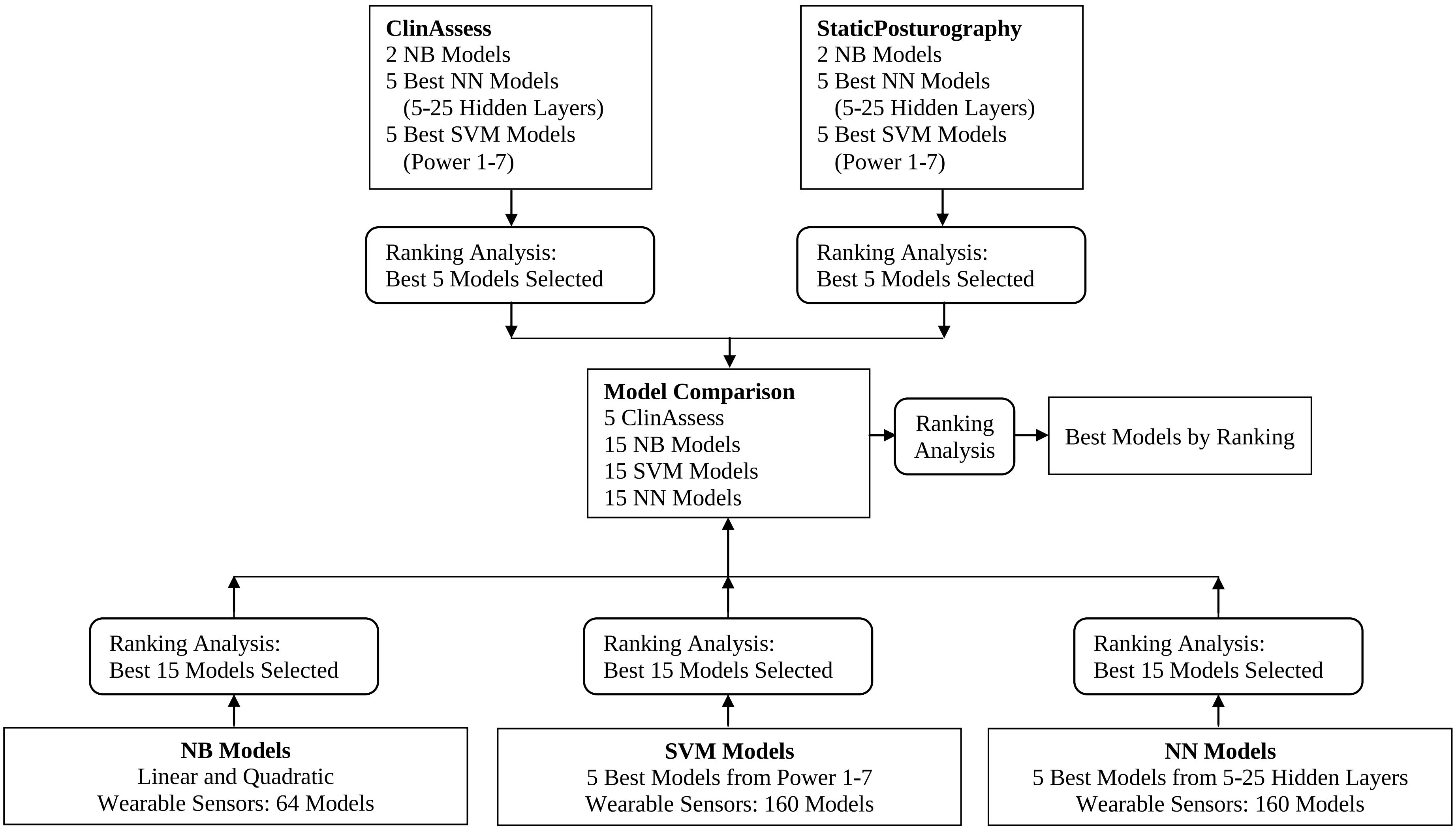

Figure 6.1. Flowchart of model development and ranking analysis for fall risk classification models without feature selection.

6.3 Results

6.3.1 Fall Prediction Models based on Retrospective Fall Occurrence

Of the best 45 wearable-sensor-based retrospective-fall-risk classifier models based on ST data (Table 6.2), the top four models (I-P SVM, I-H-P SVM, I-P NN, I-H-P-LS NN) tied for first place and achieved an accuracy of 84%, F1 score of 0.600, and MCC of 0.521. These models classified participants using support vector machines (degree 2 and 3) and neural networks (9 and 20 nodes) and included combinations of 30 pressure insole variables, 29 head accelerometer variables, 29 pelvis accelerometer variables, and 29 left shank accelerometer variables. The fifth best model (H SVM), based on 29 head accelerometer variables, achieved an accuracy of 84% and the highest scores for F1 (0.667) and MCC (0.561) but relatively low specificity and PPV prevented this model from ranking higher. The head sensor-based models ranked the highest of the single-sensor models with two models ranking in the top six. No other single-sensor models ranked among the top 10. All 55 models (Table 6.2) achieved an MCC > 0, indicating that their performance was better than chance. One model based on static posturography (SP) data ranked in the top ten (tied for 6th), and the other SP models ranked 45th (tied), 50th (tied, two models), and 53rd. The five models based solely on the collected clinical assessment (CA) data ranked 45th (tied, two models), 50th (tied), 54th (tied, two models).

Table 6.2. Best 45 wearable-sensor-based retrospective-fall-risk classifier models based on ST gait data, best 5 clinical assessment models, and best 5 static posturography assessment models

Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
I-H-P	SVM-3	84.0	50.0	94.7	75.0	85.7	0.600	0.521	52
I-H-P-LS	NN-20	84.0	50.0	94.7	75.0	85.7	0.600	0.521	52
I-P	SVM-2	84.0	50.0	94.7	75.0	85.7	0.600	0.521	52
I-P	NN-9	84.0	50.0	94.7	75.0	85.7	0.600	0.521	52
H	SVM-2	84.0	66.7	89.5	66.7	89.5	0.667	0.561	54
H	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	68
H-P-LS-RS	NN-5	84.0	33.3	100.0	100.0	82.6	0.500	0.525	68
I-H	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	68
I-P-LS	SVM-2	84.0	33.3	100.0	100.0	82.6	0.500	0.525	68
SP	NN-10	84.0	33.3	100.0	100.0	82.6	0.500	0.525	68
I-P-LS-RS	NB-Q	80.0	83.3	78.9	55.6	93.8	0.667	0.554	91
H	NB-Q	80.0	50.0	89.5	60.0	85.0	0.545	0.421	109
I-H-P-LS	NN-25	80.0	50.0	89.5	60.0	85.0	0.545	0.421	109
I-P	NN-8	80.0	50.0	89.5	60.0	85.0	0.545	0.421	109
LS-RS	NN-23	80.0	50.0	89.5	60.0	85.0	0.545	0.421	109
I-P	NB-Q	76.0	83.3	73.7	50.0	93.3	0.625	0.497	133
I-P-LS	NB-Q	76.0	83.3	73.7	50.0	93.3	0.625	0.497	133
H	SVM-6	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
H-LS-RS	NN-15	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
H-P	SVM-3	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
H-P	NN-20	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
I-H	SVM-2	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
I-H-P-LS	SVM-2	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
I-P-LS-RS	NN-21	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
LS-RS	NN-25	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
P	NN-5	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
P	NN-25	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
P-LS-RS	NN-12	80.0	33.3	94.7	66.7	81.8	0.444	0.369	138
I-P-RS	NB-Q	72.0	83.3	68.4	45.5	92.9	0.588	0.445	165
H-LS	NB-Q	76.0	50.0	84.2	50.0	84.2	0.500	0.342	175
H-P-LS	NB-Q	76.0	50.0	84.2	50.0	84.2	0.500	0.342	175
H-P-LS-RS	NB-Q	76.0	50.0	84.2	50.0	84.2	0.500	0.342	175
H	SVM-7	80.0	16.7	100.0	100.0	79.2	0.286	0.363	189
H-LS	SVM-3	80.0	16.7	100.0	100.0	79.2	0.286	0.363	189
H-P	SVM-5	80.0	16.7	100.0	100.0	79.2	0.286	0.363	189
LS	SVM-1	80.0	16.7	100.0	100.0	79.2	0.286	0.363	189
P	SVM-7	80.0	16.7	100.0	100.0	79.2	0.286	0.363	189
I-H-RS	NB-Q	68.0	66.7	68.4	40.0	86.7	0.500	0.306	217
I-P-LS	NB-L	68.0	66.7	68.4	40.0	86.7	0.500	0.306	217
H-LS-RS	NB-Q	72.0	50.0	78.9	42.9	83.3	0.462	0.275	220
H-P-RS	NB-Q	72.0	50.0	78.9	42.9	83.3	0.462	0.275	220
I-H-LS	NB-Q	72.0	50.0	78.9	42.9	83.3	0.462	0.275	220
I-H-LS-RS	NB-Q	72.0	50.0	78.9	42.9	83.3	0.462	0.275	220
I-H-P-LS	NB-Q	72.0	50.0	78.9	42.9	83.3	0.462	0.275	220

CA	NN-11	76.0	33.3	89.5	50.0	81.0	0.400	0.266	239
CA	NN-12	76.0	33.3	89.5	50.0	81.0	0.400	0.266	239
H	NN-15	76.0	33.3	89.5	50.0	81.0	0.400	0.266	239
P	NN-6	76.0	33.3	89.5	50.0	81.0	0.400	0.266	239
SP	SVM-5	76.0	33.3	89.5	50.0	81.0	0.400	0.266	239
CA	NN-10	72.0	33.3	84.2	40.0	80.0	0.364	0.187	292
SP	SVM-6	72.0	33.3	84.2	40.0	80.0	0.364	0.187	292
SP	SVM-7	72.0	33.3	84.2	40.0	80.0	0.364	0.187	292
SP	SVM-5	68.0	33.3	78.9	33.3	78.9	0.333	0.123	328
CA	SVM-1	72.0	16.7	89.5	33.3	77.3	0.222	0.081	332
CA	NN-9	72.0	16.7	89.5	33.3	77.3	0.222	0.081	332

SR: Summed Ranking, CA: Clinical assessment measures, I: Pressure-sensing insole measures, H: Head accelerometer measures, SP: Static posturography measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: Support vector machine.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian and NB-Q is quadratic Naïve Bayesian.

Of the best 45 wearable-sensor-based retrospective-fall-risk classifier models based on DT data (Table 6.3), the top model (P NN) achieved an accuracy of 80%, F1 score of 0.545, and MCC of 0.421. The second best model (I-P SVM-1) achieved an accuracy of 80%, the highest F1 score (0.706), and highest MCC (0.634), but its relatively low specificity and PPV prevented it from ranking first. All 55 models (Table 6.3) achieved an MCC > 0, indicating that their performance was better than chance. The pelvis sensor-based models ranked the highest of the single-sensor models, with three models ranking in the top ten. One model based on SP data ranked 3rd, and the other SP-based models ranked 13th (tied), 27th (tied, two models), and 49th (tied). The five models based solely on the collected CA data ranked 13th (tied, two models), 27th (tied), 53rd (tied, two models).

Table 6.3. Best 45 wearable-sensor-based retrospective-fall-risk classifier models based on DT gait data, best 5 clinical assessment models, and best 5 static posturography assessment models

Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
P	NN-7	80.0	50.0	89.5	60.0	85.0	0.545	0.421	49
I-P	SVM-1	80.0	100.0	73.7	54.5	100.0	0.706	0.634	51
SP	NN-10	84.0	33.3	100.0	100.0	82.6	0.500	0.525	57
P	NN-6	80.0	33.3	94.7	66.7	81.8	0.444	0.369	74
LS	NN-25	80.0	33.3	94.7	66.7	81.8	0.444	0.369	74
I-P	NN-14	80.0	33.3	94.7	66.7	81.8	0.444	0.369	74
I-P	NN-15	80.0	33.3	94.7	66.7	81.8	0.444	0.369	74
I-H-P	SVM-1	72.0	66.7	73.7	44.4	87.5	0.533	0.359	95
I-P-RS	SVM-1	72.0	66.7	73.7	44.4	87.5	0.533	0.359	95
I-P-LS	SVM-1	72.0	50.0	78.9	42.9	83.3	0.462	0.275	116
P	NN-10	72.0	50.0	78.9	42.9	83.3	0.462	0.275	116
I-P	NN-25	72.0	50.0	78.9	42.9	83.3	0.462	0.275	116
CA	NN11	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
CA	NN12	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
SP	SVM-5	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
I-P	SVM-5	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
I-P	NN-13	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
I-LS	NN-9	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
I-H-P	NN-15	76.0	33.3	89.5	50.0	81.0	0.400	0.266	132
LS-RS	SVM-6	80.0	16.7	100.0	100.0	79.2	0.286	0.363	149
I-H-P-LS	NN-23	80.0	16.7	100.0	100.0	79.2	0.286	0.363	149
P	NB-L	60.0	66.7	57.9	33.3	84.6	0.444	0.210	160
H-P	NB-L	60.0	66.7	57.9	33.3	84.6	0.444	0.210	160
P	SVM-3	68.0	50.0	73.7	37.5	82.4	0.429	0.217	181
LS	SVM-3	68.0	50.0	73.7	37.5	82.4	0.429	0.217	181
P-RS	SVM-1	68.0	50.0	73.7	37.5	82.4	0.429	0.217	181
CA	NN10	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
SP	SVM-6	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
SP	SVM-7	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
P	SVM-1	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
I-P	SVM-3	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
I-P-LS	SVM-3	72.0	33.3	84.2	40.0	80.0	0.364	0.187	196
P-LS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
P-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
H-P-LS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
H-P-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
P-LS-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
H-P-LS-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-P	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-H-P	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-P-LS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-P-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-H-P-LS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196
I-P-LS-RS	NB-L	56.0	66.7	52.6	30.8	83.3	0.421	0.165	196

P-LS	NN-5	76.0	16.7	94.7	50.0	78.3	0.250	0.180	202
I-H	NN-7	76.0	16.7	94.7	50.0	78.3	0.250	0.180	202
I-LS	NN-5	76.0	16.7	94.7	50.0	78.3	0.250	0.180	202
I-H-LS	NN-9	76.0	16.7	94.7	50.0	78.3	0.250	0.180	202
SP	SVM-5	68.0	33.3	78.9	33.3	78.9	0.333	0.123	261
P	SVM-5	68.0	33.3	78.9	33.3	78.9	0.333	0.123	261
RS	SVM-1	68.0	33.3	78.9	33.3	78.9	0.333	0.123	261
RS	SVM-2	68.0	33.3	78.9	33.3	78.9	0.333	0.123	261
CA	SVM1	72.0	16.7	89.5	33.3	77.3	0.222	0.081	274
CA	NN9	72.0	16.7	89.5	33.3	77.3	0.222	0.081	274
I	NB-Q	72.0	16.7	89.5	33.3	77.3	0.222	0.081	274

SR: Summed Ranking, CA: Clinical assessment measures, I: Pressure-sensing insole measures, H: Head accelerometer measures, SP: Static posturography measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: Support vector machine.

Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian and NB-Q is quadratic Naïve Bayesian.

A comparison between the ten best ST and ten best DT models (Table 6.4) shows that all but one of the ST models outranked and thus clearly outperformed the DT models.

Table 6.4. Comparison across 10 best ST and 10 best DT gait based models for retrospective-fall-risk classification

Gait Data	Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
ST	H	SVM-2	84.0	66.7	89.5	66.7	89.5	0.667	0.561	33
ST	I-P	SVM-2	84.0	50.0	94.7	75.0	85.7	0.600	0.521	35
ST	I-H-P	SVM-3	84.0	50.0	94.7	75.0	85.7	0.600	0.521	35
ST	I-P	NN-9	84.0	50.0	94.7	75.0	85.7	0.600	0.521	35
ST	I-H-P-LS	NN-20	84.0	50.0	94.7	75.0	85.7	0.600	0.521	35
ST	H	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	44
ST	I-H	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	44
ST	I-P-LS	SVM-2	84.0	33.3	100.0	100.0	82.6	0.500	0.525	44
ST	H-P-LS-RS	NN-5	84.0	33.3	100.0	100.0	82.6	0.500	0.525	44
DT	I-P	SVM-1	80.0	100.0	73.7	54.5	100.0	0.706	0.634	48
ST	I-P-LS-RS	NB-Q	80.0	83.3	78.9	55.6	93.8	0.667	0.554	49
DT	P	NN-7	80.0	50.0	89.5	60.0	85.0	0.545	0.421	73
DT	P	NN-6	80.0	33.3	94.7	66.7	81.8	0.444	0.369	84
DT	LS	NN-25	80.0	33.3	94.7	66.7	81.8	0.444	0.369	84
DT	I-P	NN-14	80.0	33.3	94.7	66.7	81.8	0.444	0.369	84
DT	I-P	NN-15	80.0	33.3	94.7	66.7	81.8	0.444	0.369	84
DT	I-H-P	SVM-1	72.0	66.7	73.7	44.4	87.5	0.533	0.359	85
DT	I-P-RS	SVM-1	72.0	66.7	73.7	44.4	87.5	0.533	0.359	85
DT	I-P-LS	SVM-1	72.0	50.0	78.9	42.9	83.3	0.462	0.275	102
DT	P	NN-10	72.0	50.0	78.9	42.9	83.3	0.462	0.275	102

SR: Summed Ranking, I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: support vector machine, ST: Single-task gait, DT: Dual-task gait.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-Q is quadratic Naïve Bayesian.

6.3.2 Fall Prediction Models based on Prospective Fall Occurrence

Of the best 45 wearable-sensor-based prospective-fall-risk classifier models based on ST gait data (Table 6.5), the top model (H-RS, SVM-1) achieved an accuracy of 79%, the second highest F1 score (0.667), and the second highest MCC (0.535). The second best model (H-LS, NN-20) had similar scores, only slightly lower for accuracy, specificity, NPV, and MCC. The third best model (I-P-LS-RS, NN-10) achieved the highest F1 score (0.714) and an accuracy of 78%, but its relatively low specificity and PPV prevented it from ranking higher. The fourth best model (H-RS, NN-18) achieved the highest MCC Score (0.567), but its relatively low sensitivity and NPV prevented it from ranking higher. All 55 models (Table 6.5) achieved an MCC > 0, indicating that their performance was better than chance. The head sensor-based models ranked the highest of the single-sensor models with one model ranking in the top ten. No CA-based or

SP-based models ranked in the top ten models. The five models based solely on the collected CA data ranked 15th, 24th, 34th (tied), 43rd (tied, two models). SP-based models ranked 22nd, 28th (tied), 46th, 50th, and 52nd.

Table 6.5. Best 45 wearable-sensor-based prospective-fall-risk classifier models based on ST gait data, best 5 clinical assessment models, and best 5 static posturography assessment models

Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
H-RS	SVM-1	78.9	57.1	91.7	80.0	78.6	0.667	0.535	35
H-LS	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	46
I-P-LS-RS	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	51
H-RS	NN-18	78.9	42.9	100.0	100.0	75.0	0.600	0.567	65
H-RS	NN-20	73.7	71.4	75.0	62.5	81.8	0.667	0.454	75
I-H-RS	NN-20	73.7	71.4	75.0	62.5	81.8	0.667	0.454	75
H	NB-Q	73.7	57.1	83.3	66.7	76.9	0.615	0.420	78
I-H-RS	SVM-1	73.7	57.1	83.3	66.7	76.9	0.615	0.420	78
H-RS	NN-15	73.7	57.1	83.3	66.7	76.9	0.615	0.420	78
I-H-RS	NN-16	73.7	57.1	83.3	66.7	76.9	0.615	0.420	78
I-LS	SVM-3	72.2	57.1	81.8	66.7	75.0	0.615	0.403	106
H-P-RS	NN-10	72.2	57.1	81.8	66.7	75.0	0.615	0.403	106
I-H-P-RS	NN-8	72.2	57.1	81.8	66.7	75.0	0.615	0.403	106
I-H-LS-RS	NN-10	77.8	33.3	100.0	100.0	75.0	0.500	0.500	111
CA	SVM-4	73.7	42.9	91.7	75.0	73.3	0.545	0.408	113
H-LS	NB-L	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
P-LS	SVM-4	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
I-P	SVM-4	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
P	NN-14	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
P-LS	NN-16	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
I-LS-RS	NN-11	72.2	42.9	90.9	75.0	71.4	0.545	0.396	133
SP	SVM-2	68.4	71.4	66.7	55.6	80.0	0.625	0.368	142
I-H-LS-RS	NN-12	72.2	50.0	83.3	60.0	76.9	0.545	0.351	145
CA	SVM-3	73.7	28.6	100.0	100.0	70.6	0.444	0.449	156
H-P-RS	NB-L	66.7	71.4	63.6	55.6	77.8	0.625	0.342	157
H-RS	NB-L	68.4	57.1	75.0	57.1	75.0	0.571	0.321	167
H-RS	NB-Q	68.4	57.1	75.0	57.1	75.0	0.571	0.321	167
I-H-LS-RS	SVM-3	72.2	16.7	100.0	100.0	70.6	0.286	0.343	187
SP	SVM4	63.2	71.4	58.3	50.0	77.8	0.588	0.288	187
H	NB-L	63.2	71.4	58.3	50.0	77.8	0.588	0.288	187
I	SVM-1	63.2	71.4	58.3	50.0	77.8	0.588	0.288	187
H-LS-RS	NB-L	66.7	57.1	72.7	57.1	72.7	0.571	0.299	192
LS	SVM-3	66.7	57.1	72.7	57.1	72.7	0.571	0.299	192
CA	NN15	68.4	42.9	83.3	60.0	71.4	0.500	0.287	201
I	SVM-5	68.4	42.9	83.3	60.0	71.4	0.500	0.287	201
I	NN-15	68.4	42.9	83.3	60.0	71.4	0.500	0.287	201
LS-RS	SVM-5	66.7	14.3	100.0	100.0	64.7	0.250	0.304	224
I-LS	SVM-5	66.7	14.3	100.0	100.0	64.7	0.250	0.304	224
H-LS-RS	NB-Q	66.7	42.9	81.8	60.0	69.2	0.500	0.269	232

I-H-LS	NB-L	66.7	42.9	81.8	60.0	69.2	0.500	0.269	232
I-H-P-LS	NB-L	66.7	42.9	81.8	60.0	69.2	0.500	0.269	232
I-H-LS	SVM-1	66.7	42.9	81.8	60.0	69.2	0.500	0.269	232
CA	NN-16	63.2	57.1	66.7	50.0	72.7	0.533	0.233	238
CA	NN-20	63.2	57.1	66.7	50.0	72.7	0.533	0.233	238
I-H-RS	NB-L	63.2	57.1	66.7	50.0	72.7	0.533	0.233	238
SP	SVM-6	57.9	71.4	50.0	45.5	75.0	0.556	0.209	245
H-LS	SVM-1	66.7	28.6	90.9	66.7	66.7	0.400	0.255	250
I	SVM-4	63.2	42.9	75.0	50.0	69.2	0.462	0.185	283
I-RS	SVM-1	63.2	42.9	75.0	50.0	69.2	0.462	0.185	283
SP	SVM-5	52.6	71.4	41.7	41.7	71.4	0.526	0.131	285
RS	NB-Q	57.9	57.1	58.3	44.4	70.0	0.500	0.150	295
SP	NN-6	63.2	28.6	83.3	50.0	66.7	0.364	0.141	303
H-P-LS-RS	NB-L	61.1	42.9	72.7	50.0	66.7	0.462	0.161	306
H-P-LS-RS	NB-Q	61.1	42.9	72.7	50.0	66.7	0.462	0.161	306
H-P	NB-Q	55.6	57.1	54.5	44.4	66.7	0.500	0.114	311

SR: Summed Ranking, CA: Clinical assessment measures, I: Pressure-sensing insole measures, H: Head accelerometer measures, SP: Static posturography measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: Support vector machine.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian and NB-Q is quadratic Naïve Bayesian.

Of the best 45 wearable-sensor-based prospective-fall-risk classifier models based on DT gait data (Table 6.6), the top three models (H-P-LS NN-10, H-P-LS NN-15, H-P-RS NN-24) achieved an accuracy of 78%, the second highest F1 score (0.750), and the second highest MCC (0.570). The fifth best model (H-P-LS-RS, NN-10) achieved the highest F1 score (0.778) and highest MCC (0.636), but its relatively low specificity and PPV prevented it from ranking higher. The pelvis sensor-based models ranked the highest of the single-sensor models with one model ranking in the top ten. No CA-based or SP-based models appeared in the top ten models. All 55 models (Table 6.6) achieved an MCC > 0, indicating that their performance was better than chance. The models based solely on the collected CA data ranked 17th, 24th, 27th, and 29th (tied, two models). The SP-based models ranked 18th, 22nd (tied), 32nd, 46th, and 47th (tied).

Table 6.6. Best 45 wearable-sensor-based prospective-fall-risk classifier models based on DT gait data, best 5 clinical assessment models, and best 5 static posturography assessment models

Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
H-P-LS	NN-10	77.8	85.7	72.7	66.7	88.9	0.750	0.570	30
H-P-LS	NN-15	77.8	85.7	72.7	66.7	88.9	0.750	0.570	30
H-P-RS	NN-24	77.8	85.7	72.7	66.7	88.9	0.750	0.570	30
P	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	41
H-P-LS-RS	NN-10	77.8	100.0	63.6	63.6	100.0	0.778	0.636	52
H-P	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	65
P-RS	NN-25	72.2	71.4	72.7	62.5	80.0	0.667	0.433	78
I-P-RS	NN-9	72.2	71.4	72.7	62.5	80.0	0.667	0.433	78
P-RS	SVM-3	72.2	85.7	63.6	60.0	87.5	0.706	0.484	81
H-P-LS	NN-5	72.2	85.7	63.6	60.0	87.5	0.706	0.484	81
H-P-LS	NN-13	72.2	85.7	63.6	60.0	87.5	0.706	0.484	81
P	NN-8	72.2	57.1	81.8	66.7	75.0	0.615	0.403	97
P	NN-25	72.2	57.1	81.8	66.7	75.0	0.615	0.403	97
LS	NN-21	72.2	57.1	81.8	66.7	75.0	0.615	0.403	97
P-LS	NN-20	72.2	57.1	81.8	66.7	75.0	0.615	0.403	97
H-P-RS	NN-21	72.2	57.1	81.8	66.7	75.0	0.615	0.403	97
CA	SVM4	73.7	42.9	91.7	75.0	73.3	0.545	0.408	121
SP	SVM2	68.4	71.4	66.7	55.6	80.0	0.625	0.368	123
H-P-LS	SVM-1	66.7	71.4	63.6	55.6	77.8	0.625	0.342	133
I-LS	SVM-2	66.7	71.4	63.6	55.6	77.8	0.625	0.342	133
P-RS	SVM-5	61.1	100.0	36.4	50.0	100.0	0.667	0.426	134
H-P	NB-Q	66.7	57.1	72.7	57.1	72.7	0.571	0.299	158
SP	SVM4	63.2	71.4	58.3	50.0	77.8	0.588	0.288	158
CA	SVM3	73.7	28.6	100.0	100.0	70.6	0.444	0.449	160
H-P-RS	SVM-3	61.1	71.4	54.5	50.0	75.0	0.588	0.255	170
I-LS	SVM-1	61.1	71.4	54.5	50.0	75.0	0.588	0.255	170
CA	NN15	68.4	42.9	83.3	60.0	71.4	0.500	0.287	176
CA	NN16	63.2	57.1	66.7	50.0	72.7	0.533	0.233	194
CA	NN20	63.2	57.1	66.7	50.0	72.7	0.533	0.233	194
H	NB-Q	68.4	28.6	91.7	66.7	68.8	0.400	0.268	196
P-LS	SVM-3	66.7	28.6	90.9	66.7	66.7	0.400	0.255	203
SP	SVM6	57.9	71.4	50.0	45.5	75.0	0.556	0.209	212
P-LS	SVM-1	61.1	57.1	63.6	50.0	70.0	0.533	0.204	216
LS	NB-L	55.6	71.4	45.5	45.5	71.4	0.556	0.169	228
I-H-LS	NB-Q	55.6	71.4	45.5	45.5	71.4	0.556	0.169	228
I-H-P-RS	NB-Q	55.6	71.4	45.5	45.5	71.4	0.556	0.169	228
H-P-RS	NB-Q	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
H-LS-RS	NB-Q	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
LS	SVM-6	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
H-P	SVM-2	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
H-P	SVM-4	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
H-LS	SVM-3	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
LS-RS	SVM-4	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
P-LS-RS	SVM-2	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231

I-LS-RS	SVM-2	61.1	42.9	72.7	50.0	66.7	0.462	0.161	231
SP	NN6	63.2	28.6	83.3	50.0	66.7	0.364	0.141	251
SP	SVM5	52.6	71.4	41.7	41.7	71.4	0.526	0.131	264
RS	NB-Q	52.6	71.4	41.7	41.7	71.4	0.526	0.131	264
I-RS	NB-Q	52.6	71.4	41.7	41.7	71.4	0.526	0.131	264
I-H-RS	NB-Q	52.6	71.4	41.7	41.7	71.4	0.526	0.131	264
P-RS	NB-Q	55.6	57.1	54.5	44.4	66.7	0.500	0.114	287
I-P-LS-RS	NB-Q	50.0	71.4	36.4	41.7	66.7	0.526	0.081	288
P	NB-Q	50.0	57.1	45.5	40.0	62.5	0.471	0.025	322
P-LS	NB-Q	50.0	57.1	45.5	40.0	62.5	0.471	0.025	322
I-LS-RS	NB-Q	50.0	57.1	45.5	40.0	62.5	0.471	0.025	322

SR: Summed Ranking, CA: Clinical assessment measures, I: Pressure-sensing insole measures, H: Head accelerometer measures, SP: Static posturography measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naïve Bayesian model, SVM: Support vector machine.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian and NB-Q is quadratic Naïve Bayesian.

A comparison between the ten best ST and ten best DT models (Table 6.7) shows that the best overall models were based on DT-gait data (H-P-LS NN-10, H-P-LS NN-15, H-P-RS NN-24, and H-P-LS-RS NN-10). The best model based on ST-gait data tied for 5th with a DT pelvis-only model.

Table 6.7. Comparison across 10 best ST and 10 best DT gait based models for prospective-fall-risk classification

Gait Data	Sensors	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
DT	H-P-LS	NN-10	77.8	85.7	72.7	66.7	88.9	0.750	0.570	31
DT	H-P-LS	NN-15	77.8	85.7	72.7	66.7	88.9	0.750	0.570	31
DT	H-P-RS	NN-24	77.8	85.7	72.7	66.7	88.9	0.750	0.570	31
DT	H-P-LS-RS	NN-10	77.8	100.0	63.6	63.6	100.0	0.778	0.636	39
ST	I-P-LS-RS	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	43
DT	P	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	43
ST	H-RS	SVM-1	78.9	57.1	91.7	80.0	78.6	0.667	0.535	46
ST	H-LS	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	53
DT	H-P	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	53
ST	H-RS	NN-18	78.9	42.9	100.0	100.0	75.0	0.600	0.567	68
ST	H-RS	NN-20	73.7	71.4	75.0	62.5	81.8	0.667	0.454	73
ST	I-H-RS	NN-20	73.7	71.4	75.0	62.5	81.8	0.667	0.454	73
DT	P-RS	SVM-3	72.2	85.7	63.6	60.0	87.5	0.706	0.484	79
DT	H-P-LS	NN-5	72.2	85.7	63.6	60.0	87.5	0.706	0.484	79
ST	H	NB-Q	73.7	57.1	83.3	66.7	76.9	0.615	0.420	83
ST	I-H-RS	SVM-1	73.7	57.1	83.3	66.7	76.9	0.615	0.420	83
ST	H-RS	NN-15	73.7	57.1	83.3	66.7	76.9	0.615	0.420	83
ST	I-H-RS	NN-16	73.7	57.1	83.3	66.7	76.9	0.615	0.420	83
DT	P-RS	NN-25	72.2	71.4	72.7	62.5	80.0	0.667	0.433	87
DT	I-P-RS	NN-9	72.2	71.4	72.7	62.5	80.0	0.667	0.433	87

SR: Summed Ranking, I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, SVM: Support vector machine, ST: Single-task gait, DT: Dual-task gait.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian and NB-Q is quadratic Naïve Bayesian.

6.4 Discussion

Models derived from this analysis predicted retrospective fall occurrence (Section 6.3.1) and prospective fall occurrence (Section 6.3.2) with varying degrees of accuracy, sensitivity, and specificity. The large number of models assessed using different combinations of sensor-based-measures, model types, and ST or DT gait data permitted determination of the optimal combination for fall risk prediction.

The posterior pelvis accelerometer provided the best single-sensor predictive capability, with at least one model ranking among the top ten for DT for both prospective and retrospective fall occurrence. The head accelerometer also performed well as a single-sensor model with at least one model ranking among the top ten for ST for both prospective and retrospective fall occurrence. The head location may have provided strong single-sensor results because it provided measurements relevant to visual input and upper body stability. However, this sensor may not perform as well under DT conditions, during which non-gait related head movements may occur during attention demanding periods (e.g., struggling to think of another word that starts with the desired letter, researcher prompts to continue with cognitive task). This means the head location is also less likely to perform well in free-living environment assessments where the participant may experience DT conditions. The pelvis location, on the other hand, is less likely to experience non-gait related movements under DT conditions. In previous studies, the pelvis or lower back location was the most frequent sensor site for fall risk prediction models [184]. This location is intuitively appropriate since it is close to the body centre of mass. The pelvis location also allows unobtrusive and easy monitoring with a belt attached sensor or accelerometer-equipped smartphone, and high user acceptance was found for a 20 day case-study with a lower back sensor [317]. The analysis presented in this thesis section is the first to compare the pelvis location directly with other locations (head, left shank, right shank) to show that an accelerometer located at the posterior pelvis is superior for DT fall risk prediction and is thus the preferred single-sensor location.

While a single sensor is practical, the best fall risk prediction results were found with multiple sensors. For prospective fall occurrence, the top models (H-P-LS, H-P-RS) were based on DT gait data and achieved an accuracy of 78%, sensitivity of 86%, and specificity of 73%. The best single-sensor model for prospective fall classification used the pelvis accelerometer and also achieved an accuracy of 78%, sensitivity of 71%, and specificity of 82%. Therefore, the multi-sensor models performed better at faller classification and the single-sensor model performed better at non-faller classification. A DT model using both the left and right shank accelerometers, in combination with head and pelvis accelerometers (i.e., H-P-LS-RS), achieved 100% sensitivity, which is desirable for a screening assessment tool because all fallers would be identified. However, the sensitivity results came at the cost of specificity, with the DT H-P-LS-RS model achieving 64% specificity and DT H-P-LS and H-P-RS models achieving 73% specificity. For retrospective fall occurrence, the best models (I-P, I-H-P, I-P, I-H-P-LS) were based on ST gait data and achieved an accuracy of 84%, sensitivity of 50%, and specificity of 95%. The best single-sensor model for retrospective fall classification used the head accelerometer and also achieved an accuracy of 84% with a sensitivity of 67% and a specificity of 89%. Therefore, for retrospective fall occurrence, the multi-sensor models performed better at non-faller classification and the single-sensor model performed better at faller classification. While multi-sensor-based models ranked higher than their single-sensor-based model counterparts (Table 6.2, Table 6.6), the use of multiple sensors would increase cost and complexity for point-of-care implementation. Therefore, a single posterior pelvis accelerometer may be considered for prospective fall risk prediction if a lower cost and faster to implement assessment is desired.

The comparison between ST and DT-gait-based models for prospective fall classification did not reveal a clearly superior gait assessment for fall risk prediction. This is in contrast to the results for retrospective fall classification where ST models outperformed DT models. For retrospective fall occurrence, some retrospective fallers may have developed fear of falling and reacted to the challenging DT condition by focusing on increasing stability and minimizing the impact of the secondary task, whereas other retrospective fallers may not have developed fear of falling and may have focused more on the cognitive task. This potential difference between retrospective fallers could have been the cause of the poorer DT classification performance compared to ST classification performance for retrospective fall risk. Retrospective fallers were excluded from the prospective groups, meaning that prospective fallers did not have a recent history of falls and were less likely to have differences in fear of falling [318] and reactions to the challenging DT condition. This difference between retrospective and prospective-based analyses emphasizes the importance of performing prospective analyses. There was no clearly superior gait assessment when predicting prospective fall occurrence with the top ST and DT-gait-based models achieving the same accuracy (78%). This is in agreement with other studies that failed to find fall prediction improvement under DT conditions, compared to ST, in older adults [262,263]. Therefore, even when controlling for recent fall history and its potential negative impacts on fear of falling and DT prioritization, DT gait assessment did not provide a clear fall risk predictive improvement compared to ST gait assessment.

Sensor-based models outperformed models based on the collected clinical assessment data for both retrospective and prospective fall classification. For prospective fall classification, clinical assessment-based models ranked 15th, 24th, 34th (tied), 43rd (tied, two models) for ST-based models and 17th, 24th, 27th, and 29th (tied, two models) for DT-based models. For retrospective fall classification, sensor-based models also outperformed clinical assessment-based models, with clinical assessment-based models ranked 45th (tied, two models), 50th (tied), 54th (tied, two models) for ST-based models and 13th (tied, two models), 27th (tied), 53rd (tied, two models) for DT-based models. These results demonstrated the advantage of using wearable sensors when assessing fall risk compared to using only clinical assessments. Weiss et al., 2013 [36], van Schooten et al., 2015 [37], and Rispens et al., 2015 [38] also found that sensor-based predictive models, or a combination of sensor and clinical assessments, improved fall risk prediction compared to clinical assessment alone. Therefore, the integration of wearable-sensors into point-of-care older adult fall risk assessments could improve fall risk identification.

The clinical assessment-based models included features from the collected clinical assessment data (i.e., ABC, 6MWT distance, 25ft walk times, fear of falling, CHAMPS features). Other clinical assessments, such as BBS, TUG, CBMS, and other assessments, have shown sensitivity to older adult fall risk and their inclusion could have improved the clinical assessment-based model performance. Therefore, the wearable-sensor-based models outperformed models based on the collected clinical assessment data but may not have outperformed clinical assessment-based models that included additional clinical assessments.

Sensor-based models also outperformed static posturography-based models for both retrospective and prospective fall classification. For prospective fall classification, static posturography-based models ranked 22nd, 28th (tied), 46th, 50th, and 52nd for ST-based models and 18th, 22nd (tied), 32nd, 46th, and 47th (tied) for DT-based models. For retrospective fall classification, sensor-based models also outperformed static posturography-based models, with static posturography-based models ranked 6th (tied), 45th (tied), 50th (tied, two models), and 53rd for ST-based models and 3rd, 13th (tied), 27th (tied, two models), and 49th (tied) for DT-based models. The static posturography assessments were based on standing balance under eyes open and eyes closed conditions, whereas the wearable sensors were used as part of a gait assessment. The gait assessment was a more challenging activity that assessed balance under dynamic conditions compared to static posturography, which assessed standing balance under stationary conditions. Dynamic walking balance requires integrated sensory inputs from visual, vestibular, and proprioceptive systems; appropriate neuromuscular coordination; and adequate muscle strength and joint mobility [68]. Therefore, a gait assessment may provide a more challenging and complete assessment of older adult fall risk than static posturography. Furthermore, the use of wearable sensors allows for gait assessment at the point-of-care.

Three different intelligent modeling techniques were assessed in this study: neural networks, naïve Bayesian classifiers, and support vector machines. For prospective fall classification, neural networks were used in 16 of the top ten ST and top ten DT gait-based models (Table 6.7), support vector machines were used in three, and naïve Bayesian were used in one. For retrospective fall classification, neural networks were used in nine of the top ten ST and top ten DT gait-based models (Table 6.4), support vector machines were used in ten, and naïve Bayesian were used in one. Therefore, neural networks appeared to consistently achieve strong modeling performance for older adult fall prediction with support vector machines also performing well.

Wearable-sensor based models were able to predict prospective and retrospective fall occurrence in older adults and outperform the predictive ability of clinical assessment-based models and static posturography-based models. The best models were based on multi-sensor input that often involved the head, pelvis, or both accelerometers in combination with other sensors. Single-sensor gait assessments provided strong prospective and retrospective fall risk prediction, using the posterior pelvis accelerometer and head accelerometer, respectively. DT gait assessments performed slightly better than ST gait assessments for evaluating prospective fall risk of older adults. Neural networks and support vector machines appear to be more appropriate than naïve Bayesian classifiers for older adult fall risk prediction. Fall risk predictive models developed for point-of-care environments should be developed using multi-sensor DT gait assessment with the pelvis location considered if assessment is limited to one sensor.

Chapter 7 Fall Prediction Models based on Reduced Feature Sets derived from Wearable Sensor Gait Data

7.1 Objectives

In developing classification and prediction models, feature selection methods are often used in order to output a reduced feature set to avoid high computational costs, the “curse of dimensionality”, and to remove irrelevant features [319,320]. Reducing feature-space size reduces the risk of prediction-model over-fitting and may improve classification performance [320,321]. In this thesis research, feature selection methods were used to identify smaller feature sets for fall risk classification from large features sets derived from wearable accelerometer and pressure-sensing insole gait data and to evaluate whether including a feature selection step improves fall risk classification performance compared to classification without feature selection.

7.2 Feature Selection Technique Background

To reduce feature-space size, feature selection techniques are preferable to projection techniques (e.g. principal component analysis (PCA)) and compression techniques (e.g. information theory) because the original features are not altered [321]. Three main feature selection methods can be considered: filter, wrapper, and embedded. Filter methods focus on intrinsic data properties, with features scored on relevance [320,321]. Wrapper methods are tailored to a specific classification method and different feature subsets are tested with the chosen classifier to optimize performance [320,321]. Wrapper methods can achieve better performance than filter methods but are computationally expensive and can result in over-fitting [321]. Embedded methods are similar to wrapper methods but feature selection is built into the classifier construction, which reduces computational complexity compared to wrapper methods [321]. Caby et al., 2011 [190] used a wrapper feature selection method to reduce a wearable-sensor-based feature space before using an intelligent classifier for fall risk prediction. While the wrapper approach is sound, this method ties the feature selection technique to a specific classifier, precluding evaluation of the feature subset across different classifier types. A classifier-independent, filter approach is preferred, because it permits direct comparisons between different classifiers and different feature sets, including a full feature set. CFS is a supervised method that identifies a subset of features that are correlated with the class label (i.e. faller or non-faller) and uncorrelated with other parameters, and eliminates irrelevant and redundant features [320]. To identify the feature subset, CFS computes the subset's heuristic measure of 'merit' based on pair-wise correlations [322,323].

FCBF is a supervised method that identifies predominant features for classification and eliminates redundant features. This method avoids pair-wise correlation analysis between all relevant features, reducing computational complexity compared to CFS [324]. The feature subset is selected based on the symmetrical uncertainty [322].

Relief-F is a supervised method that weights the parameter's relative strength, and eliminates less relevant features without eliminating redundant features [319,322]. Relief-F is useful when evaluating parameters with interdependencies and noisy data sets [323].

7.3 Methods

Filter feature selection methods were selected because feature subsets from each filter method could be evaluated using three different classifiers, which would not be possible with wrapper or embedded methods. Furthermore, filter methods reduce the computational cost and reduce the risk of over-fitting [321]. Three filter feature selection methods were used: correlation-based feature selection (CFS), fast correlation based filter (FCBF), and Relief-F. CFS and FCBF both provide a minimum subset of features whereas Relief-F provides a ranking of features.

The number of features to include in the Relief-F feature subset was determined using the runExperiment algorithm within the Arizona State University Feature Selection Repository (ASUFSR) [322], which evaluates increasingly larger feature subsets, by five-feature increments, until the entire feature set is included in the subset. Naïve Bayes (NB) and Support Vector Machine (SVM) were used as classifiers. The smallest feature subset that did not decrease accuracy, or at worst resulted in no more than a 5% decrease in accuracy from the full-feature set, was selected.

Feature selection was performed as a pre-classification step on all features for all 31 sensor combinations (Table 6.1) in Matlab R2010a using ASUFSR algorithms [322]. Pelvis accelerometer data were missing for two non-fallers (RNF and PNF) and left shank accelerometer data were missing for one non-faller (RNF and PNF) due to sensor power failure.

Following feature selection, three classifier models were used to assess each feature set: multi-layer perceptron neural network (NN), NB, and SVM (as described in Section 6.2). Retrospective and prospective fall occurrences were used separately as the classification criterion (as described in Section 6.2). For retrospective fall occurrence models, 75% of participant data (18 fallers, 57 non-fallers) were used for training and 25% were used for testing (6 fallers, 19 non-fallers). For prospective fall occurrence models, 75% of participant data (21 fallers, 35 non-fallers) were used for training and 25% were used for testing (7 fallers, 12 non-fallers). For retrospective models, only ST gait-based models were considered, because ST models outperformed DT models (Section 6.5). Therefore, the top ten ST models from the analysis without feature selection, performed as described in Section 6.2, were used to compare to the top ST models with feature selection to evaluate the effects of including feature selection on classification performance. For prospective models, ST and DT gait-based models were considered, because both ST and DT models performed well (Section 6.5). Therefore, the top ten ST and DT models from the analysis without feature selection were compared to the top ST and DT models with feature selection to evaluate the effect of including feature selection on classification performance.

Model evaluation parameters included accuracy, specificity, sensitivity, PPV, NPV [313], F1 score (harmonic mean of precision and sensitivity) [314], and MCC [315]. A ranking method similar to that used in Kendell et al., 2012 [316] was employed to determine the best models. Each model evaluation parameter was ranked from best (1) to worst (n), and ranks for all model evaluation parameters were summed to identify the overall best model (lowest summed rank) (Figure 7.1).

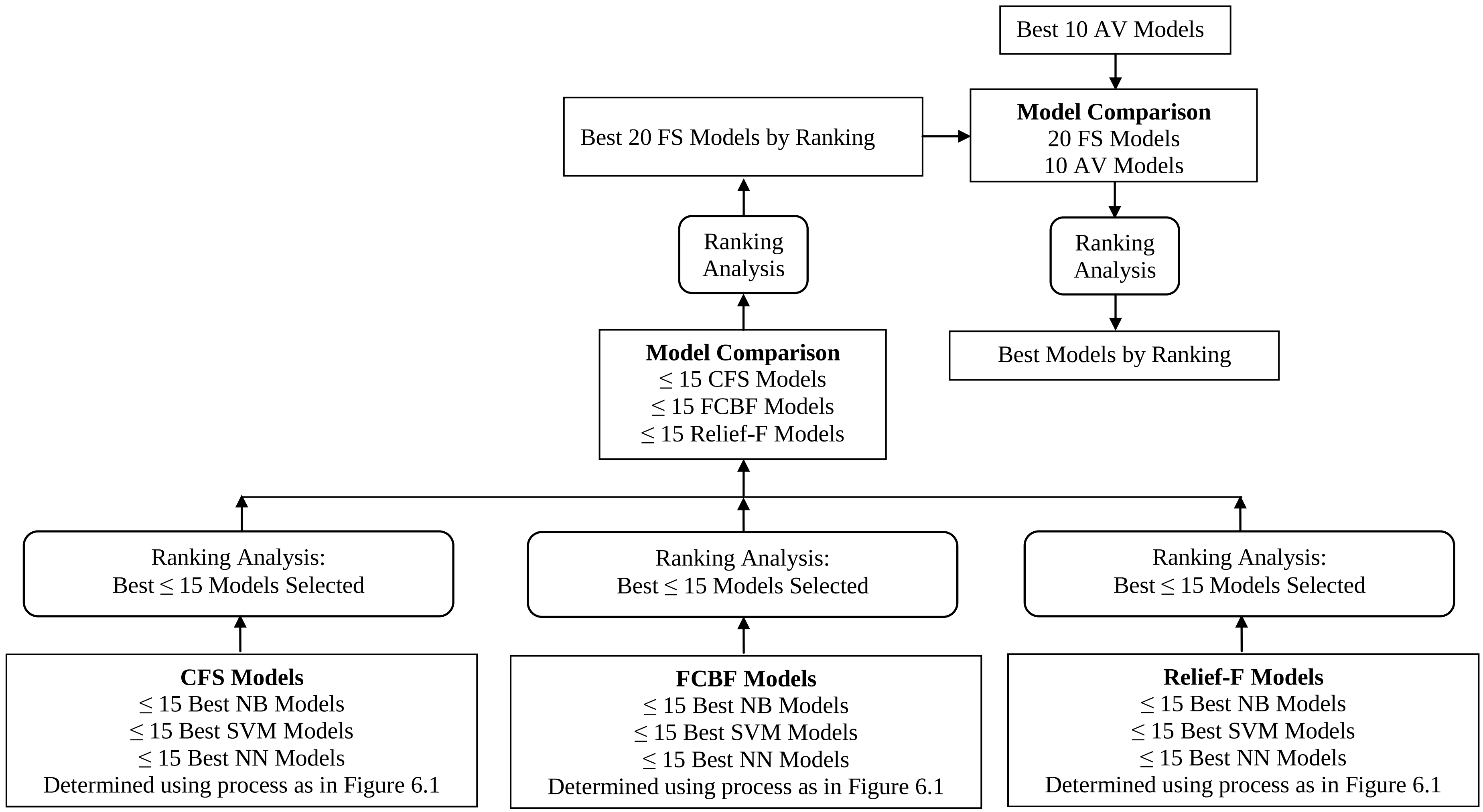

Figure 7.1. Flowchart of feature selection-based model development and ranking analysis. AV: All variable, FS: Feature selection, NB: Naïve Bayesian, NN: Neural network, SVM: Support vector machine.

7.4 Results

7.4.1 Feature Selection Faller Classification Models based on Retrospective Fall Occurrence

Nine feature subsets (eight Relief-F, one CFS, one FCBF: Table 7.1) were inputs for the twenty best models (Table 7.2). CFS and FCBF analyses outputted the same feature set (Feature Subset 9). The top fifteen models used Relief-F feature selection, with the top two models (Feature Subset 1, SVM-6 and SVM-7) including three insole measures and seven head accelerometer measures (Table 7.1). The top model (Feature Subset 1, SVM-7) achieved the highest accuracy (96%), sensitivity (100%), NPV (100%), F1 score (0.923) and MCC (0.901) and a specificity of 95%, and PPV of 86%. Two single-sensor-based models ranked 11th (Feature Subset 5 with head accelerometer sensor, SVM-4; and Feature Subset 6 with pelvis accelerometer sensor, SVM-4), achieving an accuracy of 88%, sensitivity 67%, specificity 95%, PPV 80%, NPV 90%, F1 score 0.727, and MCC 0.656. The twenty best models using feature selection were compared to the ten best models generated using all combinations of variables (AV) but no feature selection (Chapter 6.3) (Table 7.2). The top fifteen models that used feature selection outperformed the best models that did not use feature selection.

Table 7.1. Feature-selection subsets based on ST gait data used as inputs for retrospective fall risk classification models

Method	Feature-Selection Subset Output	Subset #
Relief-F	Insoles: Impulse I3, I6, and I7 Head: Maximum, mean, standard deviation posterior acceleration Maximum, mean, standard deviation anterior acceleration Mean superior acceleration	1
Relief-F	Pelvis: AP ratio of even to odd harmonics Maximum, mean, standard deviation left acceleration Left Shank: ML Lyapunov exponent	2
Relief-F	Head: Vertical ratio of even to odd harmonics Mean, standard deviation posterior acceleration Pelvis: Maximum, standard deviation left acceleration	3
Relief-F	Insole: Impulse I1, I3, I4, I6, I7 Pelvis: ML FFT first quartile AP Lyapunov exponent Maximum, mean, standard deviation left acceleration	4
Relief-F	Head: ML and vertical FFT first quartile Vertical ratio of even to odd harmonics ML Lyapunov exponent Maximum, mean, standard deviation right acceleration Maximum, mean, standard deviation posterior acceleration Maximum, mean, standard deviation anterior acceleration Maximum, mean superior acceleration	5
Relief-F	Pelvis: ML FFT first quartile AP ratio of even to odd harmonics AP, ML, vertical Lyapunov exponent Maximum, mean, standard deviation left acceleration Maximum, standard deviation inferior acceleration	6
Relief-F	Insole: Impulse I3, I6, I7 Head: Maximum, mean, standard deviation posterior acceleration Pelvis: ML FFT first quartile AP Lyapunov exponent Maximum, mean left acceleration	7
Relief-F	Pelvis: ML Lyapunov exponent Maximum, mean, standard deviation left acceleration Left Shank: ML Lyapunov exponent Maximum, standard deviation left acceleration Maximum, standard deviation superior acceleration Right Shank: AP, vertical ratio of even to odd harmonics AP, ML, vertical Lyapunov exponent Mean anterior acceleration	8
CFS/FCBF	Pelvis: Standard deviation left acceleration	9

I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, AP: Anterior-posterior, ML: Medial-lateral, FFT: Fast Fourier Transform.

Table 7.2. Best twenty ST models based on retrospective fall occurrence with feature-selection and best ten all variable (AV) models based on retrospective fall occurrence. Feature subset numbers are defined in Table 7.1. For AV, feature set indicates the sensor and number of variables (in parentheses) in the subset.

Method	Feature Set	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
Relief-F	1	SVM-7	96.0	100.0	94.7	85.7	100.0	0.923	0.901	33
Relief-F	1	SVM-6	92.0	83.3	94.7	83.3	94.7	0.833	0.781	43
Relief-F	2	NN-15	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	3	NN-21	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	3	NN-23	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	3	NN-25	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	1	NN-21	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	4	NN-9	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	4	NN-21	88.0	50.0	100.0	100.0	86.4	0.667	0.657	44
Relief-F	1	SVM-5	92.0	100.0	89.5	75.0	100.0	0.857	0.819	52
Relief-F	5	SVM-4	88.0	66.7	94.7	80.0	90.0	0.727	0.656	65
Relief-F	6	SVM-4	88.0	66.7	94.7	80.0	90.0	0.727	0.656	65
Relief-F	7	NN-21	88.0	66.7	94.7	80.0	90.0	0.727	0.656	65
Relief-F	3	SVM-3	88.0	83.3	89.5	71.4	94.4	0.769	0.693	68
Relief-F	8	NB-Q	84.0	83.3	84.2	62.5	94.1	0.714	0.618	102
AV	H(29)	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
AV	I(30),H(29)	SVM-4	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
AV	I(30),P(29), LS(29)	SVM-2	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
AV	H(29),P(29), LS(29), RS(29)	NN-5	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
CFS/ FCBF	9	NN-8	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
CFS/ FCBF	9	NN-10	84.0	33.3	100.0	100.0	82.6	0.500	0.525	104
AV	H(29)	SVM-2	84.0	66.7	89.5	66.7	89.5	0.667	0.561	107
AV	I(30),P(29), LS(29), RS(29)	NB-Q	80.0	83.3	78.9	55.6	93.8	0.667	0.554	120
AV	I(30),P(29)	SVM-2	84.0	50.0	94.7	75.0	85.7	0.600	0.521	121
AV	I(30),H(29), P(29)	SVM-3	84.0	50.0	94.7	75.0	85.7	0.600	0.521	121
AV	I(30),P(29)	NN-9	84.0	50.0	94.7	75.0	85.7	0.600	0.521	121
AV	I(30),H(29), P(29), LS(29)	NN-20	84.0	50.0	94.7	75.0	85.7	0.600	0.521	121
CFS/ FCBF	9	NB-Q	76.0	66.7	78.9	50.0	88.2	0.571	0.418	157
CFS/ FCBF	9	SVM-2	80.0	33.3	94.7	66.7	81.8	0.444	0.369	176
CFS/ FCBF	9	SVM-3	80.0	33.3	94.7	66.7	81.8	0.444	0.369	176

AV: All variables, I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right

shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: support vector machine, SR: summed rank.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-Q is quadratic Naïve Bayesian.

7.4.2 Feature Selection Fall Prediction Models based on Prospective Fall Occurrence

Twelve feature subsets (eleven Relief-F, one FCBF: Table 7.3) were inputs for the twenty best models (Table 7.4). The top thirteen models used Relief-F feature selection, with the top two models (Feature Subset 10, SVM-5 and SVM-7) including four insole measures and six left shank accelerometer measures. These top two models achieved the highest accuracy (94%), specificity (100%), PPV (100%), F1 score (0.923), and MCC (0.886) with sensitivity of 86% and NPV of 92%. Two models (Feature Subset 10, SVM-3 and Feature Subset 12, NN-16) achieved the highest sensitivity (100%) and NPV (100%) with an accuracy of 89%, specificity 82%, PPV 78%, F1 score 0.875, and MCC 0.798. Two models (Feature Subset 11 with SVM-3 and SVM-4) had intermediate rankings between the models reported above, with accuracy 89%, sensitivity 86%, and specificity 91%. One single-sensor-based model tied for seventh best model (Feature Subset 15 with pelvis accelerometer sensor, SVM-3), achieving an accuracy of 83%, sensitivity 71%, specificity 91%, PPV 83%, NPV 83%, F1 score 0.769, and MCC 0.645. The twenty best models using feature selection were compared to the ten best models generated using all combinations of variables (AV) without feature selection (Chapter 6.4) (Table 7.4). The top thirteen models that used feature selection outperformed the best models that did not use feature selection.

Table 7.3. ST and DT feature-selection subsets used as inputs for prospective fall risk classification models

Method	Gait Data	Feature-Selection Subset Output	Subset #
Relief-F	ST	Insoles: Posterior deviation duration ML CoP path stance phase CoV Impulse I1, I6 Left Shank: ML FFT first quartile Maximum left acceleration Maximum, mean, standard deviation anterior acceleration Maximum superior acceleration	10
Relief-F	DT	Insoles: Median stance phase CoP velocity ML CoP path stance phase CoV Percent stance time Percent double support time Pelvis: AP Lyapunov exponent	11
Relief-F	DT	Head: AP and vertical FFT first quartile ML, vertical ratio of even to odd harmonics Mean right acceleration Mean, standard deviation inferior acceleration Maximum, standard deviation superior acceleration Pelvis: Maximum, standard deviation left acceleration Maximum, mean, standard deviation right acceleration Maximum, standard deviation posterior acceleration Mean anterior acceleration Maximum, mean, standard deviation inferior acceleration	12
Relief-F	ST	Insoles: Posterior deviation duration Minimum stance phase CoP velocity Stride time, stance time, swing time CoV Head: ML FFT first quartile AP ratio of even to odd harmonics Standard deviation left acceleration Maximum, mean, standard deviation anterior acceleration Maximum inferior acceleration Maximum superior acceleration Left Shank: ML FFT first quartile Maximum left acceleration Maximum, mean, standard deviation anterior acceleration Mean inferior acceleration Maximum superior acceleration	13
Relief-F	ST	Insole: Lateral deviation length ML deviation duration Minimum stance phase CoP velocity Pelvis: AP, vertical ratio of even to odd harmonics ML Lyapunov exponent Standard deviation left acceleration Maximum anterior acceleration Standard deviation inferior acceleration Maximum superior acceleration	14

Relief-F	DT	Pelvis: AP Lyapunov exponent Maximum, standard deviation left acceleration Maximum, mean right acceleration Maximum, mean, standard deviation posterior acceleration Maximum, mean, standard deviation anterior acceleration Maximum, mean, standard deviation inferior acceleration Mean superior acceleration	15
Relief-F	DT	Left Shank: ML, vertical FFT first quartile AP, vertical Lyapunov exponent Right Shank: Mean posterior acceleration	16
Relief-F	ST	Insoles: Lateral deviation length ML deviation duration Minimum stance phase CoP velocity AP CoP path stance phase CoV Impulse I1 Stride time CoV Head: AP ratio of even to odd harmonics Maximum, mean, standard deviation anterior acceleration Maximum, standard deviation superior acceleration Pelvis: ML ratio of even to odd harmonics ML, vertical Lyapunov exponent Mean, standard deviation left acceleration Standard deviation right acceleration Maximum posterior acceleration Maximum anterior acceleration Maximum superior acceleration Left Shank: ML FFT first quartile Maximum, standard deviation left acceleration Mean right acceleration Maximum, standard deviation anterior acceleration Standard deviation inferior acceleration Maximum, standard deviation superior acceleration Right Shank: ML, vertical Lyapunov exponent Maximum, mean, standard deviation left acceleration Maximum, standard deviation inferior acceleration Maximum, mean, standard deviation superior acceleration	17
FCBF	DT	Head: Standard deviation superior acceleration	18
Relief-F	DT	Insole: Posterior deviation length Minimum, median stance phase CoP velocity Impulse I3 Swing time CoV Head: Mean left acceleration Mean superior acceleration Left Shank: ML, vertical FFT first quartile AP, ML, vertical Lyapunov exponent Right Shank: Mean, standard deviation posterior acceleration Maximum anterior acceleration	19
Relief-F	DT	Head: Maximum, standard deviation superior acceleration Pelvis: Standard deviation left acceleration	20

		Standard deviation inferior acceleration Right Shank: ML ratio of even to odd harmonics	
Relief-F	ST	Pelvis: Vertical Lyapunov exponent Standard deviation left acceleration Left Shank: AP Lyapunov exponent Maximum left acceleration Mean right acceleration Standard deviation anterior acceleration Maximum superior acceleration Right Shank: ML Lyapunov exponent Standard deviation left acceleration Maximum inferior acceleration	21

I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, AP: Anterior-posterior, ML: Medial-lateral, CoV: Coefficient of Variation, FFT: Fast Fourier Transform.

Table 7.4. Best twenty models using feature selection and best ten all variable (AV) models. Feature subsets are defined in Table 7.3. For AV, feature set indicates the gait data type (ST or DT), sensor and number of variables (in parentheses) in the subset. All models are based on prospective fall occurrence.

Method	Feature Set	Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	F1	MCC	SR
Relief-F	10	SVM-5	94.4	85.7	100.0	100.0	91.7	0.923	0.886	13
Relief-F	10	SVM-7	94.4	85.7	100.0	100.0	91.7	0.923	0.886	13
Relief-F	11	SVM-3	88.9	85.7	90.9	85.7	90.9	0.857	0.766	34
Relief-F	11	SVM-4	88.9	85.7	90.9	85.7	90.9	0.857	0.766	34
Relief-F	10	SVM-3	88.9	100.0	81.8	77.8	100.0	0.875	0.798	49
Relief-F	12	NN-16	88.9	100.0	81.8	77.8	100.0	0.875	0.798	49
Relief-F	13	NB-L	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	14	SVM-2	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	13	NN-23	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	15	SVM-3	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	11	SVM-5	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	16	SVM-7	83.3	71.4	90.9	83.3	83.3	0.769	0.645	66
Relief-F	17	SVM-2	83.3	57.1	100.0	100.0	78.6	0.727	0.670	83
AV	DT:H(29), P(29), LS(29), RS(29)	NN-10	77.8	100.0	63.6	63.6	100.0	0.778	0.636	100
FCBF	18	NN-20	78.9	85.7	75.0	66.7	90.0	0.750	0.587	101
AV	DT:H(29), P(29), LS(29)	NN-10	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
AV	DT:H(29), P(29), LS(29)	NN-15	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
AV	DT:H(29), P(29), RS(29)	NN-24	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
Relief-F	19	NB-L	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
Relief-F	20	SVM-3	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
Relief-F	15	NN-5	77.8	85.7	72.7	66.7	88.9	0.750	0.570	107
AV	ST:H(29), RS(29)	SVM-1	78.9	57.1	91.7	80.0	78.6	0.667	0.535	125
AV	ST:H(29), RS(29)	NN-18	78.9	42.9	100.0	100.0	75.0	0.600	0.567	128
AV	ST:H(29), LS(29)	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	134
AV	DT:H(29), P(29)	NN-20	77.8	57.1	90.9	80.0	76.9	0.667	0.523	134
Relief-F	21	SVM-3	77.8	57.1	90.9	80.0	76.9	0.667	0.523	134
Relief-F	21	SVM-4	77.8	57.1	90.9	80.0	76.9	0.667	0.523	134
Relief-F	21	SVM-6	77.8	57.1	90.9	80.0	76.9	0.667	0.523	134
AV	ST:I(30), P(29), LS(29), RS(29)	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	139
AV	DT:P(29)	NN-10	77.8	71.4	81.8	71.4	81.8	0.714	0.532	139

AV: All variables, ST: Single-task gait, DT: Dual-task gait, I: Pressure-sensing insole measures, H: Head accelerometer measures, P: Pelvis accelerometer measures, LS: Left shank accelerometer measures, RS: Right shank accelerometer measures, NN: Neural network, NB: Naive Bayesian model, SVM: support vector machine, SR: summed rank.
Models: NN-*a*, where *a* is the number of nodes in the hidden layer; SVM-*b*, where *b* is the polynomial degree; NB-L is linear Naïve Bayesian

7.5 Discussion

The three feature selection techniques, CFS, FCBF, and Relief-F, successfully reduced the feature set from up to 146 features to a viable set containing as few as one feature. Models derived using the reduced feature sets outperformed models derived using the full feature set when predicting fall risk, demonstrating the benefits of feature selection methods when creating fall risk prediction models.

The best feature selection technique for this application was Relief-F, used in the top thirteen models for prospective fall prediction and top fifteen models for retrospective fall classification. These results differed from other classification studies where CFS and FCBF provided the best feature subsets [324,325]. However, these studies were not classifying elderly fall risk and instead classified human activities such as sitting, standing, and stair walking [325] or benchmark data sets that included healthcare diagnoses and census data [324]. Relief-F feature selection has recognized strengths when dealing with noisy data sets and parameters with interdependencies [323]. These strengths may make it ideal for elderly fall risk classification where differences between fallers and non-fallers are often subtle and varied.

The best two models for prospective faller classification (Feature Subset 10, SVM-5 and SVM-7) contained ten features, four pressure-sensing insole features and six left shank accelerometer features. These models achieved an accuracy of 94%, F1 score of 0.923, and MCC of 0.866. The pressure-sensing insole features were posterior deviation duration, ML CoP path stance phase CoV, I1, and I6. The left shank accelerometer features were ML FFT first quartile; maximum left acceleration; maximum, mean and standard deviation anterior acceleration; and maximum superior acceleration. Both ML CoP path stance phase CoV and ML FFT first quartile suggest that features related to ML variability are important in fall risk identification. ML stability is particularly critical for fall risk analysis, because decreased ML stability could increase the risk of a sideways fall and hip fracture. Falls cause 90% of hip fractures and, in the year following a hip fracture, 25% of older adults die, 76% experience a decline in mobility, 50% experience a decline in performance of activities of daily living, and 22% move to a nursing home [39]. Furthermore, all three anterior acceleration measures at the left shank appeared in the feature set, suggesting that accelerations in the direction of progression are important for fall risk prediction.

While the best two models for prospective faller classification achieved strong performance, they did not achieve the best sensitivity results. With a sensitivity of 86%, if these top two models were used to screen older adults for fall risk, 14% of fallers would be missed and not identified for fall prevention programs. However, two models achieved 100% sensitivity, where all fallers were correctly identified: Features Subset 10, SVM-3 with four pressure-sensing insole features and six left shank accelerometer features; and Feature Subset 12, NN-16 with nine head accelerometer features and eleven pelvis accelerometer features (Table 7.3). A model with 100% sensitivity would make an excellent screening tool; however, with a PPV of 78%, 22% of model-identified fallers would not be at risk of falling and could receive unneeded fall prevention services. The benefit of 100% sensitivity may be worth the 5% decrease in accuracy, 18% decrease in specificity, and higher costs.

The best model (Feature Subset 1, SVM-7) for retrospective faller classification contained ten features, 3 pressure-sensing insole features and seven head accelerometer features. This model achieved an accuracy of 96%, F1 score of 0.923, MCC of 0.901, and sensitivity of 100%, making it an excellent tool for screening assessments because all fallers would be identified. This model compared well with the best faller classification results in the literature, with only Caby et al., 2011 [190] and Giansanti et al., 2008 [200] achieving better results (100% and 97% accuracy). The three pressure-sensing insole features were impulse measures. I3 and I6 measured impulse during the second half of stance and I7 measured impulse during the entire stance phase. This indicated the importance of force magnitude and timing of force application during stance phase for fall risk identification, with fallers having lower I3, I6, and I7 impulse compared to non-fallers. The lower impulse could indicate reduced force application due to muscle weakness, which is a fall risk factor [26,326]. The head features were maximum, mean, and standard deviation for posterior and anterior acceleration, and mean superior acceleration. Head accelerations in the direction of progression were important for fall risk classification, with fallers having greater posterior and lower anterior acceleration compared to non-fallers.

While a multi-sensor-based model achieved the best performance for both retrospective and prospective faller classification, a single-sensor-based model may be desirable to reduce cost and complexity for clinical and long-term assessment. For prospective faller classification, the strongest single-sensor-based model (Feature Subset 15, SVM-3), using features from only a posterior pelvis accelerometer, was ranked 7th (Table 7.4). This model achieved an accuracy of 83%, 71% sensitivity, 91% specificity, 83% PPV, 83% NPV, F1 score of 0.769, and MCC of 0.645. The pelvis accelerometer location has benefits for ease of use, because this location allows unobtrusive and easy monitoring with a belt attached sensor or accelerometer-equipped smartphone, and high user acceptance was found for a 20-day case-study with a lower back sensor [317]. However, the pelvis accelerometer model had 11% lower accuracy, 15% lower sensitivity, and 9% lower specificity compared to the best multi-sensor-based model.

For retrospective faller classification, two single-sensor-based models achieved the best single-sensor performance (ranked 11th, Table 7.2), head accelerometer alone (Feature Subset 5, SMV-4) and posterior pelvis accelerometer alone (Feature Subset 6, SVM-4). These single-sensor models achieved an accuracy of 88%, sensitivity of 67%, specificity of 95%, PPV 80%, NPV 90%, F1 score 0.727, and MCC 0.656. The single-sensor models had 8% lower accuracy and 23% lower sensitivity compared to the best multi-sensor-based model. Therefore, for both retrospective and prospective faller classification, the added complexity and cost of a multi-sensor-based system may be worth the increased fall risk predictive performance.

Models with a feature subset performed better than models with a complete feature set, demonstrating the importance of including feature reduction when defining models for fall risk prediction. Feature selection techniques removed irrelevant features and improved predictive accuracy. Improved predictive accuracy is one of the expected advantages of feature selection [320,321,325].

Feature selection provided models with smaller feature sets and improved fall risk prediction compared to fall risk prediction without feature selection. Relief-F provided the best feature subsets for fall risk classification. The best model for prospective faller classification was based on four pressure-sensing insole features and six left shank accelerometer features. The best model for retrospective faller classification was based on three pressure-sensing insole features and seven head accelerometer features. Viable single-sensor-based model performance was also achieved with posterior pelvis accelerometers, but with lower classification performance than the best models. Feature selection, particularly Relief-F, should be considered as an important data analysis step in fall risk prediction using wearable sensors.

Chapter 8 Conclusion

This thesis evaluated wearable sensors as an older adult fall risk assessment tool. Wearable sensor-derived gait data were used successfully to identify differences between ST and DT gait in elderly individuals and to classify older adults based on retrospective and prospective fall occurrence. All the objectives for this thesis were met:

Objective 1: Evaluate eyes open and eyes closed posturography in elderly people

For all participants (PNF, PF, PMF) measures sensitive to AP motion increased when visual input was removed, with the largest percent increases for PMF. For ML measures, CoP velocity increased with eyes closed for PNF and PF compared to eyes open. However, all ML measures for PMF increased with eyes closed. Since significant increases in ML range and ML RMS only occurred for PMF, ML balance control assessment with eyes closed may be particularly important for evaluating the risk of multiple falls (i.e., people at higher fall risk).

Differences were found between prospective fallers and non-fallers for RQ AP range and RQ AP RMS and between prospective multi-fallers and non-fallers for eyes closed AP velocity, eyes closed VSM velocity, RQ AP velocity, and RQ VSM velocity. These results highlighted the importance of testing postural balance with and without visual input and calculating RQ to give the clearest indication of fall risk, for both single and multi-fallers, in an older adult population.

For discriminating between PF and PNF, a clinical cut-off score of 1.68 for RQ AP range produced moderate faller classification results (63% accuracy, 71% sensitivity, 57% specificity) that were comparable to the posturography literature (Topper et al., 1993 [169] with 65% accuracy, 78% sensitivity, 46% specificity) but poorer than the best models identified in this thesis.

For discriminating between PMF and PNF, a discriminant function with AP velocity EC, VSM velocity EC, RQ AP velocity, RQ VSM velocity and a cut-off score of 0.541 achieved good fall risk classification results with 85% accuracy, 50% sensitivity, and 89% specificity.

Objective 2: Evaluate ST and DT walking in elderly people using pressure-sensing insoles and accelerometers

Greater gait variability and CoP path deviations during DT gait compared to ST gait, detected by the wearable sensor-derived measures, indicated that DT conditions challenged walking stability. The number of posterior CoP stance phase path deviations and duration of ML CoP stance phase path deviations was significantly higher during DT walking than for ST. These deviations represent potential instabilities. Greater gait variability during DT gait was also expressed by greater stride time CoV, greater AP and ML stance path CoV (PNF only), greater stride time symmetry index, lower FFT first quartile frequency, and lower ratio of even to odd harmonics. Greater stride time variability [33,250] has been reported previously.

Gait velocity, cadence, and all CoP stance velocity measures, except maximum CoP stance velocity, were lower under DT conditions than for ST. These temporal results agree with the literature [30,31,33-35,247-251] and are likely part of a compensatory, conservative strategy aimed at maintaining dynamic stability under DT conditions.

Lower standard deviations at the pelvis and shanks indicated less variability with a cognitive load. Lower acceleration variability may represent a conservative stiffening strategy, where body motions are reduced to minimize centre of mass deviations [309], as part of a DT compensatory strategy. In the prospective analysis, lower SDs occurred more consistently for non-fallers compared to fallers, with lower SD measured at the pelvis, left shank, and right shank for all axes except posterior. This may indicate that non-fallers are better than fallers at compensating for the increased DT demands by reducing acceleration variability.

Differences between PF and PNF were identified for AP FFT first quartile (head accelerometer, DT gait), ML FFT first quartile (left shank accelerometer, ST gait), superior maximum acceleration (right shank accelerometer, ST gait), and coefficient of variation AP (pressure-sensing insoles, DT gait). Fallers had significantly smaller FFT first quartile frequencies than non-fallers, indicating less low frequency content and more numerous higher-frequency gait perturbations. CoV AP during DT was significantly lower for fallers than non-fallers, suggesting lower faller CoP path variability at the foot-shoe interface. This suggests that fallers exhibit greater variability in body movements, such as at the pelvis and trunk, but lower variability at the foot-shoe interface, compared to non-fallers. Fallers also had lower maximum superior acceleration at the right shank during ST, which could also indicate reduced acceleration magnitude near the foot-shoe interface.

Objective 3: Create and evaluate elderly fall risk prediction models using plantar pressure and accelerometer-based features

The best model for prospective faller classification had ten input features (pressure-sensing insole features: posterior deviation duration, ML CoP path stance phase CoV, I1, and I6, left shank accelerometer features: ML FFT first quartile, maximum left acceleration, maximum superior, and maximum, mean, and standard deviation anterior acceleration) using a 5^{th} or 7^{th} order polynomial support vector machine. This model achieved an accuracy of 94%, sensitivity 86%, specificity 100%, F1 score 0.923, and MCC 0.866 and would provide clinically useful fall risk classification.

100% sensitivity was achieved by two models: one with four pressure-sensing insole features and six left shank accelerometer features and a 3^{rd} order polynomial support vector machine and the other model used a 16-node neural network with nine input head accelerometer features (AP and vertical FFT first quartile; ML and vertical ratio of even to odd harmonics; mean right acceleration; mean and standard deviation inferior acceleration; maximum and standard deviation superior acceleration) and eleven input posterior pelvis accelerometer features (maximum and standard deviation left acceleration; maximum, mean, and standard deviation right acceleration; maximum and standard deviation posterior acceleration; mean anterior acceleration; maximum, mean, and standard deviation inferior acceleration). These models achieved an accuracy of 89%, sensitivity 100%, specificity 82%, F1 score 0.875, and MCC 0.798.

A single-sensor-based model may be desirable to reduce cost and complexity for clinical and long-term assessment. The best single-sensor-based model used a 3^{rd} order polynomial support vector machine and fifteen posterior pelvis accelerometer features (AP Lyapunov exponent; maximum and standard deviation left acceleration; maximum and mean right acceleration; maximum, mean, and standard deviation posterior acceleration; maximum, mean, and standard deviation anterior acceleration; maximum, mean, and standard deviation inferior acceleration; and mean superior acceleration). This model achieved an accuracy of 83%, sensitivity 71%, specificity 91%, F1 score 0.769, and MCC 0.645.

The best feature selection technique for elderly fall risk classification was Relief-F. Relief-F feature selection has recognized strengths when dealing with noisy data sets and parameters with interdependencies [323]. These strengths may make it ideal for elderly fall risk classification where differences between fallers and non-fallers are often subtle and varied.

Sensor-based models outperformed clinical assessment-based models and posturography-based models for both retrospective and prospective fall classification. These results demonstrate the advantage of using wearable sensors when assessing fall risk compared to using clinical assessments or posturography assessments. A gait assessment may provide a more challenging and complete assessment of older adult fall risk than static posturography or clinical assessments. Therefore, the integration of wearable-sensors into point-of-care older adult fall risk assessments could improve fall risk identification.

8.1 Future Work

The developed predictive models provide a binary classification of individuals as fallers and non-fallers. This may oversimplify the complex nature of fall risk populations. While designating individuals as "at fall risk" is important, it oversimplifies the complex fall risk issue. A finer fall risk categorization, such as an indication of the level of biomechanical fall risk, could aid clinicians in determining which individuals should receive limited health care resources. One approach would be to define criterion classifications for model development that are dependent on the type of falls that the participants experienced. For example, participants who only fell when there was a non-biomechanical condition that increased fall risk would be classified as at 'Low Biomechanical Fall Risk'. Non-biomechanical conditions could include, but are not limited to, icy sidewalks, unexpected obstacle on the floor, or insufficient lighting. Participants who fell at least once due to a ground height change or floor surface (i.e. wood to carpet) change would be classified as at 'Medium Biomechanical Fall Risk'. Changes in ground height include uneven floor surface, stairs, ramps, and curbs. Participants who fell at least once in a level ground environment would be classified as at 'High Biomechanical Fall Risk'. Unfortunately, with only three participants classified as ‘High Biomechanical Fall Risk’, there was an insufficient sample size to proceed with this level of analysis and faller classification. Study protocol continuation to obtain a larger sample size could allow classification of levels of biomechanical fall risk.

In this thesis, wearable-sensor-based features, posturography-based features, and clinical assessment features were all evaluated separately as inputs to fall risk models. While this allowed for comparisons between these feature sets, models could be developed using features from all sources (i.e., wearable-sensor, posturography, and clinical). In addition, other readily available information, such as age, could be incorporated as model inputs. This could result in stronger model performance.

The identified models and features in this thesis could also be tested with specific disease populations that have increased fall risk. These populations include Parkinson's disease, diabetes with peripheral neuropathy, dementia, and stroke. The models developed for a general elderly population may not perform as well in disease-specific populations, which have specific risk factors that are unique to that disease. For example, diabetics with peripheral neuropathy have twice the fall risk compared to their peers [327] and have decreased lower extremity strength [327,328] and impaired joint proprioception [328], particularly at the ankle. Evaluating the developed models in disease populations to determine fall risk predictive performance and comparing this performance to models developed specifically for the disease-specific population would be useful in determining whether disease-specific models are necessary for accurate faller prediction or whether a model developed based on a general elderly population is sufficiently accurate for clinical diagnostic purposes. In addition to evaluating model performance on different disease-specific populations, the developed models could be tested on nursing-home-dwelling and home-care-recipient older adult populations. Similar to the disease-specific populations, these older adult populations are at increased fall risk compared to community-dwelling older adults (Section 2.1.3). In addition to evaluating the identified models on disease-specific populations, the models should be re-tested on a new older adult population to validate model performance.

Further examination of the derived wearable-sensor-features could also be performed to determine whether the features are more closely related to speed control versus dynamic stability. Features related to dynamic stability control that are weakly correlated to gait velocity would have greater clinical relevance, because they provide information that cannot be obtained through a simple gait velocity measurement.

While strong results were achieved based on level ground gait data, falls often occur in non-level ground environments where the environment itself contributes to the risk of falling. In this study, 33% of prospective falls occurred on stairs, suggesting that this environment in particular can challenge stability and balance in older adults. Therefore, it would be interesting to expand this work by assessing gait while walking up and down stairs. In addition, stair-based gait could be assessed in a dual-task scenario with either a physical load that ideally would obstruct or partially obstruct visual input of the stair or a cognitive load.

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Appendix A: ANOVA Results

Table A.1. Mixed-design ANOVA test results for pressure-sensing insole variables for retrospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Walking Condition Main Effect	Faller Status Main Effect	Interaction Effect
CoP Path			
PD per Stride	**$F(1,98) = 29.863$, $p < 0.001$, $\eta^2 = 0.234$**	$F(1,98) = 0.427$, $p = 0.515$, $\eta^2 = 0.004$	$F(1,98) = 0.339$, $p = 0.562$, $\eta^2 = 0.003$
PD Length (mm)	$F(1,98) = 2.489$, $p = 0.118$, $\eta^2 = 0.025$	$F(1,98) = 0.008$, $p = 0.931$, $\eta^2 < 0.001$	$F(1,98) = 1.274$, $p = 0.262$, $\eta^2 = 0.013$
PD Duration (s)	$F(1,98) = 3.012$, $p = 0.086$, $\eta^2 = 0.030$	$F(1,98) = 0.891$, $p = 0.348$, $\eta^2 = 0.009$	$F(1,98) = 0.897$, $p = 0.346$, $\eta^2 = 0.009$
Medial Deviations per Stride (#)	$F(1,98) = 3.915$, $p = 0.051$, $\eta^2 = 0.038$	$F(1,98) = 0.774$, $p = 0.381$, $\eta^2 = 0.008$	$F(1,98) = 0.018$, $p = 0.893$, $\eta^2 < 0.001$
Medial Deviation Length (mm)	$F(1,98) = 0.961$, $p = 0.329$, $\eta^2 = 0.010$	$F(1,98) = 0.278$, $p = 0.599$, $\eta^2 = 0.003$	$F(1,98) = 0.014$, $p = 0.906$, $\eta^2 < 0.001$
Lateral Deviation Length (mm)	$F(1,98) = 0.357$, $p = 0.551$, $\eta^2 = 0.004$	$F(1,98) = 1.106$, $p = 0.295$, $\eta^2 = 0.011$	$F(1,98) = 3.242$, $p = 0.075$, $\eta^2 = 0.032$
ML Deviation Duration (s)	**$F(1,98) = 12.079$, $p = 0.001$, $\eta^2 = 0.110$**	$F(1,98) = 2.627$, $p = 0.108$, $\eta^2 = 0.026$	$F(1,98) = 0.140$, $p = 0.709$, $\eta^2 = 0.001$
Min CoP Vel (m/s)	**$F(1,98) = 50.528$, $p < 0.001$, $\eta^2 = 0.340$**	$F(1.98) = 1.411$, $p = 0.238$, $\eta^2 = 0.014$	$F(1,98) = 0.313$, $p = 0.577$, $\eta^2 = 0.003$
Max CoP Vel (m/s)	$F(1,98) = 0.401$, $p = 0.528$, $\eta^2 = 0.004$	$F(1,98) = 1.525$, $p = 0.220$, $\eta^2 = 0.015$	$F(1,98) = 0.543$, $p = 0.463$, $\eta^2 = 0.006$
Mean CoP Vel (m/s)	**$F(1,98) = 98.514$, $p < 0.001$, $\eta^2 = 0.501$**	$F(1,98) = 0.088$, $p = 0.768$, $\eta^2 = 0.001$	$F(1,98) = 1.128$, $p = 0.291$, $\eta^2 = 0.011$
Median CoP Vel (m/s)	**$F(1,98) = 116.078$, $p < 0.001$, $\eta^2 = 0.542$**	$F(1,98) = 1.372$, $p = 0.244$, $\eta^2 = 0.014$	$F(1,98) = 1.015$, $p = 0.316$, $\eta^2 = 0.010$
Temporal			
Cadence (steps/minute)	**$F(1,98) = 90.242$, $p < 0.001$, $\eta^2 = 0.479$**	$F(1,98) = 0.020$, $p = 0.887$, $\eta^2 < 0.001$	$F(1,98) = 0.200$, $p = 0.656$, $\eta^2 = 0.002$
Stride Time (s)	**$F(1,98) = 67.952$, $p < 0.001$, $\eta^2 = 0.409$**	$F(1,98) = 0.004$, $p = 0.948$, $\eta^2 < 0.001$	$F(1,98) = 0.085$, $p = 0.772$, $\eta^2 = 0.001$
Stance Time (s)	**$F(1,98) = 63.568$, $p < 0.001$, $\eta^2 = 0.393$**	$F(1,98) = 0.003$, $p = 0.956$, $\eta^2 < 0.001$	$F(1,98) = 1.490$, $p = 0.225$, $\eta^2 = 0.015$
Swing Time (s)	**$F(1,98) = 34.062$, $p < 0.001$, $\eta^2 = 0.258$**	$F(1,98) = 0.017$, $p = 0.898$, $\eta^2 < 0.001$	$F(1,98) = 2.180$, $p = 0.143$, $\eta^2 = 0.022$
Stride Time CoV	**$F(1,98) = 18.939$, $p < 0.001$, $\eta^2 = 0.162$**	$F(1,98) = 0.014$, $p = 0.907$, $\eta^2 < 0.001$	$F(1,98) = 0.644$, $p = 0.424$, $\eta^2 = 0.007$
Stance Time CoV	**$F(1,98) = 4.451$, $p = 0.037$, $\eta^2 = 0.043$**	$F(1,98) = 0.036$, $p = 0.850$, $\eta^2 < 0.001$	$F(1,98) = 2.252$, $p = 0.137$, $\eta^2 = 0.022$
Swing Time CoV	$F(1,98) = 2.827$, $p = 0.096$, $\eta^2 = 0.028$	$F(1,98) = 0.669$, $p = 0.416$, $\eta^2 = 0.007$	**$F(1,98) = 4.343$, $p = 0.040$, $\eta^2 = 0.042$**
Percent Stance Time (%)	**$F(1,98) = 9.039$, $p = 0.003$, $\eta^2 = 0.084$**	$F(1,98) = 0.063$, $p = 0.803$, $\eta^2 = 0.001$	**$F(1,98) = 8.060$, $p = 0.006$, $\eta^2 = 0.076$**
Percent Double-Support Time (%)	**$F(1,98) = 9.108$, $p = 0.003$, $\eta^2 = 0.085$**	$F(1,98) = 0.050$, $p = 0.823$, $\eta^2 = 0.001$	**$F(1,98) = 8.739$, $p = 0.004$, $\eta^2 = 0.082$**
Stride Time Symmetry Index	**$F(1,98) = 18.167$, $p < 0.001$, $\eta^2 = 0.156$**	$F(1,98) = 0.007$, $p = 0.931$, $\eta^2 < 0.001$	$F(1,98) = 0.834$, $p = 0.363$, $\eta^2 = 0.008$
CoP Path Stance Phase CoV			
CoV AP	**$F(1,98) = 25.766$, $p < 0.001$, $\eta^2 = 0.208$**	$F(1,98) = 0.592$, $p = 0.444$, $\eta^2 = 0.006$	$F(1,98) = 0.033$, $p = 0.855$, $\eta^2 < 0.001$

CoV ML	**F(1,98) = 5.853, *p* = 0.017, η^2 = 0.056**	F(1,98) = 0.807, *p* = 0.371, η^2 = 0.008	F(1,98) = 1.158, *p* = 0.285, η^2 = 0.012
Impulse (Ns/kg)			
Foot-strike to first peak (I1)	**F(1,98) = 46.674, *p* < 0.001, η^2 = 0.323**	F(1,98) = 0.092, *p* = 0.762, η^2 = 0.001	F(1,98) = 1.122, *p* = 0.292, η^2 = 0.011
First peak to min (I2)	F(1,98) = 1.409, *p* = 0.238, η^2 = 0.014	F(1,98) < 0.001, *p* = 0.996, η^2 < 0.001	F(1,98) = 0.449, *p* = 0.504, η^2 = 0.005
Min to second peak (I3)	**F(1,98) = 4.988, *p* = 0.028, η^2 = 0.048**	F(1,98) = 1.809, *p* = 0.182, η^2 = 0.018	F(1,98) = 0.034, *p* = 0.854, η^2 < 0.001
Second peak to foot-off (I4)	**F(1,98) = 33.335, *p* < 0.001, η^2 = 0.254**	F(1,98) = 0.268, *p* = 0.606, η^2 = 0.003	F(1,98) = 0.496, *p* = 0.483, η^2 = 0.005
Foot-strike to min (I5)	**F(1,98) = 14.656, *p* < 0.001, η^2 = 0.130**	F(1,98) = 0.018, *p* = 0.893, η^2 < 0.001	F(1,98) = 1.696, *p* = 0.196, η^2 = 0.017
Min to foot-off (I6)	**F(1,98) = 31.105, *p* < 0.001, η^2 = 0.241**	F(1,98) = 1.170, *p* = 0.282, η^2 = 0.012	F(1,98) = 0.376, *p* = 0.541, η^2 = 0.004
Foot-strike to foot-off (I7)	**F(1,98) = 37.076, *p* < 0.001, η^2 = 0.274**	F(1,98) = 0.306, *p* = 0.581, η^2 = 0.003	F(1,98) = 1.014, *p* = 0.316, η^2 = 0.010

Table A.2. Mixed design ANOVA test results for head accelerometer variables for retrospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Walking Condition Main Effect	**Faller Status Main Effect**	**Interaction Effect**
FFT Quartile (%)			
Vertical	**F(1,98) = 32.058, p <0.001, η^2 = 0.246**	F(1,98) = 0.607, p = 0.438, η^2 = 0.006	F(1,98) < 0.001, p = 0.998, η^2 < 0.001
AP	**F(1,98) = 24.252, p <0.001, η^2 = 0.198**	F(1,98) = 0.846, p = 0.360, η^2 = 0.009	F(1,98) = 0.130, p = 0.719, η^2 = 0.001
ML	**F(1,98) = 7.741, p = 0.006, η^2 = 0.073**	F(1,98) = 3.027, p = 0.085, η^2 = 0.030	F(1,98) = 0.177, p = 0.675, η^2 = 0.002
Ratio of Even to Odd Harmonics			
Vertical	**F(1,98) = 21.021, p < 0.001, η^2 = 0.177**	F(1,98) = 0.127, p = 0.723, η^2 = 0.001	**F(1,98) = 5.387, p = 0.022, η^2 = 0.052**
AP	**F(1,98) = 10.185, p = 0.002, η^2 = 0.094**	F(1,98) = 0.101, p = 0.751, η^2 = 0.001	F(1,98) = 0.678, p = 0.412, η^2 = 0.007
ML	**F(1,98) = 6.296, p = 0.014, η^2 = 0.060**	F(1,98) = 0.625, p = 0.431, η^2 = 0.006	F(1,98) = 2.491, p = 0.118, η^2 = 0.025
Maximum Lyapunov Exponent			
Vertical	F(1,98) = 2.511, p = 0.116, η^2 = 0.025	F(1,98) = 0.002, p = 0.968, η^2 < 0.001	F(1,98) = 0.339, p = 0.562, η^2 = 0.003
AP	F(1,98) = 0.866, p = 0.354, η^2 = 0.009	F(1,98) = 2.109, p = 0.150, η^2 = 0.021	F(1,98) = 0.345, p = 0.558, η^2 = 0.004
ML	**F(1,98) = 5.261, p = 0.024, η^2 = 0.051**	F(1,98) = 0.506, p = 0.479, η^2 = 0.005	F(1,98) = 0.233, p = 0.630, η^2 = 0.002
Acceleration Descriptive Statistics (g)			
Superior Max	**F(1,98) = 22.938, p < 0.001, η^2 = 0.190**	F(1,98) = 0.202, p = 0.654, η^2 = 0.002	F(1,98) = 0.579, p = 0.448, η^2 = 0.006
Superior Mean	**F(1,98) = 15.467, p < 0.001, η^2 = 0.136**	F(1,98) = 0.371, p = 0.544, η^2 = 0.004	F(1,98) = 0.235, p = 0.629, η^2 = 0.002
Superior SD	**F(1,98) = 10.793, p = 0.001, η^2 = 0.099**	F(1,98) = 0.031, p = 0.861, η^2 < 0.001	F(1,98) = 0.635, p = 0.428, η^2 = 0.006
Inferior Max	F(1,98) = 0.195, p = 0.660, η^2 = 0.002	F(1,98) = 0.889, p = 0.348, η^2 = 0.009	F(1,98) = 1.675, p = 0.199, η^2 = 0.017
Inferior Mean	F(1,98) < 0.001, p = 0.984, η^2 < 0.001	F(1,98) = 0.454, p = 0.502, η^2 = 0.005	F(1,98) = 2.194, p = 0.142, η^2 = 0.022
Inferior SD	F(1,98) = 0.015, p = 0.902, η^2 < 0.001	F(1,98) = 0.462, p = 0.498, η^2 = 0.005	F(1,98) = 3.558, p = 0.062, η^2 = 0.035
Anterior Max	F(1,98) = 0.164, p = 0.686, η^2 = 0.002	F(1,98) = 1.250, p = 0.266, η^2 = 0.013	F(1,98) = 0.492, p = 0.485, η^2 = 0.005
Anterior Mean	**F(1,98) = 5.520, p = 0.021, η^2 = 0.053**	F(1,98) = 2.102, p = 0.150, η^2 = 0.021	F(1,98) = 0.412, p = 0.523, η^2 = 0.004
Anterior SD	F(1,98) = 1.603, p = 0.209, η^2 = 0.016	F(1,98) = 0.600, p = 0.440, η^2 = 0.006	F(1,98) = 0.056, p = 0.813, η^2 = 0.001
Posterior Max	**F(1,98) = 5.816, p = 0.018, η^2 = 0.056**	F(1,98) = 1.882, p = 0.173, η^2 = 0.019	F(1,98) = 6.507, p = 0.012, η^2 = 0.062
Posterior Mean	**F(1,98) = 10.619, p = 0.002, η^2 = 0.098**	F(1,98) = 2.576, p = 0.112, η^2 = 0.026	F(1,98) = 7.625, p = 0.007, η^2 = 0.072
Posterior SD	**F(1,98) = 10.770, p = 0.001, η^2 = 0.099**	F(1,98) = 2.332, p = 0.130, η^2 = 0.023	**F(1,98) = 7.782, p = 0.006, η^2 = 0.074**
Right Max	**F(1,98) = 5.659, p = 0.019, η^2 = 0.055**	F(1,98) = 0.305, p = 0.582, η^2 = 0.003	F(1,98) = 1.216, p = 0.273, η^2 = 0.012
Right Mean	**F(1,98) = 6.747, p = 0.011,**	F(1,98) = 0.089, p = 0.766,	F(1,98) = 0.744, p = 0.391,

	η^2 = 0.064	η^2 = 0.001	η^2 = 0.008
Right SD	**F(1,98) = 5.876, *p* = 0.017, η^2 = 0.057**	F(1,98) = 0.164, *p* = 0.686, η^2 = 0.002	F(1,98) = 1.865, *p* = 0.175, η^2 = 0.019
Left Max	F(1,98) = 0.627, *p* = 0.430, η^2 = 0.006	F(1,98) = 0.944, *p* = 0.334, η^2 = 0.010	F(1,98) = 0.182, *p* = 0.670, η^2 = 0.002
Left Mean	F(1,98) = 2.221, *p* = 0.139, η^2 = 0.022	F(1,98) = 0.341, *p* = 0.561, η^2 = 0.003	F(1,98) = 0.001, *p* = 0.974, η^2 < 0.001
Left SD	F(1,98) = 1.018, *p* = 0.316, η^2 = 0.010	F(1,98) = 0.904, *p* = 0.344, η^2 = 0.009	F(1,98) = 1.018, *p* = 0.316, η^2 = 0.010

Table A.3. Mixed-design ANOVA test results for posterior pelvis accelerometer variables for retrospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Walking Condition Main Effect	Faller Status Main Effect	Interaction Effect
FFT Quartile (%)			
Vertical	**F(1,96) = 35.034, p < 0.001, η^2 = 0.267**	F(1,96) = 0.004, p = 0.952, η^2 < 0.001	F(1,96) = 0.051, p = 0.822, η^2 = 0.001
AP	F(1,96) = 3.265, p = 0.074, η^2 = 0.033	F(1,96) = 2.800, p = 0.098, η^2 = 0.028	F(1,96) = 1.515, p = 0.221, η^2 = 0.016
ML	**F(1,96) = 11.396, p = 0.001, η^2 = 0.106**	F(1,96) = 0.406, p = 0.526, η^2 = 0.004	F(1,96) = 0.121, p = 0.729, η^2 = 0.001
Ratio of Even to Odd Harmonics			
Vertical	**F(1,96) = 4.690, p = 0.033, η^2 = 0.047**	F(1,96) = 0.940, p = 0.335, η^2 = 0.010	F(1,96) < 0.001, p = 0.983, η^2 < 0.001
AP	**F(1,96) = 4.506, p = 0.036, η^2 = 0.045**	**F(1,96) = 5.451, p = 0.022, η^2 = 0.054**	F(1,96) = 0.402, p = 0.528, η^2 = 0.004
ML	F(1,96) = 2.611, p = 0.109, η^2 = 0.026	F(1,96) = 0.399, p = 0.529, η^2 = 0.004	F(1,96) = 0.179, p = 0.673, η^2 = 0.002
Maximum Lyapunov Exponent			
Vertical	F(1,96) = 0.253, p = 0.616, η^2 = 0.003	F(1,96) = 0.834, p = 0.363, η^2 = 0.009	**F(1,96) = 8.305, p = 0.005, η^2 = 0.080**
AP	F(1,96) = 0.001, p = 0.982, η^2 < 0.001	F(1,96) = 1.555, p = 0.215, η^2 = 0.016	F(1,96) = 0.181, p = 0.672, η^2 = 0.002
ML	F(1,96) = 1.704, p = 0.195, η^2 = 0.017	F(1,96) = 0.727, p = 0.396, η^2 = 0.008	F(1,96) = 2.155, p = 0.145, η^2 = 0.022
Acceleration Descriptive Statistics (g)			
Superior Max	**F(1,96) = 12.686, p = 0.001, η^2 = 0.117**	F(1,96) = 0.137, p = 0.712, η^2 = 0.001	F(1,96) = 1.445, p = 0.232, η^2 = 0.015
Superior Mean	**F(1,96) = 23.146, p < 0.001, η^2 = 0.194**	F(1,96) = 0.955, p = 0.331, η^2 = 0.010	F(1,96) = 0.141, p = 0.708, η^2 = 0.001
Superior SD	**F(1,96) = 22.859, p < 0.001, η^2 = 0.192**	F(1,96) = 0.395, p = 0.531, η^2 = 0.004	F(1,96) = 0.841, p = 0.361, η^2 = 0.009
Inferior Max	**F(1,96) = 50.859, p < 0.001, η^2 = 0.346**	F(1,96) = 0.011, p = 0.917, η^2 < 0.001	**F(1,96) = 5.619, p = 0.020, η^2 = 0.055**
Inferior Mean	**F(1,96) = 43.509, p < 0.001, η^2 = 0.312**	F(1,96) = 0.183, p = 0.670, η^2 = 0.002	**F(1,96) = 5.128, p = 0.026, η^2 = 0.051**
Inferior SD	**F(1,96) = 59.689, p < 0.001, η^2 = 0.383**	F(1,96) = 0.002, p = 0.964, η^2 < 0.001	**F(1,96) = 5.252, p = 0.024, η^2 = 0.052**
Anterior Max	**F(1,96) = 50.172, p < 0.001, η^2 = 0.343**	F(1,96) = 0.048, p = 0.828, η^2 < 0.001	F(1,96) = 2.462, p = 0.120, η^2 = 0.025
Anterior Mean	**F(1,96) = 25.683, p < 0.001, η^2 = 0.211**	F(1,96) < 0.001, p = 0.999, η^2 < 0.001	F(1,96) = 0.791, p = 0.376, η^2 = 0.008
Anterior SD	**F(1,96) = 47.469, p < 0.001, η^2 = 0.331**	F(1,96) = 0.240, p = 0.626, η^2 = 0.002	F(1,96) = 1.430, p = 0.235, η^2 = 0.015
Posterior Max	**F(1,96) = 14.851, p < 0.001, η^2 = 0.134**	F(1,96) = 0.262, p = 0.610, η^2 = 0.003	F(1,96) = 0.781, p = 0.379, η^2 = 0.008
Posterior Mean	**F(1,96) = 17.948, p < 0.001, η^2 = 0.158**	F(1,96) = 0.206, p = 0.651, η^2 = 0.002	F(1,96) = 0.878, p = 0.351, η^2 = 0.009
Posterior SD	**F(1,96) = 20.269, p < 0.001, η^2 = 0.174**	F(1,96) = 0.209, p = 0.649, η^2 = 0.002	F(1,96) = 0.717, p = 0.399, η^2 = 0.007
Right Max	**F(1,96) = 42.893, p < 0.001, η^2 = 0.309**	F(1,96) = 0.080, p = 0.777, η^2 = 0.001	F(1,96) = 3.702, p = 0.057, η^2 = 0.037
Right Mean	**F(1,96) = 47.848, p < 0.001,**	F(1,96) = 0.014, p = 0.906,	**F(1,96) = 4.884, p = 0.029,**

	η^2 = 0.333	$\eta^2 < 0.001$	**η^2 = 0.048**
Right SD	**F(1,96) = 48.650, *p* < 0.001, η^2 = 0.336**	F(1,96) < 0.001, *p* = 0.994, $\eta^2 < 0.001$	**F(1,96) = 4.122, *p* = 0.045, η^2 = 0.041**
Left Max	**F(1,96) = 31.337, *p* < 0.001, η^2 = 0.246**	F(1,96) = 0.060, *p* = 0.806, η^2 = 0.001	F(1,96) = 3.382, *p* = 0.069, η^2 = 0.034
Left Mean	**F(1,96) = 30.504, *p* < 0.001, η^2 = 0.241**	F(1,96) = 0.002, *p* = 0.967, $\eta^2 < 0.001$	F(1,96) = 0.556, *p* = 0.458, η^2 = 0.006
Left SD	**F(1,96) = 51.562, *p* < 0.001, η^2 = 0.349**	F(1,96) = 0.008, *p* = 0.928, $\eta^2 < 0.001$	**F(1,96) = 4.257, *p* = 0.042, η^2 = 0.042**

Table A.4. Mixed-design ANOVA test results for right shank accelerometer variables for retrospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Walking Condition Main Effect	Faller Status Main Effect	Interaction Effect
FFT Quartile (%)			
Vertical	**F(1,98) = 26.366, *p* < 0.001, η^2 = 0.212**	F(1,98) = 0.751, *p* = 0.388, η^2 = 0.008	F(1,98) = 0.442, *p* = 0.508, η^2 = 0.004
AP	**F(1,98) = 44.719, *p* < 0.001, η^2 = 0.313**	F(1,98) = 0.894, *p* = 0.347, η^2 = 0.009	F(1,98) = 0.014, *p* = 0.907, η^2 < 0.001
ML	**F(1,98) = 42.903, *p* < 0.001, η^2 = 0.304**	F(1,98) = 1.975, *p* = 0.163, η^2 = 0.020	F(1,98) = 0.489, *p* = 0.486, η^2 = 0.005
Ratio of Even to Odd Harmonics			
Vertical	F(1,98) = 2.261, *p* = 0.136, η^2 = 0.023	F(1,98) = 2.189, *p* = 0.142, η^2 = 0.022	F(1,98) = 0.005, *p* = 0.943, η^2 = 0.000
AP	F(1,98) = 0.052, *p* = 0.821, η^2 = 0.001	F(1,98) = 0.453, *p* = 0.502, η^2 = 0.005	F(1,98) = 0.001, *p* = 0.981, η^2 < 0.001
ML	F(1,98) = 1.076, *p* = 0.302, η^2 = 0.011	F(1,98) = 0.024, *p* = 0.878, η^2 < 0.001	F(1,98) = 1.363, *p* = 0.246, η^2 = 0.014
Maximum Lyapunov Exponent			
Vertical	**F(1,98) = 5.479, *p* = 0.021, η^2 = 0.053**	F(1,98) = 0.173, *p* = 0.678, η^2 = 0.002	**F(1,98) = 4.250, *p* = 0.042, η^2 = 0.042**
AP	F(1,98) = 1.015, *p* = 0.316, η^2 = 0.010	F(1,98) = 0.460, *p* = 0.499, η^2 = 0.005	F(1,98) = 2.392, *p* = 0.125, η^2 = 0.024
ML	F(1,98) = 0.004, *p* = 0.949, η^2 < 0.001	F(1,98) = 0.294, *p* = 0.589, η^2 = 0.003	F(1,98) = 3.304, *p* = 0.072, η^2 = 0.033
Acceleration Descriptive Statistics (g)			
Superior Max	**F(1,98) = 16.769, *p* < 0.001, η^2 = 0.146**	F(1,98) = 0.501, *p* = 0.481, η^2 = 0.005	F(1,98) = 0.379, *p* = 0.540, η^2 = 0.004
Superior Mean	**F(1,98) = 14.403, *p* < 0.001, η^2 = 0.128**	F(1,98) = 2.380, *p* = 0.126, η^2 = 0.024	F(1,98) = 0.561, *p* = 0.456, η^2 = 0.006
Superior SD	**F(1,98) = 24.338, *p* < 0.001, η^2 = 0.199**	F(1,98) = 0.124, *p* = 0.726, η^2 = 0.001	F(1,98) = 0.528, *p* = 0.469, η^2 = 0.005
Inferior Max	**F(1,98) = 28.785, *p* < 0.001, η^2 = 0.227**	F(1,98) = 0.001, *p* = 0.971, η^2 < 0.001	F(1,98) = 0.277, *p* = 0.600, η^2 = 0.003
Inferior Mean	**F(1,98) = 50.687, *p* < 0.001, η^2 = 0.341**	F(1,98) = 0.123, *p* = 0.727, η^2 = 0.001	F(1,98) = 1.151, *p* = 0.286, η^2 = 0.012
Inferior SD	**F(1,98) = 47.224, *p* < 0.001, η^2 = 0.325**	F(1,98) = 0.072, *p* = 0.789, η^2 = 0.001	F(1,98) = 0.077, *p* = 0.781, η^2 = 0.001
Anterior Max	**F(1,98) = 49.540, *p* < 0.001, η^2 = 0.336**	F(1,98) = 0.177, *p* = 0.675, η^2 = 0.002	F(1,98) = 0.141, *p* = 0.709, η^2 = 0.001
Anterior Mean	**F(1,98) = 52.900, *p* < 0.001, η^2 = 0.351**	F(1,98) = 0.134, *p* = 0.715, η^2 = 0.001	F(1,98) = 0.708, *p* = 0.402, η^2 = 0.007
Anterior SD	**F(1,98) = 54.765, *p* < 0.001, η^2 = 0.358**	F(1,98) = 0.207, *p* = 0.650, η^2 = 0.002	F(1,98) = 0.164, *p* = 0.686, η^2 = 0.002
Posterior Max	**F(1,98) = 3.690, *p* = 0.058, η^2 = 0.036**	F(1,98) = 0.001, *p* = 0.978, η^2 < 0.001	F(1,98) = 1.549, *p* = 0.216, η^2 = 0.016
Posterior Mean	**F(1,98) = 15.037, *p* < 0.001, η^2 = 0.133**	F(1,98) = 0.009, *p* = 0.923, η^2 < 0.001	F(1,98) = 0.009, *p* = 0.924, η^2 < 0.001
Posterior SD	F(1,98) = 3.046, *p* = 0.084, η^2 = 0.030	F(1,98) = 0.164, *p* = 0.686, η^2 = 0.002	F(1,98) = 0.234, *p* = 0.630, η^2 = 0.002
Right Max	**F(1,98) = 40.019, *p* < 0.001, η^2 = 0.290**	F(1,98) = 0.279, *p* = 0.599, η^2 = 0.003	F(1,98) = 0.898, *p* = 0.346, η^2 = 0.009
Right Mean	**F(1,98) = 42.496, *p* < 0.001,**	F(1,98) = 0.139, *p* = 0.710,	F(1,98) = 2.510, *p* = 0.116,

	η^2 = 0.302	η^2 = 0.001	η^2 = 0.025
Right SD	**F(1,98) = 54.996, *p* < 0.001, η^2 = 0.359**	F(1,98) = 0.209, *p* = 0.649, η^2 = 0.002	F(1,98) = 1.830, *p* = 0.179, η^2 = 0.018
Left Max	**F(1,98) = 16.587, *p* < 0.001, η^2 = 0.145**	F(1,98) = 0.005, *p* = 0.942, η^2 < 0.001	F(1,98) = 1.175, *p* = 0.281, η^2 = 0.012
Left Mean	**F(1,98) = 30.384, *p* < 0.001, η^2 = 0.237**	F(1,98) = 0.002, *p* = 0.964, η^2 < 0.001	F(198) = 0.368, *p* = 0.546, η^2 = 0.004
Left SD	**F(1,98) = 30.962, *p* < 0.001, η^2 = 0.240**	F(1,98) = 0.003, *p* = 0.955, η^2 < 0.001	F(1,98) = 1.133, *p* = 0.290, η^2 = 0.011

Table A.5. Mixed-design ANOVA test results for left shank accelerometer variables for retrospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Walking Condition Main Effect	Faller Status Main Effect	Interaction Effect
FFT Quartile (%)			
Vertical	**$F(1,97) = 32.606$, $p < 0.001$, $\eta^2 = 0.252$**	$F(1,97) = 0.518$, $p = 0.473$, $\eta^2 = 0.005$	$F(1,97) = 0.796$, $p = 0.375$, $\eta^2 = 0.008$
AP	**$F(1,97) = 45.418$, $p < 0.001$, $\eta^2 = 0.319$**	$F(1,97) = 1.102$, $p = 0.296$, $\eta^2 = 0.011$	$F(1,97) = 0.790$, $p = 0.376$, $\eta^2 = 0.008$
ML	**$F(1,97) = 33.860$, $p < 0.001$, $\eta^2 = 0.259$**	$F(1,97) = 1.142$, $p = 0.288$, $\eta^2 = 0.012$	$F(1,97) = 1.126$, $p = 0.291$, $\eta^2 = 0.011$
Ratio of Even to Odd Harmonics			
Vertical	$F(1,97) = 3.676$, $p = 0.058$, $\eta^2 = 0.037$	$F(1,97) = 0.024$, $p = 0.877$, $\eta^2 < 0.001$	$F(1,97) = 1.402$, $p = 0.239$, $\eta^2 = 0.014$
AP	$F(1,97) = 0.026$, $p = 0.872$, $\eta^2 < 0.001$	$F(1,97) = 1.432$, $p = 0.234$, $\eta^2 = 0.015$	$F(1,97) = 0.207$, $p = 0.650$, $\eta^2 = 0.002$
ML	$F(1,97) = 0.270$, $p = 0.605$, $\eta^2 = 0.003$	$F(1,97) = 0.362$, $p = 0.549$, $\eta^2 = 0.004$	$F(1,97) = 0.424$, $p = 0.516$, $\eta^2 = 0.04$
Maximum Lyapunov Exponent			
Vertical	$F(1,97) = 2.581$, $p = 0.111$, $\eta^2 = 0.026$	$F(1,97) = 0.251$, $p = 0.617$, $\eta^2 = 0.003$	$F(1,97) = 2.684$, $p = 0.105$, $\eta^2 = 0.027$
AP	$F(1,97) = 3.166$, $p = 0.078$, $\eta^2 = 0.032$	$F(1,97) = 0.383$, $p = 0.537$, $\eta^2 = 0.004$	$F(1,97) = 0.670$, $p = 0.415$, $\eta^2 = 0.007$
ML	**$F(1,97) = 3.971$, $p = 0.049$, $\eta^2 = 0.039$**	$F(1,97) = 0.087$, $p = 0.768$, $\eta^2 = 0.001$	**$F(1,97) = 4.731$, $p = 0.032$, $\eta^2 = 0.047$**
Acceleration Descriptive Statistics (g)			
Superior Max	**$F(1,97) = 34.742$, $p < 0.001$, $\eta^2 = 0.264$**	$F(1,97) = 0.555$, $p = 0.458$, $\eta^2 = 0.006$	$F(1,97) = 0.187$, $p = 0.666$, $\eta^2 = 0.002$
Superior Mean	**$F(1,97) = 52.793$, $p < 0.001$, $\eta^2 = 0.352$**	$F(1,97) = 0.876$, $p = 0.352$, $\eta^2 = 0.009$	$F(1,97) = 0.835$, $p = 0.363$, $\eta^2 = 0.009$
Superior SD	**$F(1,97) = 48.560$, $p < 0.001$, $\eta^2 = 0.334$**	$F(1,97) = 0.707$, $p = 0.402$, $\eta^2 = 0.007$	$F(1,97) = 0.472$, $p = 0.494$, $\eta^2 = 0.005$
Inferior Max	**$F(1,97) = 29.754$, $p < 0.001$, $\eta^2 = 0.235$**	$F(1,97) = 0.089$, $p = 0.766$, $\eta^2 = 0.001$	$F(1,97) = 1.549$, $p = 0.216$, $\eta^2 = 0.016$
Inferior Mean	**$F(1,97) = 40.913$, $p < 0.001$, $\eta^2 = 0.297$**	$F(1,97) = 0.216$, $p = 0.643$, $\eta^2 = 0.002$	$F(1,97) = 0.558$, $p = 0.457$, $\eta^2 = 0.006$
Inferior SD	**$F(1,97) = 39.888$, $p < 0.001$, $\eta^2 = 0.291$**	$F(1,97) = 0.022$, $p = 0.881$, $\eta^2 < 0.001$	$F(1,97) = 0.455$, $p = 0.501$, $\eta^2 = 0.005$
Anterior Max	**$F(1,97) = 62.633$, $p < 0.001$, $\eta^2 = 0.392$**	$F(1,97) = 0.203$, $p = 0.654$, $\eta^2 = 0.002$	**$F(1,97) = 4.052$, $p = 0.047$, $\eta^2 = 0.040$**
Anterior Mean	**$F(1,97) = 62.296$, $p < 0.001$, $\eta^2 = 0.391$**	$F(1,97) = 0.310$, $p = 0.579$, $\eta^2 = 0.003$	$F(1,97) = 2.519$, $p = 0.116$, $\eta^2 = 0.025$
Anterior SD	**$F(1,97) = 71.087$, $p < 0.001$, $\eta^2 = 0.423$**	$F(1,97) = 0.254$, $p = 0.615$, $\eta^2 = 0.003$	$F(1,97) = 3.437$, $p = 0.067$, $\eta^2 = 0.034$
Posterior Max	**$F(1,97) = 9.336$, $p = 0.003$, $\eta^2 = 0.088$**	$F(1,97) = 0.656$, $p = 0.420$, $\eta^2 = 0.007$	**$F(1,97) = 7.169$, $p = 0.009$, $\eta^2 = 0.069$**
Posterior Mean	**$F(1,97) = 51.174$, $p < 0.001$, $\eta^2 = 0.345$**	$F(1,97) = 0.208$, $p = 0.649$, $\eta^2 = 0.002$	**$F(1,97) = 8.347$, $p = 0.005$, $\eta^2 = 0.079$**
Posterior SD	**$F(1,97) = 28.213$, $p < 0.001$, $\eta^2 = 0.225$**	$F(1,97) = 0.282$, $p = 0.596$, $\eta^2 = 0.003$	**$F(1,97) = 11.832$, $p = 0.001$, $\eta^2 = 0.109$**
Right Max	**$F(1,97) = 6.614$, $p = 0.012$, $\eta^2 = 0.064$**	$F(1,97) = 0.051$, $p = 0.822$, $\eta^2 = 0.001$	$F(1,97) = 0.655$, $p = 0.420$, $\eta^2 = 0.007$
Right Mean	**$F(1,97) = 27.104$, $p < 0.001$,**	$F(1,97) = 0.044$, $p = 0.834$,	$F(1,97) = 1.698$, $p = 0.196$,

	η^2 = 0.218	$\eta^2 < 0.001$	$\eta^2 = 0.017$
Right SD	**F(1,97) = 13.841, *p* < 0.001, η^2 = 0.125**	F(1,97) = 0.002, *p* = 0.966, $\eta^2 < 0.001$	F(1,97) = 0.604, *p* = 0.439, $\eta^2 = 0.006$
Left Max	**F(1,97) = 31.642, *p* < 0.001, η^2 = 0.246**	F(1,97) = 0.057, *p* = 0.812, $\eta^2 = 0.001$	F(1,97) = 0.013, *p* = 0.908, $\eta^2 < 0.001$
Left Mean	**F(1,97) = 42.047, *p* < 0.001, η^2 = 0.302**	F(1,97) = 0.005, *p* = 0.945, $\eta^2 < 0.001$	F(1,97) = 0.524, *p* = 0.471, $\eta^2 = 0.005$
Left SD	**F(1,97) = 38.632, *p* < 0.001, η^2 = 0.285**	F(1,97) = 0.080, *p* = 0.778, $\eta^2 = 0.001$	F(1,97) = 0.093, *p* = 0.761, $\eta^2 = 0.001$

Table A.6. Mixed-design ANOVA test results for pressure-sensing insole variables for prospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Mixed-Design ANOVA Analysis		
	Walking Condition Main Effect	**Faller/Non-Faller Status Main Effect**	**Interaction Effect**
CoP Path			
PD per Stride	**$F(1,73) = 31.166$, $p < 0.001$, $\eta^2 = 0.299$**	$F(1,73) = 0.102$, $p = 0.750$, $\eta^2 = 0.001$	$F(1,73) = 0.318$, $p = 0.575$, $\eta^2 = 0.004$
PD Length (mm)	$F(1,73) = 0.144$, $p = 0.705$, $\eta^2 = 0.002$	$F(1,73) = 0.070$, $p = 0.792$, $\eta^2 = 0.001$	$F(1,73) = 0.191$, $p = 0.664$, $\eta^2 = 0.003$
PD Duration (s)	$F(1,73) = 0.651$, $p = 0.423$, $\eta^2 = 0.009$	$F(1,73) = 0.568$, $p = 0.453$, $\eta^2 = 0.008$	$F(1,73) = 0.611$, $p = 0.437$, $\eta^2 = 0.008$
Medial Deviations per Stride (#)	$F(1,73) = 3.039$, $p = 0.086$, $\eta^2 = 0.040$	$F(1,73) = 0.299$, $p = 0.586$, $\eta^2 = 0.004$	$F(1,73) = 0.043$, $p = 0.836$, $\eta^2 = 0.001$
Medial Deviation Length (mm)	$F(1,73) = 1.303$, $p = 0.257$, $\eta^2 = 0.018$	$F(1,73) = 1.952$, $p = 0.167$, $\eta^2 = 0.026$	$F(1,73) = 1.655$, $p = 0.202$, $\eta^2 = 0.022$
Lateral Deviation Length (mm)	**$F(1,73) = 4.705$, $p = 0.033$, $\eta^2 = 0.061$**	$F(1,73) = 0.899$, $p = 0.346$, $\eta^2 = 0.012$	$F(1,73) = 0.346$, $p = 0.558$, $\eta^2 = 0.005$
ML Deviation Duration (s)	**$F(1,73) = 11.527$, $p = 0.001$, $\eta^2 = 0.136$**	$F(1,73) = 0.023$, $p = 0.881$, $\eta^2 < 0.001$	$F(1,73) = 0.311$, $p = 0.579$, $\eta^2 = 0.004$
Min CoP Vel (m/s)	**$F(1,73) = 35.113$, $p < 0.001$, $\eta^2 = 0.325$**	$F(1,73) = 1.024$, $p = 0.315$, $\eta^2 = 0.014$	$F(1,73) = 0.504$, $p = 0.480$, $\eta^2 = 0.007$
Max CoP Vel (m/s)	$F(1,73) = 2.223$, $p = 0.140$, $\eta^2 = 0.030$	$F(1,73) = 0.023$, $p = 0.881$, $\eta^2 < 0.001$	$F(1,73) = 1.323$, $p = 0.254$, $\eta^2 = 0.018$
Mean CoP Vel (m/s)	**$F(1,73) = 68.784$, $p < 0.001$, $\eta^2 = 0.485$**	$F(1,73) = 0.223$, $p = 0.638$, $\eta^2 = 0.003$	$F(1,73) = 0.939$, $p = 0.336$, $\eta^2 = 0.013$
Median CoP Vel (m/s)	**$F(1,73) = 91.911$, $p < 0.001$, $\eta^2 = 0.557$**	$F(1,73) = 0.209$, $p = 0.649$, $\eta^2 = 0.003$	$F(1,73) = 0.062$, $p = 0.804$, $\eta^2 = 0.001$
Temporal			
Cadence (steps/minute)	**$F(1,73) = 75.960$, $p < 0.001$, $\eta^2 = 0.510$**	$F(1,73) = 0.003$, $p = 0.957$, $\eta^2 < 0.001$	$F(1,73) = 1.891$, $p = 0.173$, $\eta^2 = 0.025$
Stride Time (s)	**$F(1,73) = 62.868$, $p < 0.001$, $\eta^2 = 0.463$**	$F(1,73) = 0.058$, $p = 0.810$, $\eta^2 = 0.001$	$F(1,73) = 1.790$, $p = 0.185$, $\eta^2 = 0.024$
Stance Time (s)	**$F(1,73) = 51.289$, $p < 0.001$, $\eta^2 = 0.413$**	$F(1,73) = 0.018$, $p = 0.894$, $\eta^2 < 0.001$	$F(1,73) = 0.764$, $p = 0.385$, $\eta^2 = 0.010$
Swing Time (s)	**$F(1,73) = 43.638$, $p < 0.001$, $\eta^2 = 0.374$**	$F(1,73) = 0.448$, $p = 0.505$, $\eta^2 = 0.006$	$F(1,73) = 1.800$, $p = 0.184$, $\eta^2 = 0.024$
Stride Time CoV	**$F(1,73) = 12.405$, $p = 0.001$, $\eta^2 = 0.145$**	$F(1,73) = 0.901$, $p = 0.346$, $\eta^2 = 0.012$	$F(1,73) = 0.523$, $p = 0.472$, $\eta^2 = 0.0074$
Stance Time CoV	$F(1,73) = 0.127$, $p = 0.723$, $\eta^2 = 0.002$	$F(1,73) = 0.695$, $p = 0.407$, $\eta^2 = 0.009$	$F(1,73) = 1.049$, $p = 0.309$, $\eta^2 = 0.014$
Swing Time CoV	$F(1,73) = 0.194$, $p = 0.661$, $\eta^2 = 0.003$	$F(1,73) = 0.354$, $p = 0.554$, $\eta^2 = 0.005$	$F(1,73) = 0.007$, $p = 0.935$, $\eta^2 < 0.001$
Percent Stance Time (%)	$F(1,73) = 0.123$, $p = 0.727$, $\eta^2 = 0.002$	$F(1,73) = 0.214$, $p = 0.645$, $\eta^2 = 0.003$	$F(1,73) = 0.435$, $p = 0.512$, $\eta^2 = 0.006$
Percent Double-Support Time (%)	$F(1,73) = 0.057$, $p = 0.812$, $\eta^2 = 0.001$	$F(1,73) = 0.168$, $p = 0.683$, $\eta^2 = 0.002$	$F(1,73) = 0.304$, $p = 0.583$, $\eta^2 = 0.004$
Stride Time Symmetry Index	**$F(1,73) = 12.003$, $p = 0.001$, $\eta^2 = 0.141$**	$F(1,73) = 0.005$, $p = 0.942$, $\eta^2 < 0.001$	$F(1,73) = 0.121$, $p = 0.729$, $\eta^2 = 0.002$
CoP Path Stance Phase CoV			
CoV AP	**$F(1,73) = 21.823$, $p < 0.001$, $\eta^2 = 0.230$**	$F(1,73) = 0.525$, $p = 0.471$, $\eta^2 = 0.007$	**$F(1,73) = 9.970$, $p = 0.002$, $\eta^2 = 0.120$**
CoV ML	**$F(1,73) = 10.331$, $p = 0.002$,**	$F(1,73) = 0.131$, $p = 0.718$,	$F(1,73) = 0.140$, $p = 0.709$,

	η^2 = 0.124	η^2 = 0.002	η^2 = 0.002
Impulse (Ns/kg)			
Foot-strike to first peak (I1)	**F(1,73) = 30.524, *p* < 0.001, η^2 = 0.295**	F(1,73) = 0.107, *p* = 0.744, η^2 = 0.001	F(1,73) = 1.953, *p* = 0.167, η^2 = 0.026
First peak to min (I2)	**F(1,73) = 6.078, *p* = 0.016, η^2 = 0.077**	F(1,73) = 0.726, *p* = 0.397, η^2 = 0.010	F(1,73) = 1.936, *p* = 0.168, η^2 = 0.026
Min to second peak (I3)	**F(1,73) = 4.115, *p* = 0.046, η^2 = 0.053**	F(1,73) = 3.075, *p* = 0.084, η^2 = 0.040	F(1,73) = 0.050, *p* = 0.824, η^2 = 0.001
Second peak to foot-off (I4)	**F(1,73) = 22.006, *p* < 0.001, η^2 = 0.232**	F(1,73) = 0.132, *p* = 0.717, η^2 = 0.002	F(1,73) = 0.257, *p* = 0.614, η^2 = 0.004
Foot-strike to min (I5)	**F(1,73) = 5.566, *p* = 0.021, η^2 = 0.071**	F(1,73) = 0.578, *p* = 0.450, η^2 = 0.008	F(1,73) = 1.921, *p* = 0.170, η^2 = 0.026
Min to foot-off (I6)	**F(1,73) = 21.351, *p* < 0.001, η^2 = 0.226**	F(1,73) = 1.449, *p* = 0.233, η^2 = 0.019	F(1,73) = 0.060, *p* = 0.807, η^2 = 0.001
Foot-strike to foot-off (I7)	**F(1,73) = 22.578, *p* < 0.001, η^2 = 0.236**	F(1,73) = 0.162, *p* = 0.688, η^2 = 0.002	F(1,73) = 1.037, *p* = 0.312, η^2 = 0.014

Table A.7. Mixed-design ANOVA test results for head accelerometer variables for prospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Mixed-Design ANOVA Analysis		
	Walking Condition Main Effect	**Faller/Non-Faller Status Main Effect**	**Interaction Effect**
FFT Quartile (%)			
Vertical	**F(1,73) = 29.151, *p* < 0.001, η^2 = 0.285**	F(1,73) = 0.334, *p* = 0.565, η^2 = 0.005	F(1,73) = 0.021, *p* = 0.884, η^2 < 0.001
AP	**F(1,73) = 21.982, *p* < 0.001, η^2 = 0.231**	**F(1,73) = 4.217, *p* = 0.044, η^2 = 0.055**	F(1,73) = 1.027, *p* = 0.314, η^2 = 0.014
ML	**F(1,73) = 10.335, *p* = 0.002, η^2 = 0.124**	F(1,73) = 0.126, *p* = 0.723, η^2 = 0.002	F(1,73) = 0.268, *p* = 0.607, η^2 = 0.004
Ratio of Even to Odd Harmonics			
Vertical	**F(1,73) = 4.297, *p* = 0.042, η^2 = 0.056**	F(1,73) = 0.384, *p* = 0.537, η^2 = 0.005	F(1,73) = 0.618, *p* = 0.434, η^2 = 0.008
AP	**F(1,73) = 7.692, *p* = 0.007, η^2 = 0.095**	F(1,73) = 0.735, *p* = 0.394, η^2 = 0.010	F(1,73) = 3.038, *p* = 0.086, η^2 = 0.040
ML	F(1,73) = 1.104, *p* = 0.297, η^2 = 0.015	F(1,73) = 1.333, *p* = 0.252, η^2 = 0.018	F(1,73) = 0.296, *p* = 0.588, η^2 = 0.004
Maximum Lyapunov Exponent			
Vertical	F(1,73) = 2.846, *p* = 0.096, η^2 = 0.038	F(1,73) = 0.315, *p* = 0.576, η^2 = 0.004	F(1,73) = 1.237, *p* = 0.270, η^2 = 0.017
AP	F(1,73) = 0.106, *p* = 0.746, η^2 = 0.001	F(1,73) = 0.741, *p* = 0.392, η^2 = 0.010	F(1,73) = 2.190, *p* = 0.143, η^2 = 0.029
ML	**F(1,73) = 5.331, *p* = 0.024, η^2 = 0.068**	F(1,73) = 0.182, *p* = 0.671, η^2 = 0.002	F(1,73) = 1.116, *p* = 0.294, η^2 = 0.015
Acceleration Descriptive Statistics (g)			
Superior Max	**F(1,73) = 29.960, *p* < 0.001, η^2 = 0.291**	**F(1,73) = 5.376, *p* =0.023, η^2 = 0.069**	F(1,73) = 0.101, *p* = 0.751, η^2 = 0.001
Superior Mean	**F(1,73) = 22.368, *p* < 0.001, η^2 = 0.235**	F(1,73) = 3.131, *p* = 0.081, η^2 = 0.041	F(1,73) = 0.793, *p* = 0.376, η^2 = 0.011
Superior SD	**F(1,73) = 18.481, *p* < 0.001, η^2 = 0.202**	F(1,73) = 3.363, *p* = 0.071, η^2 = 0.044	F(1,73) = 0.078, *p* = 0.781, η^2 = 0.001
Inferior Max	F(1,73) = 2.013, *p* = 0.160, η^2 = 0.027	F(1,73) = 0.043, *p* = 0.836, η^2 = 0.001	F(1,73) = 0.247, *p* = 0.620, η^2 = 0.003
Inferior Mean	F(1,73) = 1.931, *p* = 0.169, η^2 = 0.026	F(1,73) = 0.118, *p* = 0.732, η^2 = 0.002	F(1,73) = 0.123, *p* = 0.726, η^2 = 0.002
Inferior SD	F(1,73) = 2.328, *p* = 0.131, η^2 = 0.031	F(1,73) = 0.019, *p* = 0.891, η^2 < 0.001	F(1,73) = 0.186, *p* = 0.668, η^2 = 0.003
Anterior Max	F(1,73) = 0.955, *p* = 0.332, η^2 = 0.013	F(1,73) = 0.921, *p* = 0.340, η^2 = 0.012	F(1,73) = 0.123, *p* = 0.727, η^2 = 0.002
Anterior Mean	**F(1,73) = 7.928, *p* = 0.006, η^2 = 0.098**	F(1,73) = 1.294, *p* = 0.259, η^2 = 0.017	F(1,73) = 0.089, *p* = 0.767, η^2 = 0.001
Anterior SD	F(1,73) = 1.836, *p* = 0.180, η^2 = 0.025	F(1,73) = 0.958, *p* = 0.331, η^2 = 0.013	F(1,73) = 0.341, *p* = 0.561, η^2 = 0.005
Posterior Max	F(1,73) = 0.021, *p* = 0.885, η^2 < 0.001	F(1,73) = 0.917, *p* = 0.342, η^2 = 0.012	F(1,73) = 0.063, *p* = 0.802, η^2 = 0.001
Posterior Mean	F(1,73) = 0.287, *p* = 0.594, η^2 = 0.004	F(1,73) = 0.323, *p* = 0.571, η^2 = 0.004	F(1,73) = 0.006, *p* = 0.939, η^2 < 0.001
Posterior SD	F(1,73) = 0.287, *p* = 0.594, η^2 = 0.004	F(1,73) = 0.822, *p* = 0.368, η^2 = 0.011	F(1,73) = 0.002, *p* = 0.960, η^2 < 0.001
Right Max	**F(1,73) = 8.653, *p* = 0.004, η^2 = 0.106**	F(1,73) = 0.021, *p* = 0.884, η^2 < 0.001	F(1,73) = 1.253, *p* = 0.267, η^2 = 0.017

Right Mean	**$F(1,73) = 10.375$, $p = 0.002$, $\eta^2 = 0.124$**	$F(1,73) = 0.340$, $p = 0.562$, $\eta^2 = 0.005$	$F(1,73) = 0.075$, $p = 0.784$, $\eta^2 = 0.001$
Right SD	**$F(1,73) = 10.907$, $p = 0.001$, $\eta^2 = 0.130$**	$F(1,73) = 0.007$, $p = 0.935$, $\eta^2 < 0.001$	$F(1,73) = 0.842$, $p = 0.362$, $\eta^2 = 0.011$
Left Max	$F(1,73) = 2.022$, $p = 0.159$, $\eta^2 = 0.027$	$F(1,73) = 0.879$, $p = 0.352$, $\eta^2 = 0.012$	$F(1,73) = 2.011$, $p = 0.160$, $\eta^2 = 0.027$
Left Mean	$F(1,73) = 2.989$, $p = 0.088$, $\eta^2 = 0.039$	$F(1,73) = 1.952$, $p = 0.167$, $\eta^2 = 0.026$	$F(1,73) = 3.087$, $p = 0.083$, $\eta^2 = 0.041$
Left SD	$F(1,73) = 0.602$, $p = 0.440$, $\eta^2 = 0.008$	$F(1,73) = 0.453$, $p = 0.503$, $\eta^2 = 0.006$	$F(1,73) = 1.253$, $p = 0.267$, $\eta^2 = 0.017$

Table A.8. Mixed-design ANOVA test results for posterior pelvis accelerometer variables for prospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Mixed-Design ANOVA Analysis		
	Walking Condition Main Effect	**Faller/Non-Faller Status Main Effect**	**Interaction Effect**
FFT Quartile (%)			
Vertical	**$F(1,71) = 33.338$, $p < 0.001$, $\eta^2 = 0.320$**	$F(1,71) = 0.259$, $p = 0.612$, $\eta^2 = 0.004$	$F(1,71) = 0.422$, $p = 0.518$, $\eta^2 = 0.006$
AP	**$F(1,71) = 8.637$, $p = 0.004$, $\eta^2 = 0.108$**	$F(1,71) = 1.981$, $p = 0.164$, $\eta^2 = 0.027$	$F(1,71) = 0.023$, $p = 0.879$, $\eta^2 < 0.001$
ML	**$F(1,71) = 12.400$, $p = 0.001$, $\eta^2 = 0.149$**	$F(1,71) = 0.076$, $p = 0.784$, $\eta^2 = 0.001$	$F(1,71) = 0.478$, $p = 0.491$, $\eta^2 = 0.007$
Ratio of Even to Odd Harmonics			
Vertical	**$F(1,71) = 4.108$, $p = 0.046$, $\eta^2 = 0.055$**	$F(1,71) = 0.001$, $p = 0.971$, $\eta^2 < 0.001$	$F(1,71) = 0.162$, $p = 0.688$, $\eta^2 = 0.002$
AP	**$F(1,71) = 5.850$, $p = 0.018$, $\eta^2 = 0.076$**	$F(1,71) = 0.342$, $p = 0.560$, $\eta^2 = 0.005$	$F(1,71) = 0.084$, $p = 0.773$, $\eta^2 = 0.001$
ML	$F(1,71) = 0.792$, $p = 0.377$, $\eta^2 = 0.011$	$F(1,71) = 0.030$, $p = 0.862$, $\eta^2 < 0.001$	$F(1,71) = 0.004$, $p = 0.953$, $\eta^2 < 0.001$
Maximum Lyapunov Exponent			
Vertical	$F(1,71) = 3.627$, $p = 0.061$, $\eta^2 = 0.049$	$F(1,71) = 0.012$, $p = 0.912$, $\eta^2 < 0.001$	$F(1,71) = 0.744$, $p = 0.391$, $\eta^2 = 0.010$
AP	$F(1,71) = 0.073$, $p = 0.789$, $\eta^2 = 0.001$	$F(1,71) = 0.008$, $p = 0.928$, $\eta^2 < 0.001$	$F(1,71) = 0.051$, $p = 0.822$, $\eta^2 = 0.001$
ML	**$F(1,71) = 6.913$, $p = 0.010$, $\eta^2 = 0.089$**	$F(1,71) = 2.688$, $p = 0.106$, $\eta^2 = 0.036$	$F(1,71) = 0.002$, $p = 0.969$, $\eta^2 < 0.001$
Acceleration Descriptive Statistics (g)			
Superior Max	**$F(1,71) = 5.609$, $p = 0.021$, $\eta^2 = 0.073$**	$F(1,71) = 0.741$, $p = 0.392$, $\eta^2 = 0.010$	$F(1,71) = 0.864$, $p = 0.356$, $\eta^2 = 0.012$
Superior Mean	**$F(1,71) = 17.158$, $p < 0.001$, $\eta^2 = 0.195$**	$F(1,71) = 0.142$, $p = 0.708$, $\eta^2 = 0.002$	$F(1,71) = 0.863$, $p = 0.356$, $\eta^2 = 0.012$
Superior SD	**$F(1,71) = 18.516$, $p < 0.001$, $\eta^2 = 0.207$**	$F(1,71) = 0.473$, $p = 0.494$, $\eta^2 = 0.007$	$F(1,71) = 0.827$, $p = 0.366$, $\eta^2 = 0.012$
Inferior Max	**$F(1,71) = 21.109$, $p < 0.001$, $\eta^2 = 0.229$**	$F(1,71) = 0.605$, $p = 0.439$, $\eta^2 = 0.008$	$F(1,71) = 1.682$, $p = 0.199$, $\eta^2 = 0.023$
Inferior Mean	**$F(1,71) = 19.490$, $p < 0.001$, $\eta^2 = 0.215$**	$F(1,71) = 0.272$, $p = 0.603$, $\eta^2 = 0.004$	$F(1,71) = 1.404$, $p = 0.240$, $\eta^2 = 0.019$
Inferior SD	**$F(1,71) = 26.319$, $p < 0.001$, $\eta^2 = 0.270$**	$F(1,71) = 0.663$, $p = 0.418$, $\eta^2 = 0.009$	$F(1,71) = 2.666$, $p = 0.107$, $\eta^2 = 0.036$
Anterior Max	**$F(1,71) = 29.255$, $p < 0.001$, $\eta^2 = 0.292$**	$F(1,71) = 1.067$, $p = 0.305$, $\eta^2 = 0.015$	$F(1,71) = 2.602$, $p = 0.111$, $\eta^2 = 0.035$
Anterior Mean	**$F(1,71) = 15.505$, $p < 0.001$, $\eta^2 = 0.179$**	$F(1,71) = 1.203$, $p = 0.276$, $\eta^2 = 0.017$	$F(1,71) = 1.062$, $p = 0.306$, $\eta^2 = 0.015$
Anterior SD	**$F(1,71) = 32.727$, $p < 0.001$, $\eta^2 = 0.316$**	$F(1,71) = 1.405$, $p = 0.240$, $\eta^2 = 0.019$	$F(1,71) = 1.627$, $p = 0.206$, $\eta^2 = 0.022$
Posterior Max	**$F(1,71) = 7.766$, $p = 0.007$, $\eta^2 = 0.099$**	$F(1,71) = 1.163$, $p = 0.284$, $\eta^2 = 0.016$	$F(1,71) = 0.138$, $p = 0.711$, $\eta^2 = 0.002$
Posterior Mean	**$F(1,71) = 9.866$, $p = 0.002$, $\eta^2 = 0.122$**	$F(1,71) = 0.060$, $p = 0.807$, $\eta^2 = 0.001$	$F(1,71) = 0.324$, $p = 0.571$, $\eta^2 = 0.005$
Posterior SD	**$F(1,71) = 10.708$, $p = 0.002$, $\eta^2 = 0.131$**	$F(1,71) = 1.176$, $p = 0.282$, $\eta^2 = 0.016$	$F(1,71) = 0.070$, $p = 0.792$, $\eta^2 = 0.001$
Right Max	**$F(1,71) = 22.869$, $p < 0.001$, $\eta^2 = 0.244$**	$F(1,71) = 2.124$, $p = 0.149$, $\eta^2 = 0.029$	$F(1,71) = 3.910$, $p = 0.052$, $\eta^2 = 0.052$

Right Mean	**$F(1,71) = 21.995$, $p < 0.001$, $\eta^2 = 0.237$**	$F(1,71) = 1.866$, $p = 0.176$, $\eta^2 = 0.026$	$F(1,71) = 2.833$, $p = 0.097$, $\eta^2 = 0.038$
Right SD	**$F(1,71) = 27.996$, $p < 0.001$, $\eta^2 = 0.283$**	$F(1,71) = 2.958$, $p = 0.090$, $\eta^2 = 0.040$	$F(1,71) = 3.506$, $p = 0.065$, $\eta^2 = 0.047$
Left Max	**$F(1,71) = 11.974$, $p = 0.001$, $\eta^2 = 0.144$**	$F(1,71) = 0.319$, $p = 0.574$, $\eta^2 = 0.004$	$F(1,71) = 0.686$, $p = 0.410$, $\eta^2 = 0.010$
Left Mean	**$F(1,71) = 22.865$, $p < 0.001$, $\eta^2 = 0.244$**	$F(1,71) = 0.001$, $p = 0.972$, $\eta^2 < 0.001$	$F(1,71) = 0.841$, $p = 0.362$, $\eta^2 = 0.012$
Left SD	**$F(1,71) = 26.720$, $p < 0.001$, $\eta^2 = 0.273$**	$F(1,71) = 0.118$, $p = 0.733$, $\eta^2 = 0.002$	$F(1,71) = 0.992$, $p = 0.323$, $\eta^2 = 0.014$

Table A.9. Mixed-design ANOVA test results for right shank accelerometer variables for prospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Mixed-Design ANOVA Analysis		
	Walking Condition Main Effect	**Faller/Non-Faller Status Main Effect**	**Interaction Effect**
FFT Quartile (%)			
Vertical	**F(1,73) = 30.897, *p* < 0.001, η^2 = 0.297**	F(1,73) = 0.044, *p* = 0.834, η^2 = 0.001	F(1,73) = 0.022, *p* = 0.884, η^2 < 0.001
AP	**F(1,73) = 42.588, *p* < 0.001, η^2 = 0.368**	F(1,73) = 1.753, *p* = 0.190, η^2 = 0.023	F(1,73) = 0.301, *p* = 0.585, η^2 = 0.004
ML	**F(1,73) = 47.478, *p* < 0.001, η^2 = 0.394**	F(1,73) = 1.491, *p* = 0.226, η^2 = 0.020	F(1,73) = 0.287, *p* = 0.594, η^2 = 0.004
Ratio of Even to Odd Harmonics			
Vertical	F(1,73) = 1.463, *p* = 0.230, η^2 = 0.020	F(1,73) = 0.001, *p* = 0.975, η^2 < 0.001	F(1,73) = 0.053, *p* = 0.818, η^2 = 0.001
AP	F(1,73) = 0.021, *p* = 0.885, η^2 < 0.001	F(1,73) = 0.001, *p* = 0.975, η^2 < 0.001	F(1,73) = 0.058, *p* = 0.810, η^2 = 0.001
ML	F(1,73) = 3.334, *p* = 0.072, η^2 = 0.044	F(1,73) = 1.352, *p* = 0.249, η^2 = 0.018	F(1,73) = 2.087, *p* = 0.153, η^2 = 0.028
Maximum Lyapunov Exponent			
Vertical	F(1,73) = 0.202, *p* = 0.654, η^2 = 0.003	F(1,73) = 0.634, *p* = 0.428, η^2 = 0.009	F(1,73) = 0.059, *p* = 0.809, η^2 = 0.001
AP	**F(1,73) = 7.656, *p* = 0.007, η^2 = 0.095**	F(1,73) = 0.156, *p* = 0.694, η^2 = 0.002	F(1,73) = 0.324, *p* = 0.571, η^2 = 0.004
ML	F(1,73) = 3.249, *p* = 0.076, η^2 = 0.043	F(1,73) = 0.324, *p* = 0.571, η^2 = 0.004	F(1,73) = 0.799, *p* = 0.374, η^2 = 0.011
Acceleration Descriptive Statistics (g)			
Superior Max	**F(1,73) = 8.303, *p* = 0.005, η^2 = 0.102**	F(1,73) = 1.820, *p* = 0.182, η^2 = 0.024	**F(1,73) = 6.279, *p* = 0.014, η^2 = 0.079**
Superior Mean	**F(1,73) = 5.796, *p* = 0.019, η^2 = 0.074**	F(1,73) = 2.956, *p* = 0.090, η^2 = 0.039	F(1,73) = 1.677, *p* = 0.199, η^2 = 0.022
Superior SD	**F(1,73) = 13.103, *p* = 0.001, η^2 = 0.152**	F(1,73) = 1.753, *p* = 0.190, η^2 = 0.023	**F(1,73) = 4.513, *p* = 0.037, η^2 = 0.058**
Inferior Max	**F(1,73) = 27.457, *p* < 0.001, η^2 = 0.273**	F(1,73) = 0.488, *p* = 0.487, η^2 = 0.007	F(1,73) = 2.097, *p* = 0.152, η^2 = 0.028
Inferior Mean	**F(1,73) = 30.777, *p* < 0.001, η^2 = 0.297**	F(1,73) = 0.336, *p* = 0.564, η^2 = 0.005	F(1,73) = 0.393, *p* = 0.533, η^2 = 0.005
Inferior SD	**F(1,73) = 42.857, *p* < 0.001, η^2 = 0.370**	F(1,73) = 0.404, *p* = 0.527, η^2 = 0.006	F(1,73) = 1.987, *p* = 0.163, η^2 = 0.027
Anterior Max	**F(1,73) = 39.795, *p* < 0.001, η^2 = 0.353**	F(1,73) = 0.131, *p* = 0.718, η^2 = 0.002	F(1,73) = 2.950, *p* = 0.090, η^2 = 0.039
Anterior Mean	**F(1,73) = 43.567, *p* < 0.001, η^2 = 0.374**	F(1,73) = 0.435, *p* = 0.512, η^2 = 0.006	F(1,73) = 2.218, *p* = 0.141, η^2 = 0.029
Anterior SD	**F(1,73) = 45.927, *p* < 0.001, η^2 = 0.386**	F(1,73) = 0.691, *p* = 0.409, η^2 = 0.009	F(1,73) = 2.405, *p* = 0.125, η^2 = 0.032
Posterior Max	F(1,73) = 0.384, *p* = 0.537, η^2 = 0.005	F(1,73) = 0.210, *p* = 0.648, η^2 = 0.003	F(1,73) = 0.265, *p* = 0.608, η^2 = 0.004
Posterior Mean	**F(1,73) = 10.992, *p* = 0.001, η^2 = 0.131**	F(1,73) = 0.389, *p* = 0.535, η^2 = 0.005	F(1,73) = 2.896, *p* = 0.093, η^2 = 0.038
Posterior SD	F(1,73) = 1.438, *p* = 0.234, η^2 = 0.019	F(1,73) = 0.005, *p* = 0.943, η^2 < 0.001	F(1,73) = 0.034, *p* = 0.854, η^2 < 0.001
Right Max	**F(1,73) = 27.236, *p* < 0.001, η^2 = 0.272**	F(1,73) = 0.748, *p* = 0.390, η^2 = 0.010	F(1,73) < 0.001, *p* = 0.987, η^2 <0.001

Right Mean	**$F(1,73) = 19.773$, $p < 0.001$, $\eta^2 = 0.213$**	$F(1,73) = 1.263$, $p = 0.265$, $\eta^2 = 0.017$	$F(1,73) = 0.075$, $p = 0.786$, $\eta^2 = 0.001$
Right SD	**$F(1,73) = 35.211$, $p < 0.001$, $\eta^2 = 0.325$**	$F(1,73) = 1.197$, $p = 0.278$, $\eta^2 = 0.016$	$F(1,73) = 0.137$, $p = 0.712$, $\eta^2 = 0.002$
Left Max	**$F(1,73) = 19.078$, $p < 0.001$, $\eta^2 = 0.207$**	$F(1,73) = 0.142$, $p = 0.707$, $\eta^2 = 0.002$	$F(1,73) = 3.014$, $p = 0.087$, $\eta^2 = 0.040$
Left Mean	**$F(1,73) = 26.078$, $p < 0.001$, $\eta^2 = 0.263$**	$F(1,73) = 0.157$, $p = 0.693$, $\eta^2 = 0.002$	$F(1,73) = 3.015$, $p = 0.087$, $\eta^2 = 0.040$
Left SD	**$F(1,73) = 32.828$, $p < 0.001$, $\eta^2 = 0.310$**	$F(1,73) = 0.032$, $p = 0.859$, $\eta^2 < 0.001$	$F(1,73) = 1.906$, $p = 0.172$, $\eta^2 = 0.025$

Table A.10. Mixed-design ANOVA test results for left shank accelerometer variables for prospective fallers and non-fallers. Bold indicates a significant difference ($p < 0.05$)

	Mixed-Design ANOVA Analysis		
	Walking Condition Main Effect	**Faller/Non-Faller Status Main Effect**	**Interaction Effect**
FFT Quartile (%)			
Vertical	**$F(1,72) = 20.535$, $p < 0.001$, $\eta^2 = 0.222$**	$F(1,72) = 0.623$, $p = 0.433$, $\eta^2 = 0.009$	$F(1,72) = 0.536$, $p = 0.467$, $\eta^2 = 0.007$
AP	**$F(1,72) = 36.656$, $p < 0.001$, $\eta^2 = 0.337$**	$F(1,72) = 0.846$, $p = 0.361$, $\eta^2 = 0.012$	$F(1,72) = 0.373$, $p = 0.543$, $\eta^2 = 0.005$
ML	**$F(1,72) = 21.428$, $p < 0.001$, $\eta^2 = 0.229$**	**$F(1,72) = 4.360$, $p = 0.040$, $\eta^2 = 0.057$**	$F(1,72) = 0.619$, $p = 0.434$, $\eta^2 = 0.009$
Ratio of Even to Odd Harmonics			
Vertical	$F(1,72) = 1.492$, $p = 0.226$, $\eta^2 = 0.020$	$F(1,72) = 0.010$, $p = 0.921$, $\eta^2 < 0.001$	**$F(1,72) = 4.279$, $p = 0.042$, $\eta^2 = 0.056$**
AP	$F(1,72) = 0.082$, $p = 0.775$, $\eta^2 = 0.001$	$F(1,72) = 0.006$, $p = 0.940$, $\eta^2 < 0.001$	$F(1,72) = 0.593$, $p = 0.444$, $\eta^2 = 0.008$
ML	$F(1,72) = 0.003$, $p = 0.958$, $\eta^2 < 0.001$	$F(1,72) = 0.305$, $p = 0.583$, $\eta^2 = 0.004$	$F(1,72) = 0.719$, $p = 0.399$, $\eta^2 = 0.010$
Maximum Lyapunov Exponent			
Vertical	$F(1,72) = 0.088$, $p = 0.768$, $\eta^2 = 0.001$	$F(1,72) = 0.464$, $p = 0.498$, $\eta^2 = 0.006$	$F(1,72) = 0.207$, $p = 0.651$, $\eta^2 = 0.003$
AP	**$F(1,72) = 8.853$, $p = 0.004$, $\eta^2 = 0.109$**	$F(1,72) = 0.206$, $p = 0.651$, $\eta^2 = 0.003$	$F(1,72) = 3.730$, $p = 0.057$, $\eta^2 = 0.049$
ML	**$F(1,72) = 18.213$, $p < 0.001$, $\eta^2 = 0.202$**	$F(1,72) = 0.156$, $p = 0.694$, $\eta^2 = 0.002$	$F(1,72) = 0.853$, $p = 0.359$, $\eta^2 = 0.012$
Acceleration Descriptive Statistics (g)			
Superior Max	**$F(1,72) = 27.371$, $p < 0.001$, $\eta^2 = 0.275$**	$F(1,72) = 0.068$, $p = 0.795$, $\eta^2 = 0.001$	$F(1,72) = 0.865$, $p = 0.355$, $\eta^2 = 0.012$
Superior Mean	**$F(1,72) = 33.402$, $p < 0.001$, $\eta^2 = 0.317$**	$F(1,72) = 0.259$, $p = 0.612$, $\eta^2 = 0.004$	$F(1,72) = 2.604$, $p = 0.111$, $\eta^2 = 0.035$
Superior SD	**$F(1,72) = 35.620$, $p < 0.001$, $\eta^2 = 0.331$**	$F(1,72) = 0.052$, $p = 0.820$, $\eta^2 = 0.001$	$F(1,72) = 1.000$, $p = 0.321$, $\eta^2 = 0.014$
Inferior Max	**$F(1,72) = 15.530$, $p < 0.001$, $\eta^2 = 0.177$**	$F(1,72) = 0.105$, $p = 0.746$, $\eta^2 = 0.001$	$F(1,72) = 0.353$, $p = 0.554$, $\eta^2 = 0.005$
Inferior Mean	**$F(1,72) = 28.405$, $p < 0.001$, $\eta^2 = 0.283$**	$F(1,72) = 0.874$, $p = 0.353$, $\eta^2 = 0.012$	$F(1,72) = 1.235$, $p = 0.270$, $\eta^2 = 0.017$
Inferior SD	**$F(1,72) = 25.728$, $p < 0.001$, $\eta^2 = 0.263$**	$F(1,72) = 0.257$, $p = 0.614$, $\eta^2 = 0.004$	$F(1,72) = 0.877$, $p = 0.352$, $\eta^2 = 0.012$
Anterior Max	**$F(1,72) = 43.355$, $p < 0.001$, $\eta^2 = 0.376$**	$F(1,72) = 0.493$, $p = 0.485$, $\eta^2 = 0.007$	$F(1,72) = 0.540$, $p = 0.465$, $\eta^2 = 0.007$
Anterior Mean	**$F(1,72) = 46.233$, $p < 0.001$, $\eta^2 = 0.391$**	$F(1,72) = 0.714$, $p = 0.401$, $\eta^2 = 0.010$	$F(1,72) = 0.290$, $p = 0.592$, $\eta^2 = 0.004$
Anterior SD	**$F(1,72) = 52.633$, $p < 0.001$, $\eta^2 = 0.422$**	$F(1,72) = 0.263$, $p = 0.610$, $\eta^2 = 0.004$	$F(1,72) = 1.052$, $p = 0.309$, $\eta^2 = 0.014$
Posterior Max	$F(1,72) = 0.474$, $p = 0.493$, $\eta^2 = 0.007$	$F(1,72) = 0.290$, $p = 0.592$, $\eta^2 = 0.004$	$F(1,72) = 1.918$, $p = 0.170$, $\eta^2 = 0.026$
Posterior Mean	**$F(1,72) = 19.140$, $p < 0.001$, $\eta^2 = 0.210$**	$F(1,72) = 0.985$, $p = 0.324$, $\eta^2 = 0.013$	$F(1,72) = 1.246$, $p = 0.268$, $\eta^2 = 0.017$
Posterior SD	**$F(1,72) = 5.384$, $p = 0.023$, $\eta^2 = 0.070$**	$F(1,72) = 0.481$, $p = 0.490$, $\eta^2 = 0.007$	$F(1,72) = 2.833$, $p = 0.097$, $\eta^2 = 0.038$
Right Max	$F(1,72) = 3.181$, $p = 0.079$, $\eta^2 = 0.042$	$F(1,72) = 0.002$, $p = 0.967$, $\eta^2 < 0.001$	$F(1,72) = 0.108$, $p = 0.743$, $\eta^2 = 0.002$

Right Mean	**$F(1,72) = 17.639$, $p < 0.001$, $\eta^2 = 0.197$**	$F(1,72) = 0.118$, $p = 0.732$, $\eta^2 = 0.002$	$F(1,72) = 0.019$, $p = 0.891$, $\eta^2 < 0.001$
Right SD	**$F(1,72) = 8.560$, $p = 0.005$, $\eta^2 = 0.106$**	$F(1,72) = 0.483$, $p = 0.489$, $\eta^2 = 0.007$	$F(1,72) = 0.102$, $p = 0.751$, $\eta^2 = 0.001$
Left Max	**$F(1,72) = 23.183$, $p < 0.001$, $\eta^2 = 0.244$**	$F(1,72) = 0.014$, $p = 0.905$, $\eta^2 < 0.001$	$F(1,72) = 1.351$, $p = 0.249$, $\eta^2 = 0.018$
Left Mean	**$F(1,72) = 25.453$, $p < 0.001$, $\eta^2 = 0.261$**	$F(1,72) = 0.886$, $p = 0.350$, $\eta^2 = 0.012$	$F(1,72) = 1.577$, $p = 0.213$, $\eta^2 = 0.021$
Left SD	**$F(1,72) = 25.796$, $p < 0.001$, $\eta^2 = 0.264$**	$F(1,72) = 0.147$, $p = 0.703$, $\eta^2 = 0.002$	$F(1,72) = 1.434$, $p = 0.235$, $\eta^2 = 0.020$