An Investigation of Clinical and Sensor-Based Fall-Risk Assessment in Community-Dwelling Older Adults

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ABSTRACT

Title: An Investigation of Clinical and Sensor-Based Fall-Risk Assessment in Community-Dwelling Older Adults

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Accurate, efficient methods of assessing fall-risk are required to identify at-risk community-dwelling older adults and implement timely falls prevention interventions. Sensor-based fall-risk assessment (SBFRA) methods have been developed to objectively assess and quantify fall-risk by analysing functional task performance, but research exploring their clinical applications is lacking.

The current research aimed to investigate if SBFRA could perform clinically-meaningful fall-risk assessment in community-dwelling older adults (i.e. could it accurately classify older adults according to their level of fall-risk), and to explore its use among high-risk older adults participating in a community-based falls prevention intervention.

Following thorough examination of current evidence and issues of feasibility, clinical and SBFRA was carried out among High-Risk (n=38) and Low-Risk (n=33) groups of older adults in the community, the High-Risk group being participants in a community-based falls prevention intervention.

An array of sensor-derived variables extracted from static and dynamic task performances distinguished between High-Risk and Low-Risk groups; among them, novel sensor-derived variables that quantified standing balance and TUG performance strategy and quality, as well as simple sensor-derived gait variables e.g. cadence, mean step time. Some improvements in sensor-based indicators of standing balance performance were observed following intervention. Simple sensor-derived gait variables classified High-Risk participants more accurately than clinical tools e.g. cadence (sensitivity/specificity: 90.9%) and mean step time (sensitivity: 87.9%, specificity: 90.9%) versus Berg Balance Scale (sensitivity: 86.8%, specificity: 81.8%). Classification tree models comprised of 1) clinical, 2) sensor-based variables and 3) both combined, exhibited excellent fall-risk classification properties, with 95.8% accuracy for all models.

This research confirms that SBFRA can be used to perform clinically-meaningful fall-risk assessment among community-dwelling older adults. With further research to develop specific evidence-based and user-friendly methods, SBFRA could be used to augment clinical fall-risk assessments, thereby assisting healthcare providers with clinical reasoning and outcome measurement in community falls prevention.
DECLARATION

I, the undersigned, declare that the work contained within this thesis is my own original work, aside from the counsel of my supervisors: Dr. Amanda Clifford of the Department of Clinical Therapies and Dr. Pepijn Van de Ven and Dr. John Nelson of the Department of Electronic and Computer Engineering, University of Limerick. Where the use has been made of the work of others it has been fully acknowledged and referenced. This work has not been submitted for any academic award, or part thereof, at this or any other educational establishment. I also declare that the data presented is authentic.

___________________________
Valerie Power
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LIST OF ABBREVIATIONS

AP – Antero-posterior

AUC – Area Under the (ROC) Curve

BBS – Berg Balance Scale

BoS – Base of Support

CASP – Critical Appraisal Skills Programme

CoG – Centre of Gravity

CoM – Centre of Mass

CRT – Classification and Regression Tree

DGI – Dynamic Gait Index

FaB – Falls Behavioural Scale for the Older Person

FITT – Frequency, Intensity, Time and Type

FTBS – Four Test Balance Scale

FTSS – Five Times Sit-to-Stand test

GDS – Geriatric Depression Scale (15-item)

GP – General Practitioner

HEP – Home Exercise Programme

HSE – Health Service Executive

MFES – Modified Falls Efficacy Scale

ML – Medio-lateral

NCPOP – National Clinical Programme for Older People

NPV – Negative Predictive Value

PA – Physical Activity
PASE – Physical Activity Scale for the Elderly
PCCC – Primary Community and Continuing Care
POMA – Performance Oriented Mobility Assessment
PPA – Physiological Profile Assessment
PPV – Positive Predictive Value
ProFaNE – Prevention of Falls Network Europe
RMS – Root-Mean-Square
ROC – Receiver Operator Characteristic curve
RSS – Root of the Sum of the Squares
SBFRA – Sensor-Based Fall-Risk Assessment
SEF – Spectral Edge Frequency
STS – Sit-to-Stand
TUG – Timed Up and Go test
VAS – Visual Analogue Scale
WTW – Walk-Turn-Walk
5m Walk – Five metre walk test
GLOSSARY OF TERMS

Accuracy
The overall probability that a test will correctly classify individuals based on test results.
Accuracy = (True Positives + True Negatives) / Total number of participants

Balance (Mechanical)
The state achieved when an object or system’s centre of gravity is contained within its base of support and the resultant forces acting upon the object or system are zero

Balance (In Humans)
A state of balance considered to exist in both static and dynamic conditions, as follows:
• Static balance: The condition in which the summed forces acting on the body are balanced, such that the body remains static in an intended position
• Dynamic balance: The condition in which the summed forces acting on the body allow the body to move in a controlled manner

Jerk
The derivative of acceleration with respect to time, expressed in ms$^{-3}$ or g/s

Negative Predictive Value
The proportion of individuals in a sample with negative test results who do not meet the specified criteria.
Negative Predictive Value = True Negatives / (True Negatives + False Negatives)

Positive Predictive Value
The proportion of individuals in a sample with positive test results who meet the specified criteria.
Positive Predictive Value = True Positives / (True Positives + False Positives)

Postural Control
The process of controlling the body’s position in space in order to maintain, achieve or restore its centre of gravity within its base of support.
**Postural Sway**
Displacement of the body’s centre of mass or centre of gravity

**Sensitivity**
The ability of a test to correctly identify individuals who meet specified criteria.
Sensitivity = True Positives / (True Positives + False Negatives)

**Specificity**
The ability of a test to correctly identify individuals who do not meet specified criteria.
Specificity = True Negatives / (True Negatives + False Positives)

**Sway Angle**
Used throughout this thesis to describe the angle of the acceleration vector – measured via accelerometer – on a given sensor axis relative to the true horizontal plane.
LIST OF PUBLICATIONS

The following peer-reviewed journal articles and conference presentations have been published based on the work contained in this thesis, to date.

Journal Publications


Conferences: Oral and Poster Presentations


CHAPTER 1. BACKGROUND AND
THESIS INTRODUCTION
1.1 Introduction

This thesis will describe research conducted to examine the use of clinical and sensor-based fall-risk assessment (SBFRA) methods among community-dwelling older adults. In order to understand the purpose of investigating novel or improved methods of assessing fall-risk, it is necessary to appreciate why and how fall-risk is assessed in this population. Therefore, this chapter will initially describe the scope of the problem of falls among older adults in the community and why it is desirable to prevent their occurrence, including a brief overview of falls prevention strategies. The chapter will then introduce key concepts in fall-risk assessment, including the rationale for using wireless inertial sensors for this purpose. Current research on SBFRA will then be briefly described and the research gaps which this thesis aims to address will be identified. Finally, the primary and secondary research questions will be introduced and the structure of the thesis will be described.

1.2 Falls and Ageing: Prevalence and Implications

Falls, defined as “unexpected event[s] in which the participants come to rest on the ground, floor, or lower level” (Lamb et al. 2005), are prevalent among community-dwelling older adults. Approximately 15-30% of those aged 65 years and over fall each year and this prevalence increases with age, with up to 50% of those aged 80 and over falling annually (Soriano et al. 2007, Tinetti et al. 1988, Campbell et al. 1989, Shin et al. 2009). Recent data shows a similar pattern among older adults in Ireland, with 22% of individuals aged 52-64 years reporting a fall in the past year, rising to approximately 30% among those aged 75 years or over (The Irish Longitudinal Study on Ageing 2014).

The changing age profile of the global population is bringing the issue of falls among older adults increasingly to the fore. The global population aged 60 years and over is predicted to more than double to approximately 2 billion people by 2050, which will represent 21.1% of the total world population (United Nations Department of Economic and Social Affairs Population Division 2013). This change will have extensive economic and social implications. Demands for health and social care services will rise due to the higher rates of disability and service utilisation among older age groups (Barrett et al. 2011).
Falls among older adults have a significant economic impact (Heinrich et al. 2010). In 2008 alone, falls among older adults in the community cost US $23.3 billion in the United States of America and US $1.6 billion in the United Kingdom (Davis et al. 2010). The incidence of falls and the associated direct and indirect costs are expected to increase in line with population ageing, which will amplify this economic impact and present challenges to health and social care systems globally. For example, in Ireland, recent figures show that approximately 130,000 older people fall each year leading to estimated annual healthcare costs of €404 million (Gannon et al. 2008). Given current population ageing trends, it is predicted that by 2030 approximately 320,000 Irish older people will fall annually with associated healthcare costs of up to €2 billion (Health Service Executive et al. 2008). In a service with a total annual budget of approximately €13 billion (Department of Finance 2014), this situation would clearly be unsustainable.

For the individual, the immediate and long-term consequences of falling can be severe. Older adults tend to be more susceptible to injury following a fall than younger populations due to the prevalence of age-related physiological changes and pathologies (Rubenstein 2006). Research has shown that 40-60% of falls among older adults result in injuries, approximately 5-10% result in serious injuries (e.g. fractures or head injuries) and a small proportion result in fatality (Rubenstein 2006, Rubenstein and Josephson 2002, Masud and Morris 2001, Korhonen et al. 2011). Older adults who are unable to get up after a fall can experience complications such as dehydration, hypothermia and pressure sores due to the ensuing ‘long lie’ (Tinetti et al. 1993). Falls can have profound behavioural and psychological consequences, leading to inactivity, functional decline (Stel et al. 2004), functional dependence, loss of autonomy (Kannus et al. 2005) and depression (Scheffer et al. 2008) among those who fall, and increased burden on their families and caregivers (Kuzuya et al. 2006). Even in cases where only minor injuries occur, older adults can experience reduced quality of life for a number of months following a fall (Hatholt et al. 2011). Furthermore, over a three-year follow-up period, multiple fallers are approximately five times more likely than non-fallers to be admitted to long-term care and more than twice as likely to die (Donald and Bulpitt 1999, Tinetti and Williams 1997).
1.3 **Falls Prevention Strategies**

In light of these undesirable consequences, efforts to prevent the occurrence of falls and their subsequent impacts have been undertaken. In Ireland, the Health Service Executive (HSE) has developed the Strategy to Prevent Falls and Fractures in Ireland’s Ageing Population (Health Service Executive et al. 2008). This strategy highlights the need to identify older adults who are at risk of falling and implement structured, evidence-based, low-cost interventions to prevent these falls. The strategy has been incorporated into the National Clinical Programme for Older People (NCPOP) (National Clinical Programme for Older People 2012), and outlines a clear multi-level pathway by which older adults in Ireland are identified as being at risk of falling via simple evidence-based screening, referred for more in-depth multifactorial assessment where appropriate, and provided with multifactorial intervention according to their specific needs (Figure 1.1), a process which is in line with the current falls prevention guidelines (Close and Lord 2011, American Geriatrics Society and British Geriatrics Society 2011). This pathway is designed to ensure timely and appropriate access to interventions which have been shown to reduce both the rate and/or risk of falls among older adults in the community (Gillespie et al. 2012, Michael et al. 2010).

![Flowchart illustration of a falls screening, assessment and intervention pathway of care, adapted from HSE (2008) and NCPOP (2012).](image-url)
In Ireland, community falls prevention services are still being established in many areas in accordance with the aforementioned Strategy, and so the availability and type of services vary greatly across the country (Health Service Executive et al. 2008). Thus, there is a desire among service providers to evaluate their falls prevention services, in order to ensure that service provision is targeting appropriate individuals and achieving quality in terms of clinical outcomes. This underpins the secondary research question of this thesis, namely the exploration of a range of clinical and sensor-based features related to fall-risk among older adults participating in a falls prevention intervention. Aligning this research with clinical partners – as will be described in Chapter 3 – facilitated the exploration of a novel clinical application of wireless inertial sensors and provided unique information on the fall-risk profiles of those being referred to a current falls prevention service in Ireland, as well as the impacts of the service on its users.

1.4 Identifying Risk Factors and Assessing Fall-Risk

The ability to identify risk factors for falls in older adults is essential to ensuring that falls prevention interventions are targeted towards those who require them and are appropriate to the individual’s needs (Voermans et al. 2007). For this reason, a large body of evidence has identified a broad range of factors among older adults in the community which indicate an increased risk of falling. These risk factors may be categorised as follows (World Health Organization 2008):

- **Biological:** Greater age, female gender (Kwan et al. 2011), impaired balance and gait, poor muscle strength, visual impairment, dizziness, pain, impaired cognition, urinary incontinence (Tinetti and Kumar 2010, Deandrea et al. 2010)
- **Behavioural:** A history of previous falls, walking aid usage (Deandrea et al. 2010), use of psychoactive and/or multiple medications (Tinetti and Kumar 2010), fear of falling and fear-related activity avoidance (Delbaere et al. 2004)
- **Environmental:** Home hazards such as loose rugs or insufficient lighting (Lord et al. 2006), hazards in public places such as cracked footpaths or slippery surfaces (Demura et al. 2011), inappropriate footwear (Tencer et al. 2004)
- **Socioeconomic:** Low income, low education, inadequate and/or poor quality housing, lack of social interaction, limited access to health and social care (World Health Organization 2008)
The examples of risk factors cited above are not exhaustive, but serve to highlight the broad range of characteristics which are associated with increased fall-risk.

Since fall-risk is evidently a multifactorial concept, it follows that assessments of fall-risk must also be multifactorial in nature (Close and Lord 2011). Comprehensive fall-risk assessments usually incorporate details of the client’s medical history, demographic information, measures of psychosocial and behavioural factors that are related to fall-risk and a physical assessment including assessments of balance or postural control and mobility (Persad et al. 2010). This thesis will focus primarily on the balance and mobility component of fall-risk assessment, since it is for this aspect of fall-risk assessment that wireless inertial sensors are being developed and applied (Ni Scanaill et al. 2011).

1.5 The Concept of ‘Balance’

To understand why balance and mobility evaluation is an integral component of fall-risk assessment, and how wireless inertial sensors can be used for this purpose, it is necessary to first understand the concept of ‘balance’.

Falls among older adults in the community can occur in a variety of circumstances, for example via slips, trips, loss of balance, missteps or due to external forces (Berg et al. 1997). By definition, falls are “unintentional” (Lamb et al. 2005), and therefore represent a loss of control, specifically a loss of ‘postural control’ or ‘balance’. ‘Postural control’ in humans is defined as the process of controlling the body’s position in space in order to maintain, achieve or restore its centre of gravity (CoG) within its base of support (BoS) (Pollock et al. 2000, Shumway-Cook and Woollacott 2012). From a mechanical perspective, when the CoG is contained within the BoS and the resultant forces acting upon an object or system are zero, it is said to be in a state of equilibrium or ‘balance’, in accordance with Newton’s First Law (Nordin and Frankel 2001, p.6). Figure 1.2 illustrates the relationships between an object’s CoG – the vertical projection of its centre of mass (CoM) – and BoS in states of balance and imbalance.
When considering humans rather than inanimate objects, the definition of ‘postural control’ clearly encompasses the concept of ‘balance’; postural control can be thought of as the process by which a state of balance is sought or achieved. In clinical practice, this distinction between the state of balance and the processes used to achieve it is rarely made, and so the terms ‘balance’ and ‘postural control’ are often used interchangeably (Pollock et al. 2000). Since the terms are so closely entwined, the term ‘balance’ will be used throughout this thesis to refer to both the state and the processes, for the sake of consistency and clarity.

Traditionally, the term ‘balance’ was used in relation to humans in the mechanical sense, to describe the ability of an individual to keep the body’s CoG over its BoS (Berg 1989a). While this may be applicable in quiet standing or sitting, it does not apply in activities such as walking, where the CoG follows a path running between the medial borders of alternating feet (Winter 1995), or in running, in which there are periods where neither foot is in contact with the ground and thus there is no BoS (Novacheck 1998). More recent perspectives on human balance have sought to rectify this by

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**Figure 1.2.** A. This object is balanced as its CoG is contained within its BoS. B. The CoG lies outside the small BoS, thus this object is in a state of imbalance and will fall due to the influence of gravity.
considering balance from a more functional, task-oriented perspective, consisting of static and dynamic components defined as follows:

- **Static balance**: The condition in which the summed forces acting on the body are balanced, such that the body remains static in an intended position;
- **Dynamic balance**: The condition in which the summed forces acting on the body allow the body to move in a controlled manner (Bronstein et al. 2004, p.386).

These concepts of static and dynamic balance will be used to provide structure throughout the latter chapters of this thesis.

### 1.6 Assessing Balance in the Context of Falls

A wide variety of objective and subjective methods to assess balance have been developed, in keeping with the broad scope of the concept. The aims of these assessment methods can be to detect fall-risk, identify the presence of specific balance deficits and/or determine the underlying reasons for balance deficits (Mancini and Horak 2010). Fall-risk is most often determined in clinical practice using functional balance assessment tools or rating scales, which can reveal balance impairments by assessing the performance of a broad range of static and/or dynamic functional tasks (Mancini and Horak 2010, Langley and Mackintosh 2007). Although many clinician-rated assessment tools exhibit acceptable validity and reliability (Langley and Mackintosh 2007), the search for more accurate and objective assessment methods continues.

### 1.7 Current Standing of Sensor-Based Fall-Risk Assessment Research

Recent advances have seen technology being increasingly used to assess functional balance and fall-risk (Mancini and Horak 2010). Previously, objective balance assessment was limited to the use of expensive and unwieldy equipment, such as force plates, optical motion analysis systems and electromyography, and confined to highly-specialised laboratory settings (Kavanagh and Menz 2008, Ni Scanaill et al. 2011). SBFRA presents an alternative to such methods, and is based on the concept that human
movement during functional tasks can be measured by wearable devices containing sensors (e.g. accelerometers, gyroscopes). The signals obtained from these sensors can then be analysed to obtain a vast array of variables which can describe how a task is performed. These variables can then be used to classify individuals’ levels of fall-risk or predict future falls as accurately as possible, either as single variables or by incorporating them into more complex algorithms (Shany et al. 2012a).

SBFRA presents a potentially useful method of objectively assessing functional balance in clinical practice, as it could be less costly, less time-consuming, more user-friendly and more feasible to use in clinical and community settings than previous objective methods (Howcroft et al. 2013, Wong et al. 2007). Despite this promise, the use of SBFRA has thus far been limited mainly to research settings and implemented by those with primarily technological expertise (Shany et al. 2012b). This has resulted in a number of gaps in current SBFRA research, specifically in relation to the clinical applications of SBFRA and how it may be translated to use in clinical practice.

Research which bridges the gap between the technical development of SBFRA and the application of SBFRA in clinical practice is still lacking, despite observations of deficits in this area spanning a number of years (Culhane et al. 2005, Ni Scanaill et al. 2011, Howcroft et al. 2013). Therefore, this thesis will provide unique clinical perspectives on the implementation of innovative SBFRA methods in the community, the methods of analysing the sensor data obtained and the interpretation of the findings observed from a clinical standpoint. Blending both clinical and technological perspectives in this way will provide new insights into the clinical meaningfulness of SBFRA and its practical applications.

Current SBFRA research has identified a wide range of sensor-derived variables that can be used to assess fall-risk among older adults, but with no consensus regarding the optimal tasks to evaluate, sensor-based assessment methods to employ or the optimal variables to examine from the sensor data obtained (Shany et al. 2012b). Therefore, these issues will initially be addressed in this thesis by systematically reviewing the literature on task performance-based fall-risk assessment tools in order to determine the most clinically meaningful tasks to assess (Chapter 2), as well as reviewing the current literature on SBFRA from a clinical perspective to establish the optimal assessment procedures to adopt and variables to examine (Chapter 5).
The findings of these reviews will be used to inform the development of an evidence-based SBFRA procedure for use in a community setting and to inform the selection of clinically relevant variables to extract from the sensor data obtained. A combination of novel sensor-derived variables and variables which have previously been associated with fall-risk in older adults will be extracted, with an emphasis on the selection of clinically-meaningful variables. This will allow the findings of this thesis to both consolidate previous research findings and build upon these findings with original, clinically-focused contributions.

Current SBFRA literature also gives little consideration to the practical relevance of findings to specific populations encountered in clinical settings (Howcroft et al. 2013). Research focused on the clinical application of SBFRA has been carried out among inpatients in a geriatric clinic (Marschollek et al. 2009, Marschollek et al. 2011b), but this is a separate clinical population to community-dwelling older adults and may exhibit markedly different levels of balance, mobility and overall indicators of fall-risk. Equally, SBFRA has been studied in community-dwelling older Irish adults, but mainly in research clinic settings (O'Sullivan et al. 2009, Greene et al. 2012a, Greene et al. 2012b). No previous research has explored the use of SBFRA in the context of a community-based falls prevention intervention. Therefore, this thesis will examine issues relating to the feasibility of using wireless inertial sensors for this purpose. Sensor-derived variables of potential clinical relevance will also be explored in a group of older adults before and after participating in a community falls prevention intervention to enable preliminary observations on the clinical relevance of SBFRA findings in this context to be obtained and recommendations for future research on this aspect of SBFRA to be made. The combination of setting, population and clinical context selected for this research represents a novel application of SBFRA, which will allow this work to establish original SBFRA findings and provide new evidence on the clinical utility of SBFRA.

Finally, the wide range of heterogeneous literature on SBFRA struggles to establish clear links between SBFRA and specific fall-risk factors (Howcroft et al. 2013). Previous studies which have attempted to establish such links have compared SBFRA to a limited selection of clinical fall-risk assessment tools (Greene et al. 2012a, O'Sullivan et al. 2009), which fails to identify how SBFRA relates to the comprehensive fall-risk assessments which are carried out in clinical practice. Therefore, this thesis will address this shortcoming of previous research by using a comprehensive selection of clinical
fall-risk assessment tools with which to compare our SBFRA findings. The capacity of SBFRA to augment the clinical assessment findings will also be examined, since SBFRA need not compete with current assessment methods, but may be useful as an adjunct to them.

### 1.8 Research Questions

The primary research question of this thesis is:

- Can the evaluation of task performance via body-worn wireless inertial sensors be used as a clinically-meaningful method of fall-risk assessment for community-dwelling older adults?

The term “clinically-meaningful” is used in this context to refer to the value that SBFRA may have to clinicians in practice, specifically the capacity to classify individuals as being at high or low risk of falls and how this capacity compares with commonly used clinical measures of fall-risk. This is original in the sense that SBFRA has not been applied in this context in this population previously, nor has previous research adopted a focus on the clinical applicability of SBFRA to the extent of that which will be adopted in this thesis.

The secondary research question – linked to establishing the clinical meaning of SBFRA – is:

- What are the fall-risk profiles of community-dwelling older adults before and after participating in a standardised community-based falls prevention intervention, in terms of clinical and sensor-based fall-risk assessment results?

This question aims to deliver original and clinically relevant information on two counts. Firstly, it provides new information on the types of individuals currently being referred to a sample community-based falls prevention intervention in Ireland and the impacts of this intervention on its participants. Secondly, considering both clinical and sensor-based assessment results is a novel exploratory aspect of this thesis, since SBFRA has not been applied for this purpose in this population previously.
1.9 Thesis Structure

This thesis will answer the research questions described according to the following structure:

A systematic review of the literature on task performance-based fall-risk is provided in Chapter 2, which was carried out to inform the clinical and sensor-based fall-risk assessment procedures adopted throughout this research.

Preparatory work for the main study undertaken to answer the overarching research questions is described in Chapters 3 and 4. Chapter 3 first describes a feasibility study which was undertaken in the initial stages of this research to ascertain the feasibility of conducting fall-risk assessments using wireless inertial sensors in a community setting, to collect sample SBFRA data sets to develop and inform sensor data interpretation and data analysis techniques, and to inform further study design and methodological features. Chapter 3 goes on to describe details of how vital clinical research partnerships were established in order to facilitate the conduct of the main study, along with a commentary on how evidence from a systematic review of the literature on optimal exercise programming for falls prevention in the community was integrated into this planning and development process.

A review of the literature on SBFRA methods and sensor-derived variables that are related to fall-risk is included in Chapter 4. This review places a particular emphasis on the clinical utility and applications of the findings, as it was used to inform the SBFRA and data analysis procedures used in the main study.

Chapter 5 describes the methodology of the main study undertaken. This study gathered clinical and sensor-based fall-risk assessment data from two groups of community-dwelling older adults: a high fall-risk group composed of participants in a community-based falls prevention intervention, and a low fall-risk group composed of healthy community-dwelling older adults without a history of falls.

The results of this study are then streamed into categories for initial analysis and discussion in the subsequent chapters. Chapter 6 presents the clinical assessment data. Chapter 7 presents the sensor-based fall-risk assessment data, first for the static balance tasks and then for the dynamic tasks undertaken. Each chapter reports the results for each category of data in both study groups, along with an in-depth discussion which synthesises these results and contextualises the most relevant and interesting findings.
These chapters primarily focus on identifying variables that differ between the high and low fall-risk groups, in line with the primary research question, but also explore changes in the high-risk group following intervention, as per the secondary research question.

Chapter 8 focuses on the primary research question by comparing the most relevant clinical and sensor-derived variables identified in the preceding three chapters in terms of their capacities to classify individuals as being at high or low risk of falls, both as single assessments and in various combinations in order to quantify the utility of SBFRA in comparison to and/or as an adjunct to clinical assessment methods.

Finally, Chapter 9 summarises the key findings of the thesis, identifies the main strengths and limitations of the present research and highlights suggested directions for further research arising from this work.
CHAPTER 2. PREDICTING FALLS IN COMMUNITY-DWELLING OLDER ADULTS: A SYSTEMATIC REVIEW OF TASK PERFORMANCE-BASED ASSESSMENT TOOLS
2.1 Chapter Introduction

This chapter contains a systematic review of the literature on assessment tools which aim to predict falls in community-dwelling older adults based on the performance of functional tasks. The initial review of this topic was carried out in 2011 during the design stage of this research to inform the selection of the most appropriate battery of assessments; the aim being to identify a set of tasks whose performance could predict the occurrence of falls, which could then be instrumented using wireless inertial sensors to gather clinically meaningful fall-risk data as part of a concise overall fall-risk assessment.

The systematic review was updated in 2013 to ensure an up-to-date search strategy was achieved for the purposes of publication. The following sections (Sections 2.2 to 2.7) therefore contain the updated version of the review which was published in Physiotherapy Practice and Research in January 2014 (Power et al. 2014). Some minor edits have been made to Section 2.2 to avoid repetition of information already discussed in Chapter 1. Section 2.8 has also been added at the end of this chapter to summarise the implications of the findings of the review for the research described in this thesis.

2.2 Introduction

To assess balance and mobility, clinicians often use assessment tools that evaluate the performance of various functional tasks (Mancini and Horak 2010), and a number of standardised assessment tools have been developed with the aim of predicting falls based solely on task performance (Fabre et al. 2010). The range of assessment tools available can present a challenge to clinicians when deciding which tools are most appropriate for use in their practice, and no clear evidence supporting the use of specific tools over others has been demonstrated (Gates et al. 2008). Important factors that determine how clinicians select an assessment tool include its applicability to the given population, its validity and reliability, the feasibility of conducting the assessment given the space, time and equipment available, and its value in terms of predicting falls (Langley and Mackintosh 2007). Using assessment tools that can accurately predict falls enables clinicians to be more efficient in their practice, as these tools will contribute more useful information to aid clinical decision-making, can help to identify those in
need of intervention in a timely manner, and also serve as informative outcome measures (Langley and Mackintosh 2007).

The aim of this review is to identify which measures of task performance can best predict falls among community-dwelling older adults. By focusing on measures of task performance only, the findings of this review will help clinicians to select the best performance-based predictors of falls from the many available to include in their overall assessments, thereby improving their efficiency. It will also benefit researchers who wish to make advancements in the area of falls prediction.

2.3 Methods

The literature search was carried out in May 2013. The following databases were searched from 1983 to 2013: Academic Search Complete, AMED – The Allied and Complementary Medicine Database, Biomedical Reference Collection: Expanded, CINAHL Plus, MEDLINE, General Science, and SPORTDiscus. The search terms used were ‘falls predict*’ AND ‘community’ AND (‘older adults’ OR ‘elderly’) AND ‘physical performance’. Articles were also sourced via reference lists of relevant articles. In order to meet the aim of determining the ability of the task performance-based assessment tools identified to predict falls, only prospective cohort studies were reviewed. Articles were excluded if they were not available in English, were not full text peer-reviewed articles, did not include a measure of task performance, did not measure falls incidence, related to populations with specific conditions only or populations other than community-dwelling adults aged 60 years or over. A second reviewer was consulted if queries arose regarding the inclusion or exclusion of articles.

2.4 Results

Thirty-seven studies, dating from 1996-2013, which investigated tools for assessing task performance in relation to falls incidence were identified. The screening process is displayed in Figure 2.1. For the purpose of this review, the assessment tools identified were divided into two categories: clinic-based assessments and laboratory-based assessments. Clinic-based measures were defined as those which can be carried out in usual clinical settings, whereas laboratory-based measures were those which required specialist equipment predominantly available in research settings or highly specialised
clinical settings. Twenty studies utilised clinic-based measures only, 10 studies included measures from both categories, while seven studies examined laboratory-based measures only. Summaries of each of the studies reviewed, including outlines of the assessment tools used, are presented in Appendix A.

A number of measures with the potential to predict falls incidence based on task performance in clinical settings were identified. The most frequently observed measures were the Timed Up and Go Test (TUG) (13 studies), Five Times Sit-to-Stand Test (FTSS) (10 studies), assessments of standing balance (nine studies), gait speed measurement (eight studies), and the Berg Balance Scale (BBS) (six studies). Seven studies examined laboratory-based assessments only, with a further 10 studies including a combination of laboratory and clinic-based assessments. The most frequently-observed laboratory measures were those examining postural sway and gait analysis.
Figure 2.1. Flow diagram of the literature search and screening process.
2.5 Methodological Quality

To facilitate appraisal of the studies reviewed, a checklist based on the Critical Appraisal Skills Programme (CASP) tool for cohort studies was used (Critical Appraisal Skills Programme 2013). This checklist appraised each study based on the clarity of its focus, the use of an appropriate methodology, a clear and appropriate recruitment strategy, the inclusion of fall-risk measures, the use of a valid and reliable method of reporting falls, the consideration of confounding factors (either in design or analysis), a sufficient follow-up period, the significance and accuracy of results and the applicability of the findings to an older community-dwelling population. Most studies were of high methodological quality, meeting all or almost all of the checklist criteria. Due to the inclusion and exclusion criteria used for this review, all studies were clear in their aims, used an appropriate study design and were applicable to the population of interest. The most commonly identified weakness were inadequate or unclear participant recruitment, the use of suboptimal falls incidence reporting methods and poor consideration of confounding factors.

The majority of studies recruited large samples, although 13 studies had sample sizes of less than 100 participants, including one preliminary study with only 13 participants (Pai et al. 2010). Fall-risk was evaluated using multiple measures in most studies. Although only measures of task performance were evaluated in this review, many studies included measures of other factors potentially associated with fall-risk as part of their battery of assessments e.g. physical activity (Chan et al. 2007), executive function (Herman et al. 2010), falls efficacy, depression and anxiety (Delbaere et al. 2010b). Falls incidence measurement was identified as a potential source of bias, since 11 studies relied on recall-based methods of recording falls. Such methods can lead to significant underreporting of falls among older adults, and the use of falls calendars or diaries is preferable (Hannan et al. 2010). Factors such as age, sex, and falls history were identified as potential confounding factors in determining fall-risk, and were accounted for in various ways. Zhang et al. (2013) altered their study design to exclude those with a recent history of falls at baseline. Other studies accounted for confounding factors in their analyses e.g. by creating subgroups according to baseline fall status (Panzer et al. 2011), by creating multivariate logistic regression models to account for many factors (Herman et al. 2010), or by using classification and regression tree analysis to partition the sample into optimal subgroups (Delbaere et al. 2010b). Most studies monitored outcomes over a sufficient length of time, with follow-up periods
greater than six months in all but five studies (Aoyama et al. 2011, Brauer et al. 2000, Makizako et al. 2010, Morrison et al. 2011, Wrisley and Kumar 2010).

A notable methodological feature of all studies reviewed was the heterogeneity in the methods of reporting results. Most studies calculated Rate Ratios or Relative Risks of falls occurring, a logical approach given their prospective study designs and recording of actual falls incidences, but some based their analyses on Odds Ratios. Odds Ratio can be more difficult to interpret than Relative Risk, and also can be misleading if interpreted similarly to Relative Risk values in high-risk populations (Davies et al. 1998, Schmidt and Kohlmann 2008), making comparison of results between studies more challenging. Many studies presented sensitivity and specificity values for assessment tools, which can tell clinicians how helpful these tests may be in ruling out or ruling in the possibility of an individual being at risk of falls but, unlike positive and negative predictive values, they do not indicate the actual probability of falling and so may be less useful to clinicians overall (Akobeng 2007a). A more standardised approach to reporting the utility of assessment tools in future studies would be helpful to clinicians and academics alike.

2.6 Discussion

2.6.1 Clinic-Based Assessments

The TUG is a quick and simple measure used to assess fall-risk in practice, with individuals who take more than 13.5s to complete the test often classified as being at risk for falls (Shumway-Cook et al. 2000). Its popularity both clinically and in research is reflected in this review, as it was the most frequently studied measure, being used in 13 of the studies reviewed. In the studies reviewed, cut-off times between 12 and 13s were found to predict falls with moderate to high sensitivity and specificity in some samples (Alexandre et al. 2012, Olsson Muller et al. 2012, Wrisley and Kumar 2010). Some studies indicated that slightly lower (Boulgarides et al. 2003, Buatois et al. 2010, Herman et al. 2011, Pai et al. 2010, Srygley et al. 2009) or higher (Aoyama et al. 2011, Inoue et al. 2012, Viccaro et al. 2011) cut-off times may be required to accurately predict future falls, although these discrepancies may simply reflect the variability in functioning of different samples of community-dwelling older adults. Pooled reference times of 8.1s to 11.3s have been described for healthy older adults in distinct age categories (Bohannon 2006b). When considered in relation to the findings of this
review, it appears that individuals completing the TUG in approximately 12s or more may be at risk of future falls. From a practical standpoint, using a cut-off time close to this value could enable clinicians to identify at-risk clients in a quick and inexpensive manner. It must be noted that the TUG only measures how quickly an individual can complete the task, and does not necessarily consider the quality or safety of the performance. As such, it may be of most value to clinicians as part of a comprehensive fall-risk assessment.

Like the TUG, the FTSS is another simple means of predicting falls, since most fallers take longer to complete the test than non-fallers (Chan et al. 2007, Doi et al. 2013). The FTSS is a quick test that requires little equipment and can be performed in small spaces; therefore it may be useful in a variety of clinical settings. Buatois et al. (2010) selected 15s as the cut-off time for identifying recurrent fallers based on their previous work (Buatois et al. 2008). This is supported by the results of Doi et al. (2013) and inferred from two studies in which the FTSS did not predict falls, since the average FTSS times were less than or close to 15s in those samples (Faulkner et al. 2009, Stel et al. 2003b). Inability to complete the test was shown to predict single and multiple falls (Graafmans et al. 1996, Kelsey et al. 2010, Tromp et al. 2001), and also future need for assistance in carrying out activities of daily living e.g. bathing, dressing, and eating (Zhang et al. 2013). The FTSS is therefore a highly useful tool for clinicians to include in their battery of fall-risk assessments.

Assessing an individual’s ability to maintain various standing postures appears to be a simple yet effective method of predicting future falls. Maintaining one-legged balance for less than five seconds was found to predict recurrent falls (Buatois et al. 2010), although a separate study found that sensitivity and specificity values for this test were low to moderate (Beauchet et al. 2010). Beauchet et al.’s (2010) study noted that observed changes in arm position during the first five seconds of the task was a more sensitive and specific predictor of recurrent falls. For clinicians, it may be helpful to document both time and any observed changes in arm position as measures of performance in this task. Failure to maintain tandem stance for three seconds (Graafmans et al. 1996) or 10 seconds (Chu et al. 2005, Faulkner et al. 2009) was also found to predict single and multiple falls, with one exception (Tromp et al. 2001). For clients who are unable or unwilling to attempt single-leg stance, this may be a useful alternative test. The predictive value of the Romberg test was unclear based on the studies reviewed, as only two studies examined its use and they differed in their
conclusions: Olsson Muller et al. (2012) found that no variation of the test showed predictive validity, whereas Stalenhoef et al. (2002) found that a positive Romberg test was indicative of increased odds of falling (Odds Ratio=3.7, 95% Confidence Interval 1.8-7.8).

All studies that examined gait speed found it to be predictive of falls. Slow gait speeds – particularly speeds under 0.6m/s – were associated with greater fall-risk (Viccaro et al. 2011). However, both Quach et al. (2011) and Kelsey et al. (2010) noted similarly high proportions of fallers among groups with slow (<0.6m/s) and fast (>1.3m/s) gait speeds, while fewer fallers were noted among those with speeds of 0.6-1.3m/s, a group which made up the majority of the cohort. This suggests a U-shaped relationship between gait speed and falls. Kelsey et al. (2010) also showed a difference in the environmental context of these falls – the slow group fell indoors more often whereas the fast group experienced more outdoor falls. This may reflect the environments in which these groups are most active, and hence most at risk, and may be important to consider when educating clients regarding fall-risk reduction strategies. Notably, the methods of measuring gait speed varied between studies. Most studies measured usual gait speed, but some measured maximal speed (Chan et al. 2007, Panzer et al. 2011). The distance over which gait speed was calculated also varied, from four metres (Kelsey et al. 2010, Quach et al. 2011, Viccaro et al. 2011) to 8.1 metres (Panzer et al. 2011), with variations in the use of standing starts or rolling starts. Although there appears to be no clear consensus on the optimal protocol for measuring gait speed, it is still clear that it may be a useful predictor of falls. This flexibility may be helpful in practice, as clinicians can adopt the most feasible gait speed measurement protocols for their clinical environments while still obtaining a good estimation of fall-risk.

The BBS is a widely-used, valid and reliable outcome measure (Bogle Thorbahn and Newton 1996). However, only one of the six studies reviewed identified it as a useful predictor of falls (2010). The lack of predictive value seems to be due to a ceiling effect. A cut-off score of less than 40 is intended to indicate moderate fall-risk (Berg 1989b), but many studies reported mean scores or ranges of scores for their samples close to the maximum score of 56 for the BBS (Boulgarides et al. 2003, Brauer et al. 2000, Herman et al. 2011, Srygley et al. 2009), despite the fact that these groups experience falls. This suggests that the BBS is not sufficiently challenging to predict falls in a general older community-dwelling population. It may be useful among groups with more apparent balance and mobility deficits not considered in this review e.g. individuals recovering
from hip fractures (Shumway-Cook et al. 2005). Clinicians should therefore consider using other more appropriate methods to predict falls in community-dwelling older adults who do not display marked balance and/or gait deficits.

Although included as a component of the BBS, the Functional Reach Test was also investigated as a stand-alone measure in five of the studies reviewed. Results were inconsistent, with Stalenhoef et al. (2002) finding that a functional reach of \( \leq 15 \text{cm} \) approximately doubled the risk of falling, while other studies showed that neither functional (Hausdorff et al. 2001, Inoue et al. 2012) nor lateral reach (Brauer et al. 2000) could prospectively discriminate between fallers and non-fallers. Butler et al. (2011) found that those with poor maximal reach distances were more prone to falls, and also tended to incorrectly judge their own reaching ability. This error between estimated and actual reach distance was found to discriminate between recurrent and non-recurrent fallers with an 83.5% success rate in a separate study (Inoue et al. 2012), and may be a useful addition to this assessment tool which could be easily incorporated in practice to improve its predictive value.

Two other clinical assessments tools, the Dynamic Gait Index (DGI) and Performance-Oriented Mobility Assessment (POMA), were evaluated in four studies and three studies, respectively. Despite assessing gait as opposed to predominantly static balance, the DGI appears to be subject to a similar ceiling effect as the BBS among high functioning older adults, with most studies not supporting its predictive value (Boulgarides et al. 2003, Herman et al. 2011, Srygley et al. 2009). However, it can be a highly sensitive and specific predictor of falls among individuals with gait deficits who score poorly (Wrisley and Kumar 2010), so clinicians may find it useful for clients who have specific gait concerns. Mixed results regarding the POMA were observed (Chu et al. 2005, Hausdorff et al. 2001), and some doubts regarding its sensitivity in predicting injurious falls were raised (Panzer et al. 2011). This may be considered a significant weakness, since sensitivity may be more important than specificity in a fall-risk measure i.e. it may be more pertinent for clinicians to recognise those who require intervention than those who do not (Panzer et al. 2011).

As seen in Appendix A, a wide range of other clinical assessment tools were used in insufficient numbers of studies to allow conclusions to be drawn on their effectiveness in predicting falls. Some of these tools e.g. Balance Outcome Measure for Elder Rehabilitation (Morrison et al. 2011), Short Physical Performance Battery (Kelsey et al.
2010), combine other assessment tools or facets of them to create composite ordinal measures. While this may potentially enhance the value of the selected tasks, other issues may arise e.g. the selection of appropriate cut-off points for scoring, the potential for ceiling effects when using an ordinal rather than a continuous measure, which can make such assessment tools difficult for clinicians to interpret and apply across a range of clients in practice.

2.6.2 Laboratory-Based Assessments

2.6.2.1 Postural Sway
Postural sway was assessed under a variety of different conditions in the studies reviewed, predominantly using force plates to monitor movements of the body’s centre of pressure in standing. Overall, greater postural sway was associated with increased fall-risk, although the sway-related variables of interest varied between studies. One study cited abnormal sway as a useful predictor of falls, although the definition of abnormal sway and the methods of measuring sway were not adequately described (Stalenhoef et al. 2002). In other cases, measures of sway amplitude (Swanenburg et al. 2010), total length of sway (Stel et al. 2003b), sway area and excursion (Panzer et al. 2011) were all found to predict falls. Most studies focused on medio-lateral (frontal plane) sway (Brauer et al. 2000, Stel et al. 2003b, Swanenburg et al. 2010), but sway in the antero-posterior (sagittal plane) direction was also seen to be predictive of falls (Aoyama et al. 2011). These findings indicate that greater sway can broadly be said to predict falls, although the variations in the measurement protocols adopted and the sway variables analysed make it challenging to compare the results of studies and do not allow definitive conclusions to be drawn on the optimal protocols, variables and precise sway values for falls prediction.

2.6.2.2 Gait Analysis
Gait was analysed in the reviewed studies using varying technologies, including force-sensitive insoles (Hausdorff et al. 2001, Herman et al. 2010, Srygley et al. 2009), instrumented walkways (Callisaya et al. 2012, Callisaya et al. 2011) and body-worn sensors (Doi et al. 2013, Lord et al. 1996). Similar to the clinic-based assessment, a U-shaped relationship between gait speed and multiple falls was observed, both at
participants’ usual walking speed (Callisaya et al. 2011) and fast walking speed (Callisaya et al. 2012). A low cadence was shown to predict falls (Lord et al. 1996), although a U-shaped relationship may also exist in this case (Callisaya et al. 2011). Step length may also be a useful marker, since greater step length variability was found to predict greater fall-risk (Callisaya et al. 2011). The relationship between step length and cadence could be used to characterise those at risk of falling, since those with a shorter step length and higher cadence when attempting fast walking – indicating a shuffling pattern – were seen to have a greater risk of multiple falls (Callisaya et al. 2012). Gait variability measures – specifically variability of overall step time, double-support phase time (Callisaya et al. 2011), stride time and swing time (Hausdorff et al. 2001) – were also found to predict falls, as did swing time variability under dual-task conditions (Herman et al. 2010). At present, the equipment required to record such gait parameters may not be available to clinicians working outside of specialist gait laboratories. However, one recent novel study used small body-worn accelerometers to successfully predict future faller status, with fallers demonstrating less stable and smooth trunk movements during gait (Doi et al. 2013). Such devices could provide a convenient means of objectively analysing gait outside the laboratory setting, as well as quantifying performance on a range of other fall-risk assessment tasks, although the clinical utility of these devices is not yet well established and further studies are required to determine their potential applications in clinical practice (Shany et al. 2012a).

A wide range of additional laboratory-based measures were also examined. In single studies, lower limb stepping reaction times did not distinguish between fallers and non-fallers (Brauer et al. 2000), but upper limb reaction times when dual-tasking were slower among fallers (Makizako et al. 2010). Other single studies examined lower limb muscle activation patterns (Brauer et al. 2000), motion analysis of 360° turns (Wright et al. 2012) and reactions to experimentally-induced slips (Pai et al. 2010) with some promising results, but there is insufficient evidence from the studies reviewed to reach conclusions on their value as predictors of future falls.

2.6.3 Limitations

Although every effort was made to ensure the search was as extensive and inclusive as possible, some potentially relevant articles may have been omitted in error. Articles which dealt with assessment methods not based on actual performance of tasks were not
included. Although this may be considered a limitation given the multi-factorial nature of fall-risk, it was the intention of this review to focus on this particular aspect of falls prediction. A number of previously-published reviews deal with the overall assessment of fall-risk among older adults (Chang and Ganz 2007, Fabre et al. 2010, Persad et al. 2010, Soriano et al. 2007).

Only studies which prospectively monitored falls incidence were included in this review, therefore a considerable amount of evidence from retrospective studies was not considered. However, the aim of this review was to determine the value of assessment tools in predicting future falls, rather than discriminating between those with and without a history of falls, and prospective studies were deemed to be the optimal design to meet this aim.

Due to the inclusion criteria for this review, assessment tools designed for use in populations with specific conditions or in settings other than the community were not reviewed. Some such tools may also be useful in a general community-dwelling population, although until research has been carried out to confirm this, it is not possible to confirm or refute their value.

2.7 Conclusions

This review identified numerous task performance-based assessment tools which can predict falls in community-dwelling older adults – both clinic-based and laboratory-based. In terms of clinic-based tools, the TUG, FTSS and measures of gait speed all displayed strong evidence that they can predict falls incidence in this population. Some evidence for tests of standing balance and reaching task performance was also found. Laboratory-based measurements of postural sway and gait variability were also found to predict falls, despite a lack of consistency in the reported protocols for assessing these variables. A feasible means of assessing these variables in clinical practice – e.g. via the use of body-worn sensors – may improve the accuracy with which clinicians can predict falls among their clients, although further prospective studies using rigorous falls reporting methods are required to confirm this. The studies included were largely of high methodological quality, thus the findings of this review can help to guide clinicians in the selection of the most valuable tests for predicting falls among older adults in the community. Incorporating the recommended assessment tools into a comprehensive overall assessment can lead to improved client care and more efficient practice.
2.8 Chapter Summary

The review achieved its aim to identify the optimal functional tasks to assess in order to predict falls among community-dwelling older adults. The findings of this review will be used to inform the selection of functional tasks for our clinical and sensor-based fall-risk assessment procedures, as well as to provide initial guidance to our sensor data analysis methods.

The best-performing clinic-based measures identified – TUG, FTSS, tests of gait speed – will be considered for inclusion in the fall-risk assessment procedures which are to be implemented during this research and described in subsequent chapters. These tasks have been shown in this chapter to be predictive of falls as clinical assessment tools in their own right, but can also be instrumented for the purposes of sensor-based fall-risk assessment. By assessing tasks which are simultaneously meaningful as both clinical and sensor-based fall-risk assessment tools, the efficiency of our assessment procedures can be optimised, which is beneficial for both the assessor and the older adults being assessed.

The laboratory-based measures of postural sway and gait variability noted in the review highlight the need to consider the inclusion of tests of standing balance and gait in future fall-risk assessment procedures. They also underline the need to consider how sensor-based data may be analysed to obtain variables which reflect postural sway and gait performance, and emphasise the importance of defining clear and consistent data analysis methods, so that our results can be compared with the findings of others and also so that they may be reproduced in future research.
CHAPTER 3. A FEASIBILITY STUDY EXPLORING THE USE OF WIRELESS INERTIAL SENSORS TO ASSESS FALL-RISK IN COMMUNITY-DWELLING OLDER ADULTS AND PREPARATORY WORK FOR FURTHER RESEARCH
3.1 Chapter Introduction

In Chapter 1, the concept of sensor-based fall-risk assessment (SBFRA) was introduced. Research on this topic has evolved rapidly in recent years, with recent publications considering the practical requirements and challenges to applying SBFRA for clinical purposes (Ni Scanaill et al. 2011, Shany et al. 2012a, Shany et al. 2012b).

This chapter initially describes a feasibility study which was conducted in the very early stages of this research project, in late 2010 to early 2011. At this point in time, methods of using accelerometers to estimate fall-risk by analysing the performance of specific activities had been developed and their potential relevance in clinical practice had been proposed in published research (Aminian and Najafi 2004, Culhane et al. 2005, Narayanan et al. 2007, Narayanan et al. 2008, Narayanan et al. 2009, Wong et al. 2007), but research aiming to translate these findings into clinical practice was very much in its infancy (Greene et al. 2010, Narayanan et al. 2010). Given this context, it was deemed necessary at that time to conduct a feasibility study as an exploratory exercise to inform the objectives and methods of further research.

This chapter will go on to describe how the outcomes of the feasibility study were built upon in order to establish key methodological aspects of the main study conducted to answer the overarching research questions listed in Chapter 1. First, the establishment and development of collaborative research partnerships with clinicians involved in the provision of primary care-based falls prevention interventions will be described. Second, a summary of literature reviewed to inform optimal exercise-based falls prevention intervention design will be provided. A commentary on how this evidence was incorporated into the planning process to optimise and standardise the exercise-based falls prevention interventions to be included in this collaborative research will be included. Finally, the outcomes of the planning and partnership development process will be summarised, along with the implications of this process for the design of the main study.

3.2 Feasibility Study Introduction

‘Feasibility study’ is a term used to describe any type of research study which helps to inform and prepare for full-scale research (Bowen et al. 2009, Shanyinde et al. 2011). As such, the purposes of a feasibility study can be very broad; such studies can be used
to inform future study design and related methodological parameters, to determine target variables, to identify practical issues in research protocol implementation, to develop data analysis techniques, to examine the effectiveness of interventions or to explore dissemination methods for further larger studies (Arain et al. 2010, Bowen et al. 2009). Feasibility studies differ from pilot studies in that they are not necessarily “miniature versions” of the intended large-scale study (Charlesworth et al. 2013), but rather they aim to try out aspects of a proposed larger study to determine whether or not it can be done and what modifications in methodology may be required (Tickle-Degnen 2013).

In this feasibility study, the objectives were:

1. To determine the feasibility of conducting fall-risk assessments using wireless inertial sensors in a community setting. This included:
   a. Assessing the practicalities of implementing the assessment and identifying any barriers to its implementation e.g. knowledge and skills of the author; usability for a single assessor, as only the author would be conducting future assessments; environmental factors to consider in the assessment procedure
   b. Examining the SBFRA protocol with respect to safety and feasibility for participants and the assessor

2. To collect sample SBFRA data sets to aid the development of the author’s skills in sensor data interpretation and data analysis techniques

3. To inform study design and methodological features of future research, specifically with respect to:
   a. Developing research partnerships and identifying future recruitment strategies for participants of varying levels of fall-risk
   b. Exploring the feasibility of implementing a home-based falls prevention intervention among study participants, as well as the use of SBFRA for measuring outcomes of this intervention
   c. The selection of an appropriate, feasible and user-friendly battery of fall-risk assessment tools for use among community-dwelling older adults in further research, including the potential use of a wireless inertial sensor to objectively monitor physical activity (PA). The literature review in Chapter 2 noted appropriate fall-risk assessment tools to use from an evidence-based perspective, so the focus in this study was to determine
the practicality of implementing a selection of these in a community setting and a reasonable timeframe, and their acceptability in the chosen population.

The final point on the method of PA assessment was included in the study objectives at that time as accelerometers were becoming increasingly common in PA monitoring and their potential advantages over self-report PA questionnaires were widely reported (Godfrey et al. 2008, Murphy 2009, Denkinger et al. 2010, Wong et al. 2007, Yang and Hsu 2010). Since PA behaviour is an important factor in determining fall-risk (Heesch et al. 2008, Ribom et al. 2009, Wijlhuizen et al. 2007, Peeters et al. 2010a, Peeters et al. 2010b), it was deemed appropriate at the time of conducting this study to consider the possibility of using sensors for this purpose also.

This feasibility study was carried out as part of a broader pilot study entitled ‘A Pilot Study to Evaluate the Feasibility of Implementing a Community-Based, Evidence-Focused Falls Prevention Programme’, which was conducted in collaboration with Dr. Lynette Mackenzie from the University of Sydney, Australia and Primary Care Team staff in the Health Service Executive (HSE) Mid-Western region from November 2010 to April 2011. The larger pilot study had wider aims than those listed above, however only the aspects which relate to the aims of this research will be discussed in this chapter.

3.2 Methods

3.2.1 Participants

Participants were recruited via general practitioners (GPs) from one Primary Care Team in Ennis, Co. Clare, Ireland. GPs were asked to identify appropriate individuals from their patient databases according to the inclusion and exclusion criteria listed below, and to mail an information leaflet (Appendix B) and consent form to each (Appendix C). Individuals wishing to participate mailed signed consent forms to the principal investigator of the study, and a completed Medical Clearance Form for each participant was then obtained from the relevant GP prior to commencing the study (Appendix D). Ethics approval was obtained from the HSE Mid-Western Regional Scientific Research Ethics Committee prior to commencement of the study (Appendix E).
Participants eligible for inclusion were those aged 75 years or over who had experienced a fall in the past year and/or had a fear of falling, as determined by their GP. Participants were also required to have the ability to stand and walk independently with or without an assistive device, have a reasonable expectation of completing the programme, have a healed fracture or be at least 3 months post hip replacement (if applicable) and obtain medical clearance from their GP to participate.

Exclusion criteria were on-going medical investigations to determine the causes of falls, unstable angina, uncontrolled heart disease or blood pressure, tachycardia or uncontrolled arrhythmia, severe breathlessness or dizziness, unmanaged pain or acute systemic illness (e.g. cancer), severe cognitive impairment, a history of Parkinson’s disease or stroke, and the wearing of a pacemaker or other internal electronic device.

Since this study was carried out as part of a larger pilot study, conducted over a limited timeframe and with limited resources, a small sample of participants was anticipated and sought. As a feasibility study with exploratory objectives and no planned hypothesis testing, it was considered possible to meet the objectives of the study with a small sample (Billingham et al. 2013, Tickle-Degnen 2013).

3.2.2 Home-Based Falls Prevention Intervention

A home-based falls prevention intervention was provided as part of the overall pilot study. It was also included in the feasibility study aims to explore the use of SBFRA before and after a falls prevention intervention and the feasibility of providing such an intervention in further studies to be conducted as part of this research, in line with our secondary research question. The home-based intervention consisted of two components: exercise prescribed by a physiotherapist and home safety advice and home modifications provided by an occupational therapist. These components were selected as they have been shown to be the most effective single interventions for community falls prevention (Gillespie et al. 2012). The design of the intervention was aligned with a companion intervention which was provided under the Enhanced Primary Care Programme in New South Wales, Australia, the feasibility of which was also evaluated in the Australian health service context (Mackenzie et al. 2011, Middlebrook and Mackenzie 2012, Mackenzie and Clemson 2014).

The exercise intervention was a modified version of the Otago Exercise Programme, and thus included an individualised progressive home exercise programme incorporating specific strength and balance training, and a walking programme.
The programme was delivered by a physiotherapist (the author) via three home visits conducted over five weeks, rather than the traditional Otago Programme approach of four to five visits over eight weeks, plus a six-month follow-up, as the shorter intervention was posited to be more feasible from a service provision perspective. Participants were asked to complete the prescribed 30-minute strength and balance exercise sessions three times per week and exercise diaries were provided to encourage adherence. Ankle cuff weights were used for lower limb strengthening exercises and were progressed as appropriate over the duration of the intervention. At the final home visit strategies were identified to encourage continued adherence to the programme beyond the intervention period.

The home safety assessment and modifications were delivered by an occupational therapist working in the Primary Care Team over two home visits. The Westmead Home Safety Assessment (Clemson et al. 1999) was completed at the initial visit. Equipment and recommendations were provided based on the findings and were implemented and monitored at the follow-up visit. Fall-risk behaviours were also assessed at the initial visit using the Falls Behavioural Scale for the Older Person (FaB) (Clemson et al. 2008), and strategies to minimise risk behaviours were agreed upon with the participant and monitored at follow-up.

### 3.2.3 Systems and Procedures Used for Sensor-Based Assessments

Sensor-based assessments were carried out using the Shimmer2R wireless sensor platform (Shimmer, Dublin, Ireland). The Shimmer2R (Figure 3.1) is a wearable device which allows real-time recording and transmission of a variety of kinematic and physiological data via a tri-axial accelerometer, with optional add-on inertial sensors such as gyroscope and magnetometer (dimensions 5.6 x 7.14 x 1.85cm, approximately 57g). Shimmer2R devices were used to monitor two distinct aspects of physical functioning in this feasibility study: fall-risk via instrumented functional task performance and free-living physical activity patterns. Both aspects were assessed prior to the home-based falls prevention intervention and at follow-up ten weeks from the start of the intervention.
3.2.3.1 Sensor-Based Fall-Risk Assessment

For monitoring movement parameters related to fall-risk, a system of five Shimmers was used. Four of these were body-worn and were placed at distinct locations at the chest, left axilla (side), waist, and in the right-hand pocket of the participant’s trousers (Figure 3.2A). A range of locations were chosen at this stage so that the optimal location in terms of data collection and acceptability to participants could later be selected. A lightweight vest was worn by participants over their usual clothing to facilitate the placement of the Shimmers at the chest and axilla, with each Shimmer attached to the appropriate site on the vest using Velcro. The waist-worn Shimmer was attached to a belt using a small carry-case and worn by the participant. The Shimmer in the pocket was packed into a small box (approximately 6 x 8 x 2cm) to minimise excess movement within the pocket. A fifth Shimmer was fitted to a push-button switch which was operated by the assessor and used to mark specific time points during the tests performed. All body-worn Shimmers used for fall-risk assessment contained tri-axial accelerometer and gyroscope sensors.

Data from each Shimmer was streamed wirelessly via Bluetooth to a laptop computer operated by a researcher. Accelerometer and gyroscope data was recorded during the performance of three standardised clinical tests:

- The Five Times Sit-to-Stand Test (FTSS) (Buatois et al. 2008, Buatois et al. 2010, Tiedemann et al. 2008) – The FTSS was carried out using a hard chair (approximate seat height of 46cm). The back of the chair was placed against a
wall to prevent movement during the test. Participants began sitting as far back as possible in the chair seat while keeping their feet on the floor, approximately hip width apart, and the back of their lower legs away from the chair. With arms crossed over the chest, participants were instructed to stand all the way up and sit down, returning completely to the starting position. One practice sit-to-stand repetition was allowed to ensure participants could stand successfully with arms remaining folded and without the back of their legs touching the chair. Participants were then instructed, on the word “go”, to stand up and sit back down five times as quickly and safely as possible. Each repetition was counted aloud once the participant reached a standing position, and verbal encouragement was provided throughout. Sensor data was recorded for the entire test, and the test was also timed using a stopwatch. Timing and recording began once the participant began to rise from the chair and stopped once they made contact with the chair seat at the end of the fifth repetition. One trial of the FTSS was completed. Participants who were unable to rise from the chair without assistance or who could not complete five successful sit-to-stand repetitions were deemed to have failed the test.

- The Four Test Balance Scale (FTBS) (Rossiter-Fornoff et al. 1995) – This scale tested standing balance in four progressively challenging positions:
  a. Feet together
  b. Semi-tandem stance i.e. feet together with one foot slightly forward.
  c. Tandem stance i.e. one foot is placed in front of the other, with the heel touching the opposite toe
  d. Single-leg stance

If a participant could stand for 10 seconds in a given position without stepping or needing support, he/she moved on to the next position. If not, the test was stopped at that level and the time for which the final position was held was recorded. Each position was described and demonstrated before testing. Participants could be assisted to assume the required position, but could not use support or an assistive device during the test.

- The Timed Up and Go Test (TUG) – The TUG protocol used in this study is in line with previously published descriptions of the test (Podsiadlo and Richardson 1991, Bohannon 2006b). Participants began seated in a standard arm chair (approximate seat height of 46cm) with their back against the chair.
Participants were instructed, on the word “go”, to get up and walk at a safe and comfortable pace to a marker on the floor 3 meters away, turn, return to the chair and sit down again. Participants wore their usual footwear for the test. No physical assistance was provided, but participants could use their usual walking aid if required. If a walking aid was used at the baseline assessment it was also used at follow-up. Participants walked through the test once to ensure they were familiar with the procedure. Sensor data was then recorded for the second trial, which was timed using a stopwatch also.

Each participant was given standardised instructions and demonstrations for these tests and was given the opportunity to practice each test once prior to data collection. Ratings and data collection were then carried out on a single performance of each test. The push-button was used by the assessor to mark the following events in each test: in the FTSS, the beginning and end of each sit-to-stand repetition; in the FTBS, the start and end points of each stance; in the TUG, the moment when the participant rose from the chair and the moment at which he/she sat down at the end of the test. These points were chosen as markers of discrete events within each test and were considered to be potentially useful for subsequent data analysis.
Figure 3.2. A. System of 5 Shimmer2R sensors used to record movement data during clinical balance tests. B. Single waist-mounted Shimmer2R used to record PA data over 3 days.

3.2.3.2 Physical Activity Monitoring via Wireless Inertial Sensor

To evaluate physical activity patterns, a single waist-mounted Shimmer with tri-axial accelerometer was worn by each participant for a three-day period (Figure 3.2B). The device was to be worn using a small carry-case mounted on a belt. A standard belt was provided if participants did not possess a suitable one. Participants were asked to wear the Shimmer during waking hours only and to charge the device each night. Each Shimmer used for these three-day monitoring periods was programmed to begin recording data to an on-board one gigabyte Micro SD card once disconnected from the charger and to cease recording while charging. All participants were supplied with a Shimmer (containing a Micro SD card), a carry-case to attach the Shimmer to a belt, a charger, a digital clock and a record sheet on which they recorded the times – correct to the nearest second – at which the Shimmer was removed from the charger and returned to the charger each day. All equipment was collected at the end of the three-day monitoring period.
3.2.4 Data Analysis

Individual participant characteristics and performances on clinical fall-risk measures were summarised in table format due to the small number of participants. Performance times for each test were considered in relation to age and gender-related norms. Since the aim of the study was to determine the feasibility of various methodological aspects of the study rather than to analyse the effects of the programme, no formal hypothesis testing or further statistical analysis was carried out (Lee et al. 2014).

Data obtained from each sensor for each SBFRA test was filtered and plotted with the assistance of a post-doctoral researcher with expertise in the analysis of sensor data using MATLAB Version 7.9.0.529 (R2009b) (The Mathworks Inc., Natick, USA). Signal processing and analysis was not undertaken by the author for the data obtained in this study since one of the aims of conducting the feasibility study was to identify the author’s learning needs and skills that needed to be developed in relation to these aspects of SBFRA. Equally, further sensor-derived variables were not extracted from the sensor data since the focus at this stage was the development of the author’s skills in sensor data interpretation and knowledge of basic data processing techniques.

Daily PA data was classified using a previously-developed activity-classification algorithm (Godfrey et al. 2011). This section of the analysis was implemented by a post-doctoral researcher with expertise in the field of activity recognition via inertial sensors, who also modified acceleration thresholds within this algorithm to take into account the waist-mounted position of the sensor and inter-participant variation. Periods of physical activity were classified into five possible categories: lying, sitting, standing, shuffling (irregular slow walking) and walking, using the activity-classification algorithm. Data indicating the total percentage of daily wear-time spent on each activity were then obtained.
3.3 Results

3.3.1 Participants

Four participants were recruited to the study. One participant (L03) withdrew during the study due to illness; therefore completed data sets were obtained for three participants. Baseline characteristics for all four recruited participants are summarised in Table 3.1.

<table>
<thead>
<tr>
<th>ID</th>
<th>Gender</th>
<th>Age (years)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Medications (n)</th>
<th>Lives Alone</th>
<th>Uses Walking Aid</th>
</tr>
</thead>
<tbody>
<tr>
<td>L01</td>
<td>F</td>
<td>87</td>
<td>168.9</td>
<td>70.0</td>
<td>8</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>L02</td>
<td>F</td>
<td>76</td>
<td>162.6</td>
<td>64.9</td>
<td>2</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>L03</td>
<td>M</td>
<td>75</td>
<td>175.3</td>
<td>95.3</td>
<td>11</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>L04</td>
<td>M</td>
<td>76</td>
<td>170.2</td>
<td>71.7</td>
<td>2</td>
<td>Y</td>
<td>N</td>
</tr>
</tbody>
</table>

*Note.* F = female; M = male; Y = yes; N = no.

3.3.2 Clinical Fall-Risk Assessment Battery

Summaries of participants’ performances on the selected measures of fall-risk at baseline and follow-up are presented in Table 3.2. Only the time for the single-leg stance aspect of the FTBS is displayed, as all participants completed 10 seconds for the feet together, semi-tandem and tandem sections of the test. Despite having a recent history of falls and being identified as being at risk, only one participant was identified as being at risk of falls according to TUG time >13.5 seconds (Shumway-Cook et al. 2000) and FTSS time >15 seconds (Buatois et al. 2008). However, all but one participant (L04) performed worse than their age and gender-related single-leg stance time norms (Springer et al. 2007).
Table 3.2. Summary of performances on measures of fall-risk, including comparative fall-risk classifying times (Shumway-Cook et al. 2000, Buatois et al. 2008) and normative times (Springer et al. 2007).

<table>
<thead>
<tr>
<th>ID</th>
<th>Test</th>
<th>Baseline (s)</th>
<th>Follow-Up (s)</th>
<th>Difference (s)</th>
<th>Comparative Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L01</td>
<td>FTSS</td>
<td>35.8*</td>
<td>29.7*</td>
<td>- 6.1†</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>SLS</td>
<td>8.1*</td>
<td>4.5*</td>
<td>- 3.6</td>
<td>10.6</td>
</tr>
<tr>
<td></td>
<td>TUG</td>
<td>23.8*</td>
<td>18.8*</td>
<td>- 5.0†</td>
<td>13.5</td>
</tr>
<tr>
<td>L02</td>
<td>FTSS</td>
<td>11.8</td>
<td>13.5</td>
<td>+ 1.7</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>SLS</td>
<td>15.5*</td>
<td>30.0</td>
<td>+ 14.5†</td>
<td>16.7</td>
</tr>
<tr>
<td></td>
<td>TUG</td>
<td>9.3</td>
<td>10.3</td>
<td>+ 1.0</td>
<td>13.5</td>
</tr>
<tr>
<td>L04</td>
<td>FTSS</td>
<td>12.9</td>
<td>13.3</td>
<td>+ 0.4</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>SLS</td>
<td>11.4*</td>
<td>8.9*</td>
<td>- 2.5</td>
<td>25.9</td>
</tr>
<tr>
<td></td>
<td>TUG</td>
<td>10.0</td>
<td>8.9</td>
<td>- 1.1†</td>
<td>13.5</td>
</tr>
</tbody>
</table>

Note. FTSS = Five Times Sit-to-Stand test; SLS = Single-Leg Stance section of Four Test Balance Scale; TUG = Timed Up and Go test. * = times that indicate a risk of falls or failure to meet age-related norms. † = an improvement in performance from baseline to follow-up.

3.3.3 Sensor-Based Fall-Risk Assessment Data

Sample graphs of the accelerometer and gyroscope data obtained are presented in Figures 3.3 and 3.4. In Figure 3.3, which shows sample data from an FTSS performance, the clearest visualisation of the five distinct sit-to-stand repetitions are found in the graphs of the accelerometer data from the waist and pocket sensors (seen as five distinct ‘M’ shapes in the acceleration signals). The ‘button’ graph shows that the button pushes did not correspond accurately to the start and end of each sit-to-stand repetition, as these were manually performed at the time of testing and thus subject to error on the part of the assessor.
Figure 3.3. Accelerometer and gyroscope data from all sensor locations during the FTSS for L01 at baseline. White blocks in the ‘Button’ plots indicate the push-button recorded individual sit-stand-sit repetitions.
Figure 3.4. Accelerometer and gyroscope data from all sensor locations during the TUG for L01 at follow-up.
The accelerometer and gyroscope data from a TUG performance, shown in Figure 3.4, present an overview of the type of data that may be acquired during a complex task such as this test. It is clear that the sit-to-stand (at the beginning of the test) and the stand-to-sit (at the end of the test) can be easily detected from all accelerometer locations, since they appear as large amplitude accelerations/decelerations on all graphs. The walking sections of the test can also be observed as reasonably regular acceleration patterns from the chest, side and waist sensors. The turn, which occurs approximately in the middle of the test, is unclear based on acceleration data, but is clearly visible as large amplitude ‘spikes’ in angular velocity from all gyroscope locations.

From the experience of using the sensor set-up and inspecting the plots of the data obtained, it was determined that the sensor located in the pocket was not feasible for use in further studies. Consistent pocket sensor placement could not be achieved due to variations in participants’ clothing and, as illustrated by the gyroscope data in Figure 3.3, it was prone to excess movement within the pocket which resulted in extraneous noise in its signal. Some participants also reported that they felt very much aware of the presence of the ‘side’ sensor, located under the axilla, and may have altered their movement patterns to avoid contact with it. Thus, sensor placement in this area was also considered impractical for further studies. Based on participant feedback, the experiences of the author in conducting the assessments and visual inspection of the data obtained, the chest and waist-mounted sensors were deemed to be most feasible for future use.

3.3.4 Physical Activity Monitoring

The numbers of valid hours of sensor-derived PA data obtained for each participant are listed in Table 3.3. No valid hours of PA data were obtained for L04 on Day 3 at follow-up; therefore baseline data is not presented, as there is no follow-up data for comparison. All PA data was collected during daytime hours only.
Sample three-day PA data for participants L01, L02 and L04 are presented in Figure 3.5. Daily data is shown for baseline and follow-up periods for all days on which valid data was available. No consistent trends in PA can be seen across participants. L01 exhibited a quite sedentary pattern overall, with little time spent mobilising (walking or shuffling) during all monitoring periods. This participant also demonstrated an increase in time spent sitting at follow-up. Little change can be observed in L02’s daily PA between baseline and follow-up. Interpretation of L04’s PA behaviour is difficult, as only 2 days of valid data are available, and these days show great variation in the types of PA undertaken. At follow-up for L04, it is interesting to note the relatively large amount of time spent mobilising on Day 1, followed by a large amount of time spent lying on Day 2. This may be indicative of the individual having an unusually active day and following this with a day of rest.

In terms of the feasibility of gathering objective PA data using the body-worn sensors, it was observed that adherence among participants was fair to moderate (L01), some data was lost or unusable (L04) and considerable time and resources were required to implement this method of PA monitoring, both in the assessment stages and later when analysing the data.
Figure 3.5. Daily PA classification data for all participants at baseline and follow-up. Percentage of the total daily monitoring period (as per Table 3.3) spent in each activity state are illustrated.
3.4 Discussion

This study identified a range of valuable findings and considerations in relation to the feasibility of using wireless inertial sensors to assess fall-risk in community-dwelling older adults. Many points were specific to the context of this research (e.g. the availability of resources, partnership development, structures of clinical service provision etc.) yet many of the points raised in the following discussion may be of interest in the design of SBFRA research beyond the scope of this research project also.

3.4.1 Feasibility of Clinician-Led Sensor-Based Fall-Risk Assessment

This study demonstrated that the selected SBFRA procedures were feasible to perform in the home. The home environments of all participants allowed all tests to be completed, as the only requirements were a standard kitchen chair and approximately four metres of space in which to complete the TUG. The time-frame for the assessment was also largely acceptable, as the battery of tests took approximately 20 minutes to complete, including the set-up of the sensors, providing instructions and demonstrations to participants and recording the performance of the tests. However, some issues with Bluetooth connectivity were encountered, such that all five sensors did not always establish or maintain their connections, which introduced some delays during the assessment. A more simple system, perhaps using a single sensor, was considered to be a better option for further studies as part of this research, as this would reduce the set-up time and potentially reduce the occurrence of issues with device discovery time and connectivity (Volovikov et al. 2008). Reducing assessment time in this way would also reduce the level of inconvenience for participants and make the SBFRA procedure more realistic from a clinical standpoint, since the time available for assessing a client in practice is limited.

The decision to use a single sensor for SBFRA raises the issue of optimal sensor placement. In this study, four sites were chosen to allow for feedback from participants and researchers to aid selection of the most useful site(s) for future research. The sensor located in the pocket was deemed to be the least useful, as it was prone to excess movement within the pocket which resulted in extraneous noise in its signal. It was also not practical for participants who wore clothing without suitable pockets and its placement was inconsistent as it depended on the design of the clothing worn. The sites on the chest and waist were deemed to be the most practical locations based on the
findings of this study, as these sensors could be placed consistently, did not interfere with participants’ performances and the signals obtained from these sites could be easily interpreted. These considerations must be viewed in combination with the findings of published research on SBFRA (reviewed in Chapter 4) to inform the choice of sensor location for future research.

At the outset of the study, probably the most significant barrier to successfully implementing the SBFRA protocol was the knowledge and skills of the author in relation to performing the assessments, as SBFRA was a relatively new concept to the author at this stage and the author had no previous practical experience in using wireless inertial sensors for this purpose. This barrier was overcome by engaging in training using the sensors and the software required to record the data, as well as conducting informal practice trials of the assessment procedure with supervisors and other researchers, prior to the commencement of the study.

Considering this lack of experience, safety considerations for both the assessor and participants were also paramount in this study. A key point which was learned in this regard was that a more simple SBFRA system (e.g. a single body-worn sensor and no additional ‘button’ sensor) would facilitate improved safety, as it would allow the assessor to focus less on the equipment and more on monitoring the participants closely, or providing assistance if required. Ensuring safety is vital when carrying out assessments which involve challenging the balance of older adults who are at risk of falls. The shorter assessment time using a simple sensor system could also help to prevent excessive mental and/or physical fatigue in participants, which may influence performance quality and safety (Lord et al. 2003).

### 3.4.2 Sensor-Based Fall-Risk Data Analysis

The primary barrier to the analysis of the SBFRA data collected was the lack of knowledge and experience in this area on the part of the author. For example, simple errors in the consistency of sensor alignment were identified which presented challenges to data analysis and interpretation. Such errors were noted to be easily rectifiable in future studies by using a single-sensor system, engaging in appropriate assessor training and clearly labelling equipment. The overall deficits in the author’s knowledge and experience were overcome by collaborating with supervisors and a post-doctoral researcher with technical expertise in this area. This allowed the author to obtain
visualisations of the data gathered in this study in order to learn to interpret accelerometer/gyroscope signals from SBFRA tasks, to begin to acquire skills in using the MATLAB software, to gain knowledge of some basic concepts in signal processing required for the analysis of human movement data, and to identify further skills that needed to be acquired for the analysis of data obtained in future studies.

Throughout this process, an appreciation of the quantity of data that is collected during SBFRA and the range of potential variables that can be extracted from this data was gained. Conducting this study made it apparent that the most relevant variables which quantify features of task performance related to fall-risk needed to be established to facilitate analysis in further studies. For the fall-risk assessment tests chosen in this study, many potentially relevant variables have been identified in published literature, including body sway during standing balance tests (Mayagoitia et al. 2002), temporal characteristics and sway during discrete phases in the TUG (Narayanan et al. 2007, Narayanan et al. 2009, Greene et al. 2010), and also medio-lateral acceleration and power estimates during the FTSS (Doheny et al. 2011, Zijlstra et al. 2010). However, due to the rapidly-expanding, heterogeneous nature of published research on SBFRA, no clear recommendations on the optimal data collection methods, signal processing techniques and sets of variables to extract for fall-risk assessment purposes could be found. Therefore, it was deemed necessary to conduct a thorough review of the literature on SBFRA to inform the functional tasks to assess, the SBFRA procedures to adopt, the data processing methods to use and the variables to extract from the sensor data obtained in further studies. This review is presented in Chapter 4.

3.4.3 Study Design and Methods

A highly important aspect of conducting this feasibility study was the development of research partnerships with clinicians involved in community falls prevention initiatives. Partnership development is recognised as a useful function of conducting feasibility studies (Bowen et al. 2009). In research such as this, which aims to examine the potential translation of a novel assessment method into clinical practice, it is vital to establish working relationships with clinicians who have expertise in falls prevention and fall-risk assessment to inform future study design and to expand the network of contacts for further partnership development (Jones and Wells 2007). Of particular benefit was the partnership established with a member of the Primary Care Team who
was a Clinical Specialist Physiotherapist in elderly rehabilitation. Her expertise and management-level experience in the area of falls prevention was crucial to informing the design of further studies, for example via establishing a broader network of primary care clinicians to facilitate the recruitment of appropriate high fall-risk participants via feasible methods.

Another aspect of study design which was scrutinised in this study was the provision of a home-based falls prevention intervention. The intervention in this study was provided as part of a larger pilot study, as described previously, but also served to allow the feasibility of conducting such an intervention as part of further studies to be examined. Also, it allowed more SBFRA data be collected, since assessments were carried out before and after the intervention. This one-to-one home-based intervention was found to be feasible to implement for the small number of participants in this study, but would not be possible to implement as part of a larger study. With only the author conducting the assessments and providing the physiotherapy component of the intervention, it would be inefficient and impracticable to provide an intervention of this type in further studies, as only a small number of participants could be recruited at any one time and considerable travel time and expenses would be involved. Also, coordination of such an intervention on a larger scale with occupational therapy services in primary care would not be feasible, since issues with occupational therapist availability and competing caseload demands were encountered in this small-scale study. Thus, the possibility of linking this research with evidence-based group falls prevention interventions which are already established and provided by Primary Care services was explored and appeared to be the most viable option for future research. Linking with such services would be mutually beneficial for all concerned, as the researchers would have a means of fulfilling the research questions and recruiting participants who are at risk of falls in a safe and ethically sound manner, the clinicians providing the intervention could use the research findings to evaluate their existing service (using additional outcomes which they may not have the time or resources to implement in their usual practice), and the older adults participating in the intervention would have the option of receiving additional fall-risk assessment results and feedback via novel methods which would not be available to them as part of the standard falls prevention service.

This feasibility study highlighted the limitations to the use of SBFRA for measuring outcomes of an intervention. Reports on the use of SBFRA for clinical outcomes measurement are scarce in present literature, most likely due to the absence of well-
established rigorous evidence-based SBFRA protocols (Shany et al. 2012a). Without clearly-defined assessment protocols, constructs such as validity, reliability and responsiveness cannot be determined. This is a major barrier to the translation of SBFRA into clinical practice, since these are essential psychometric properties of clinical assessment tools (Andresen 2000). Since exploring clinical and SBFRA outcomes among a group of older adults participating in a falls prevention intervention is the secondary research question of this thesis, these limitations to SBFRA as an assessment tool must be taken into account.

This feasibility study also emphasised that a more comprehensive range of clinical fall-risk measures would be required in future studies to adequately identify and quantify participants’ levels of fall-risk. Only one feasibility study participant was identified as being at risk of falls according to TUG and FTSS times (Table 3.2), despite all being identified as a being at risk by their GPs. As reviewed in Chapter 2, a wide range of functional tasks can be used to assess fall-risk, with the TUG, FTSS and FTBS included in this feasibility study. Thus, the findings of this study were considered in tandem with the review findings in Chapter 2 in order to refine the assessment battery for future studies, such that it could provide optimal fall-risk evaluation and opportunities for SBFRA data collection. For example, a measure of gait performance would be clinically important to include (Peel et al. 2012) and may provide a range of relevant sensor data (Muro-de-la-Herran et al. 2014). Aside from the functional task performance aspect, other features of a comprehensive overall fall-risk assessment should be included in further studies, in line with multifactorial assessment recommendations (as described in Chapter 1). Behavioural and psychological constructs such as fear of falling, self-efficacy, depression, self-perceived health status and quality of life may be useful markers to consider, as they are related to fall-risk in older adults (Jørstad et al. 2005, Lamb et al. 2005). Physical activity is also an important behavioural factor to consider and, since it was monitored in detail in this study, will be discussed in greater detail in the following subsection.

3.4.3.1 Sensor-Based Physical Activity Monitoring

A notable observation from the sensor-based PA data obtained is the high proportions of sedentary time displayed by all participants. Sitting made up between 25-50% of recorded daily activity in the majority of cases. However, the method of classifying PA
used in this study may not be capable of accurately detecting certain types of PA; for example, the seated lower limb strengthening exercise prescribed as part of the intervention will be classified as sitting. The ability to monitor sedentary time is a positive feature of this monitoring method, but alterations to the algorithm to determine the distribution of the various activity states throughout the monitoring periods would also be useful to investigate PA behaviours in greater detail (Taraldsen et al. 2012).

A further limitation of this PA monitoring method is that it does not provide data on the context in which PA took place e.g. inside or outside the home. Understanding the context in which PA occurs is important among older adults who are at risk of falls, since it allows clinicians to understand and manage fear of falling (Sjosten et al. 2008) and subsequent activity restriction (Delbaere et al. 2004) in this population.

Other methodological issues with using the sensors as PA monitors were identified e.g. the battery-life of the PA monitors was sufficient to cover a three-day period, thus daily charging was not required and presented an unnecessary complication for participants. Compliance with sensor-based PA monitoring was reasonable, with most participants wearing the sensor for between six to eight hours per day. However, it is unlikely that the times for which data was recorded represent total waking hours for these individuals (Ohayon and Vecchierini 2005), thus some relevant PA may have gone undetected. Necessary improvements to the data analysis process were also identified since, despite being based on a previously validated algorithm, further validation of the modified algorithm specific to the waist-mounted sensor placement used in this study would be necessary to ensure the accuracy of the physical activity classifications obtained.

Overall, the use of sensors to objectively monitor PA was not considered feasible for future studies as part of this research. Implementing such methods would require disproportionate time and resources for what is a relatively small aspect of the overall research questions. Self-report PA assessment tools were deemed to be more appropriate for our purposes, despite their limitations, since they can provide more relevant PA data (e.g. type, intensity, context of PA) in a less time-consuming manner (Jørstad-Stein et al. 2005).
3.4.4 Limitations

The constraints on time and resources for this study limited the number of participants that could be included. This small sample size may also be considered a limitation of this study, as it did not allow for meaningful statistical analysis of the results obtained. However, as a feasibility study, the aim was not to evaluate outcomes but to explore issues relating to feasibility, study design and implementation. Considering the valuable experiences gained and the breadth of factors identified for consideration in further research design, the objectives of the study can be said to have been met despite these limitations.

3.5 Summary of Feasibility Study Findings and Implications for Further Research

Based on the results of this study and the experiences gained, numerous factors were identified to inform the design of further research and optimise the feasibility of using sensors to measure fall-risk in a community setting. As per the objectives of this study, these factors are summarised according to their influences on the feasibility of implementing SBFRA in this setting, implications for SBFRA data collection and analysis and overall study design and methodological considerations.

Feasibility of Conducting SBFRA in the Community:

- Selecting a single sensor location for use in further studies was considered necessary to improve user-friendliness for the assessor, to facilitate closer supervision of participants, to enable a more consistent and less time-consuming set-up and data recording process, and to reduce signal processing and data analysis workload, particularly since multiple sensors may gather similar data which would render some data and time spent on analysis redundant. Based on the findings of this feasibility study, either a waist or chest-mounted sensor would be most acceptable to participants and provide the most useful data. The review of SBFRA literature in Chapter 4 will further inform the choice of sensor location for the main study.
• Valuable training and skill development in the implementation of SBFRA was gained by the author and key points in the assessment procedure to consider for improved safety and consistency were identified.

Considerations for SBFRA Procedures and Data Analysis:

• Further skill development requirements on the part of the author were identified and learning needs were highlighted in the areas of sensor data interpretation, signal processing and variable extraction for SBFRA.

It was deemed necessary to conduct a comprehensive literature review of SBFRA methods and findings in order to inform study design and data collection methods, signal processing techniques and to identify variables to extract from the data obtained which may be clinically-relevant in fall-risk assessment. A systematic review of this literature is presented in Chapter 4.

Study Design and Methodological Considerations:

• Partnerships were established with key clinicians involved in falls prevention service provision in the Mid-West region of Ireland. These partnerships proved to be vital for expanding our network of clinical contacts and informing further study design, particularly for establishing feasible methods of recruitment for high fall-risk individuals.

• Providing a home-based falls prevention intervention was found to be impractical given the time and resources available for this research project, especially considering that such an intervention is a secondary aspect of the overall research questions. However, a link with already established group falls prevention interventions was developed through the clinical partnerships created in this study. This link was noted to be potentially beneficial to all parties involved and considered worthy of carrying forward to further studies as part of this research project, as will be discussed further in the following sections.

• It was noted that a more comprehensive battery of fall-risk assessment tools must be chosen for future studies, incorporating the most relevant evidence-based assessments of functional task performance along with a range of psychosocial measures related to fall-risk.

• PA monitoring using sensors was not deemed to be a feasible or appropriate use of time and resources for further studies to be undertaken as part of this research.
Thus, other methods must be considered for further studies e.g. age-appropriate self-report PA assessment tools.

### 3.6 Development of Research Partnerships within Primary Care

A particularly vital outcome of the feasibility study was the establishment of working research partnerships with clinicians working in primary care. Such partnerships were deemed to be crucial to the conduct of further studies, since the ability to identify and recruit community-dwelling older adults who were at high risk of falling was a key aspect of our primary research objective. Linking with clinicians involved in the provision of falls prevention interventions in primary care settings could present an ideal collaborative partnership for further research, whereby the clinicians could benefit from researchers’ knowledge and skills to evaluate and improve their services; the researchers could benefit from access to established referral pathways and interventions to address the primary and secondary research questions, plus study design and recruitment challenges; and the older adults referred to these falls prevention services could receive interventions based on up-to-date evidence and have the option to receive additional in-depth fall-risk assessments and feedback through involvement in research.

The initial partnership established during the feasibility study was with a Clinical Specialist Physiotherapist in elderly rehabilitation, who was involved in the Ennis Primary Care Team. This Clinical Specialist Physiotherapist coordinated a group falls prevention intervention for community-dwelling older adults which took place in the local community hospital (St. Joseph’s Hospital, Ennis), and expressed interest in collaborating on research following the feasibility study. A follow-up meeting in Ennis in April 2011 was arranged to discuss the existing falls prevention intervention and to establish how further study design and recruitment strategies could potentially link with this intervention, considering the overall research questions.

A further partnership was established with the Acting Physiotherapy Manager in the North/South Lee Primary Community and Continuing Care (PCCC) areas in Cork in May 2011. The Physiotherapy Manager was also interested in collaborating in this research, as the North/South Lee PCCC services were providing a physiotherapy-led group falls prevention intervention for community-dwelling older adults which was well-established and similar in design to the intervention provided in Ennis.
Other primary care-based falls prevention interventions were sought in the Limerick and North Tipperary regions by searching the directory included in the Strategy to Prevent Falls and Fractures in Ireland’s Ageing Population (Health Service Executive et al. 2008) and through verbal and email contact with physiotherapy colleagues in the region, but it was found that none existed at that point in time. Therefore, a joint meeting between the author, one of the supervisors of this research (AC) and the two Physiotherapists coordinating the interventions in Ennis and Cork was arranged for July 2011. The main purpose of this meeting was to standardise the interventions in both regions to ensure uniformity in their content for the purpose of this research. Both interventions were similar, in that they were physiotherapy-led and consisted primarily of exercise in small groups, since exercise is one of the most vital aspects of any community falls prevention strategy (American Geriatrics Society and British Geriatrics Society 2011, Gillespie et al. 2012), with an additional educational component.

3.7 Evidence-Based Exercise Interventions for Falls Prevention in Community-Dwelling Older Adults

In preparation for the design of the main study and the standardisation process involving the collaborating Physiotherapists, a review of the literature to determine the optimum exercise programme content for community falls prevention was conducted. This review was carried out to ensure familiarity with the relevant programme design and implementation factors for an exercise intervention of this type, and also because the collaborating Physiotherapists wanted to ensure that their interventions could be aligned with recommendations from recent evidence, insofar as was feasible within their service provision contexts.

Sherrington et al.’s systematic reviews and meta-analyses on the effects of exercise on falls contain valuable recommendations regarding the type, dosage and delivery of exercise for effective falls prevention (Sherrington et al. 2011, Sherrington et al. 2008), but these recommendations are based on combined evidence from older adults in the community and in residential care. Since older adults’ fall-risk profiles and levels of physical function vary according to residential status (Scott et al. 2007), there is a need to clarify the optimum elements of exercise programme design for falls prevention in community-dwelling older adults specifically (Arnold et al. 2008).
Thus an original literature review was undertaken, which has been published in the *European Review of Aging and Physical Activity* (Power and Clifford 2013). A summary table of the 31 studies included in this review is presented in Appendix F. All studies were of level one or two evidence, according to Oxford Centre for Evidence-Based Medicine ratings (Howick et al. 2011). The following sections will present excerpts of the main findings of the review, with added commentary on how these findings applied to the intervention design and were incorporated into the intervention standardisation process within the current research.

3.7.1 *Elements of Falls Prevention Exercise Programme Design*

The main elements of exercise programme design can be described in terms of the FITT principle i.e. the frequency of exercise, the target intensity, the time spent exercising and the type(s) of exercise undertaken (Heyward 2010). Further aspects which must be considered are the delivery format (e.g. group or individual) and setting (e.g. home, hospital, community centre). All elements of the exercise programme will influence uptake and adherence, which are essential to success, since poor uptake and/or adherence will render a programme ineffective regardless of its design and content (Nyman and Victor 2011). The following sections will describe each of these elements with reference to their implications for the current research.

3.7.2 *Frequency*

In the studies reviewed, the minimum exercise frequency reported to be effective for falls prevention was twice per week (Weerdesteyn et al. 2006), although this effect was noted in the short-term only and was not supported by studies of longer duration (Carter et al. 2002, Haines et al. 2009, Lord et al. 2005). Exercising three times per week was the most commonly-adopted and most consistently effective approach across all studies reviewed (Campbell et al. 1997, Campbell et al. 1999, Robertson et al. 2001a, Robertson et al. 2001b, Buchner et al. 1997, Huang et al. 2010, Lin et al. 2006, Means et al. 2005, Rubenstein et al. 2000, Skelton et al. 2005, Suzuki et al. 2004, Wu et al. 2010, Shumway-Cook et al. 2007, Woo et al. 2007). A higher exercise frequency can also be effective, but may not be acceptable to programme participants and thus

The existing falls prevention interventions in Ennis and Cork consisted of one group exercise class per week supplemented by a home exercise programme (HEP), which was recommended to be performed at least twice per week. Encouraging attendance at the exercise class and adherence to the twice weekly HEP would ensure that both interventions achieved the optimum exercise frequency.

3.7.3 Intensity

Clear guidelines exist describing appropriate strength and endurance training intensities for older adults (Nelson et al. 2007). Many of the studies reviewed did not provide adequate detail of exercise intensity, but where guideline intensities were explicitly not met, the interventions failed to significantly reduce falls incidence (Kamide et al. 2009, Reinsch et al. 1992, Inokuchi et al. 2007, Steinberg et al. 2000). This highlights that strength and endurance components of a falls prevention intervention must be of an appropriate intensity to achieve training effects and the ensuing clinical benefits.

Neither of the existing interventions included an endurance training component but both included exercises aimed at building strength. The intensity of the strengthening exercises was variable. Body-weight exercises such as sit-to-stand and half-squats were predominantly used for lower limb strengthening, with the level of support and number of repetitions varied according to each individual’s abilities. Where dumbbells or cuff weights were used they were generally of a standard variety for all participants and were quite light e.g. one to two kilograms. It was agreed that strength training intensities would be monitored more closely in both interventions and that participants would be encouraged to increase their exercise intensities where appropriate by reducing support during body-weight exercises or adding additional weight or repetitions.

Defining an optimal intensity for balance training is problematic, since there is currently no standard measure by which to express its intensity. Sherrington et al. (2008) categorised balance training intensity according to the presence or absence of certain exercise components: moving the body’s centre of mass, reducing the base of support and minimising upper limb support. Progression of intensity is vital for continuing training gains to be obtained, but maintaining safety while providing adequate challenge
is essential. Costello and Edelstein (2008) proposed that balance training should therefore be conducted at the highest possible level of difficulty without falling or near-falling to ensure sufficient training intensity, and that each exercise should be mastered before progressing to ensure safety.

The interventions in both Cork and Ennis were very similar in that their HEPs were modelled on the Otago Exercise Programme, which provides a useful framework for clinicians to prescribe progressive balance training (Campbell et al. 1997, Campbell et al. 1999, Robertson et al. 2001a, Robertson et al. 2001b). The balance exercises undertaken in the group settings were more challenging than the HEP in both interventions, since the supervision allowed participants to more safely challenge their balance in that setting. Since intensity is determined for each participant on an individual basis, this aspect of the programmes cannot and should not be truly standardised. A standard approach to adjusting the intensities of specific balance exercises across both interventions were discussed and agreed upon. For example, in a standing or walking exercise, upper limb support would first be reduced to increase the difficulty, followed by reduced base of support. Further challenges would be added by occluding visual input, introducing head-turns to challenge the vestibular system, or adding a cognitive dual-task, such as counting backwards aloud or recalling lists of items.

### 3.7.4 Time

Time spent exercising may be considered as the duration of each exercise bout, the duration of the intervention, or the total exercise volume i.e. the cumulative time spent exercising throughout an intervention. No precise optimal exercise bout duration was identified in the review, although the majority of effective interventions included some bouts of at least 60 minutes duration or more in supervised settings – including time for explanation, demonstration etc. – rather than as single, continuous bouts of exercise.

Effective interventions were observed with durations ranging from five weeks (Weerdesteyn et al. 2006) to two years (Campbell et al. 1999). Most effective interventions were of 16 weeks (Day et al. 2002, Fitzharris et al. 2010, Wolf et al. 1996, Inokuchi et al. 2007) to 12 months in duration (Campbell et al. 1997, Yamada et al. 2010, Robertson et al. 2001a, Robertson et al. 2001b, Lin et al. 2006, Wu et al. 2010, Shumway-Cook et al. 2007, Barnett et al. 2003).
The duration of the Cork intervention was eight weeks, with six weeks including exercise, as weeks one and eight were devoted to conducting pre- and post-intervention assessments. The Ennis intervention was 10 weeks in duration at the time of the initial meeting, but with plans to reduce the duration in order to run additional repetitions of the intervention per year to meet the demands of a growing waiting list. Thus, the Ennis intervention was reduced to six weeks duration in line with the Cork intervention. Although longer interventions may be more effective, the pressure to provide falls prevention services to a growing number of individuals with limited resources could not facilitate longer duration interventions within these primary care services.

All effective interventions in the studies reviewed were found to involve at least one hour of exercise per week, and comprised of at least 40 hours of exercise over the course of the intervention, which is lower than the recommendation of 50 hours suggested in previous reviews (Sherrington et al. 2008, Sherrington et al. 2011). Interventions with very high exercise volumes experienced problems with participant adherence (Lin et al. 2006, Shumway-Cook et al. 2007). Thus, it was apparent that exercise programmes must meet certain minimum exercise volume requirements while remaining acceptable to participants in order to be effective.

Both the Cork and Ennis interventions involved approximately two hours of exercise per week in total, which is in line with evidence-based recommendations. However, the short durations of the interventions limited the total exercise volume to approximately 12 hours, once the Ennis intervention shortened its duration. This is clearly far lower than the optimal volume of 40 hours, but was unfortunately the maximum that could be provided within the contexts of these primary care services.

3.7.5 Type

A number of the studies reviewed implemented a comprehensive programme of balance, strength, endurance, and flexibility training – as recommend for all adults aged 65 and over by the American College of Sports Medicine/American Heart Association guidelines (Nelson et al. 2007). Such programmes were effective in preventing falls (Yamada et al. 2010, Barnett et al. 2003, Kemmler et al. 2010, Freiberger et al. 2007, Skelton et al. 2005, Thomas et al. 2010). Many of the studies reviewed included walking as the chosen form of endurance exercise (Campbell et al. 1997, Yamada et al.
2010, Campbell et al. 1999, Robertson et al. 2001a, Robertson et al. 2001b, Rubenstein et al. 2000, Barnett et al. 2003, Kemmler et al. 2010, Freiberger et al. 2007), but walking was not consistently associated with the effectiveness of these interventions and was noted to potentially increase fall-risk in one study (Rubenstein et al. 2000). Neither intervention included a walking nor endurance training component so, given the findings of the review, it was agreed to continue with this policy.

Both interventions focused predominantly on functional balance and mobility exercises, which is in line with evidence that balance training should constitute at least one-third of the total programme content (Day et al. 2002), be given at least equal emphasis compared to other types of exercise (Freiberger et al. 2007), and be of functional relevance in order to be effective (Kamide et al. 2009, Latham et al. 2003).

### 3.7.6 Delivery and Adherence

The most commonly observed settings for exercise programmes among the studies reviewed were community centres and participants’ homes. Exercise in either location was effective, as were combined centre- and home-based programmes. A convenient location and accessibility via transport links are vital, as a lack of these was cited by participants as major contributing factors to dropping-out of a programme (Nitz and Choy 2004). The Cork intervention was delivered in two primary care centres located within a large urban area, with participants being referred to their local centre. This made the exercise classes easily accessible to all participants. The Ennis intervention was based in a local community hospital in moderate-sized regional town and catered for residents of the town and surrounding rural areas. As such, accessibility may have been an issue in this intervention for some individuals living in rural areas.

Combining supervised group exercise with supplementary individual HEPs – as used in both interventions – was found to be a common and effective choice of intervention delivery. This format offers the beneficial leadership, social support and social outlet provided by group interventions (Bunn et al. 2008), as well as empowering individuals and encouraging self-regulated behaviour change through a HEP, which are recommended to achieve long-term motivation and exercise participation (Brawley et al. 2003, Robinson et al. 2008).
3.8 Outcomes of Partnership Development Process and Implications for Further Study Design

Following the joint meeting between the researchers and Physiotherapists in July 2011, a procedure to standardise the interventions in both Cork and Ennis was agreed upon, according to the elements described throughout Section 3.7. Considering the matched delivery formats of both interventions, together with the relatively well-matched frequency, intensity, time, types and settings of these exercise interventions, the minor alterations mentioned throughout Section 3.7 were sufficient to achieve a standardised intervention across both regions.

This joint meeting also facilitated discussions on overall study design, recruitment processes, assessment procedures and the manner in which these research procedures could be efficiently aligned with the existing service provision and administration structures. Clarifying these aspects of methodology at an early stage was essential, as ethics committee approval in both regions needed to be sought in advance of commencing the study. Further meetings with the Senior Physiotherapists in Cork who implemented the interventions at a local level were conducted in September 2011, to establish an initial working relationship with these Physiotherapists and to obtain their input in finalising the practical aspects of the study procedures, and again in December 2011 to confirm the procedures prior to commencement of the study. Full details of the methodology adopted will be provided in Chapter 5.
CHAPTER 4. A SYSTEMATIC REVIEW OF SENSOR-BASED FALL-RISK ASSESSMENT AND ITS RELEVANCE IN CLINICAL PRACTICE
4.1 Introduction

As described in Chapter 1, the use of wireless inertial sensors to objectively measure human posture and movement for the purpose of fall-risk assessment has been well acknowledged (Godfrey et al. 2008, Wong et al. 2007). Recent literature has sparked inter-disciplinary discussions across the fields of electronic and computer engineering, medicine and rehabilitation on the applications of sensors in falls prevention (Ni Scanaill et al. 2011, Shany et al. 2012a), and to date, a wide variety of approaches to assessing fall-risk using sensors to instrument task performance have been taken (Shany et al. 2012b).

From a researcher’s perspective, the recent review by Howcroft et al. (2013) provides an excellent insight into the current state of the literature on sensor-based fall-risk assessment (SBFRA) for older adults, focusing on the assessment protocols used and the sensor-derived variables found to be related to fall-risk. That review had not yet been published at the time of conducting this research, hence the specific learning needs in relation to the implementation of SBFRA and the analysis of the data obtained identified in Chapter 3. Furthermore, the review by Howcroft et al. (2013) does not discuss how this knowledge translates to practice and how it can be meaningful in a clinical context.

To address the learning needs identified in Chapter 3 and to inform the SBFRA procedures to be used in the main study conducted to answer our research questions, a systematic review of current literature on SBFRA among older adults was undertaken. The aims of this review were to identify, evaluate and synthesise the current literature on SBFRA from a clinical perspective, in keeping with the overall research questions. Specifically, sensor-derived variables which have been found to be associated with fall-risk will be discussed in terms of their clinical relevance, including how they may relate to or augment existing fall-risk assessment methods in clinical practice. Factors identified in current evidence relating to the applications of SBFRA in clinical practice will also be discussed.
4.2 Methods

4.2.1 Search Strategy
A literature search of the following databases was performed in July 2013: Academic Search Complete, AMED - The Allied and Complementary Medicine Database, Applied Science & Technology Source, Biomedical Reference Collection: Expanded, CINAHL Plus, General Science Full Text, MEDLINE, OmniFile Full Text Mega, SPORTDiscus. The search terms used were “sensor” AND “fall risk” AND (“older adults” OR “elderly”).

4.2.2 Study Selection
Only full-text papers from peer-reviewed academic journals were included. Other inclusion criteria were the use of body-worn sensors to monitor a specific functional task or tasks, a comparison of sensor data to a measure of falls incidence or fall-risk, and a sample aged 50 years or over. Articles were excluded if they were not available in English, monitored general physical activity rather than a specified task or tasks, or included a population with a specific clinical condition only. Further articles were obtained via the reference lists of relevant articles. One reviewer screened the titles and abstracts according to the selected criteria. A second reviewer was consulted if eligibility was unclear, and any discrepancies in opinion were discussed until consensus was reached. The screening process is illustrated in Figure 4.1.
**Figure 4.1** Flow diagram illustrating the literature search and screening process.
4.2.3 Methodological Quality Appraisal

Since the studies reviewed were of varying methodologies, a specific critical appraisal tool was not used to examine quality. The overall quality of evidence was considered in terms of the Oxford Centre for Evidence-Based Medicine Levels of Evidence (Howick et al. 2011).

4.2.4 Data Extraction and Synthesis

Details of study design, setting, sample size, participant characteristics and the methods used to classify fall-risk in the sample were summarised for each study. Further data relating to the SBFRA methods used were extracted, specifically the sensor type(s) used, their locations and wear time, the task(s) analysed, the sensor sampling frequencies, data filtering techniques applied, the sensor variables extracted and significant results relating sensor variables to fall-risk.

A meta-analysis was not possible due to the variations in study methodologies, sensor variables extracted and falls-related outcomes used. Hence, a descriptive synthesis of the findings was conducted instead, with key information tabulated as described to facilitate comparison between studies.

4.3 Results

Twenty-two papers were included in this review. A table summarising the methodological features of the studies reviewed is included in Appendix G.

4.3.1 Study Design and Participants

Nineteen studies (86%) utilised a cross-sectional design and the remaining three studies were prospective. According to the Oxford Centre for Evidence Based Medicine (Howick et al. 2011), this approximately equates to Level Three evidence overall. Community-dwelling older adults were assessed in 11 studies (50%), hospital inpatients in four (18%), older adults in residential care in two studies (9%), while single studies examined day hospital (O'Sullivan et al. 2009) and falls clinic (Narayanan et al. 2010) attendees and a combination of community-dwellers and inpatients (Gietzelt et al. 2009). Two studies (9%) did not provide sufficient information to determine the residential status of their participants. The settings in which sensor-based assessments
were carried out also varied considerably. Nine studies were based in hospitals or clinics; five were based in the community, including one which was carried out in participants’ homes. One study assessed participants in a combination of hospital and community settings (Gietzelt et al. 2009). Three studies took place in laboratory settings; two were carried out in residential care facilities; and a further two did not specify their setting.

4.3.2 Fall-Risk Classification Methods
The measures used to classify fall-risk in participants varied greatly among the studies reviewed. Most commonly used was self-reported falls history. Other studies used various standardised clinical fall-risk assessment tools e.g. the Physiological Profile Assessment (PPA) (Menz et al. 2003a, Narayanan et al. 2010) or the Berg Balance Scale (BBS) (Greene et al. 2010), which have been validated as estimators of fall-risk. Four studies combined falls history and clinical assessment tools to determine fall-risk, which is representative of actual clinical practice (Itoh et al. 2012, Marschollek et al. 2009, Najafi et al. 2002, O'Sullivan et al. 2009). Two studies did not describe specific, reproducible criteria for how they assessed and categorised fall-risk among their participants (Caby et al. 2011, Itoh et al. 2012).

4.3.3 Characteristics of Sensor-Based Fall-Risk Assessment
Appendix H contains a table summarising the key features of the sensor-based assessment protocols adopted in the studies reviewed, including sensor-derived variables significantly associated with fall-risk. The main findings in relation to these features will be reported in the following sections and discussed in Section 5.4.

4.3.3.1 Task Selection
The tasks for which sensor data were collected can be divided into static and dynamic types, as described in Chapter 1. Most studies focused on a single type of task, with only two studies reporting on both static and dynamic tasks (de Bruin et al. 2007, Doheny et al. 2012a). Five studies examined sensor-based features of quiet standing (Doheny et al. 2012a, Doheny et al. 2012b, Giansanti et al. 2008, Greene et al. 2012a, Greene et al. 2012b, O'Sullivan et al. 2009). All studies included some measurements of
stance conditions altered in terms of visual input (eyes open or closed), stance width (normal, narrow or semi-tandem stance) and/or the compliance of the surface (firm surface or foam mat). Most studies gathered data for 30 to 40 seconds, except Giansanti et al. (2008) who recorded 60 seconds of data. Ten studies examined gait, although the protocols used to obtain sensor-based gait data varied greatly, from a short three metre walk (Doheny et al. 2012a) to prolonged periods of treadmill walking (Riva et al. 2013, Toebes et al. 2012). Thirteen studies chose to analyse instrumented functional tasks, either in the form of standardised task-based assessment tools e.g. Timed Up and Go test (TUG), Five Times Sit-to Stand test (FTSS), or simply instrumented performance of common tasks such as sit-to-stand and other postural transitions. The TUG was by far the most commonly used functional assessment, being adopted by seven studies (Gietzelt et al. 2009, Greene et al. 2010, Greene et al. 2012a, Marschollek et al. 2009, Marschollek et al. 2011a, Narayanan et al. 2010, Weiss et al. 2011).

4.3.3.2 Sensor Variables Extracted

4.3.3.2.1 Static Tasks

In standing balance assessments, a variable consistently found to be related to increased fall-risk was a higher root-mean-square (RMS) of acceleration measured in medio-lateral (ML) and antero-posterior (AP) directions, as well as the resultant acceleration vector based on three axes. Higher RMS values were noted among fallers compared to non-fallers when standing with eyes open (Doheny et al. 2012b, Greene et al. 2012b), eyes closed (Doheny et al. 2012a) and standing on compliant foam (Doheny et al. 2012a, O'Sullivan et al. 2009). Greene et al. (2012b) also included RMS acceleration in a model that could classify individuals as fallers with 72% accuracy. Other variables related to higher frequency acceleration among fallers were also included in this model. The significance of frequency-related variables was not consistent across studies, since a higher AP spectral edge frequency (SEF) was noted among fallers when standing on foam, but a lower SEF in the ML direction when standing on a firm surface with eyes closed (Doheny et al. 2012a). Measures of displacement and velocity calculated from accelerometer data were also found to be higher among fallers than non-fallers (Doheny et al. 2012b). In terms of gyroscope-derived variables, Greene et al. (2012b) also included increased AP angular velocity in their fall-risk classification model. Other such
variables found to discriminate between high and low fall-risk individuals were squared modular angular velocity and rotational kinematic energy (Giansanti et al. 2008).

4.3.3.2.2 Dynamic Tasks

Gait speed – although not a sensor-specific measure – was found to be significantly slower among fallers compared to non-fallers (0.73 ± 0.22 m/s versus 1.24 ± 0.19 m/s) (Auvinet et al. 2003). Accelerometer-derived gait speed was also found to be slower among high fall-risk individuals (0.98 ± 0.21 m/s) compared to those at low risk (1.16 ± 0.15 m/s) (Menz et al. 2003a). Sensor-derived temporal features of gait which were significantly associated with greater fall-risk were stride times longer than 1.19s (Schwesig et al. 2013), and single-support phase times less than 76% of total stride time (Doheny et al. 2012a). Greater variability in stride time (Schwesig et al. 2013) and step time (Menz et al. 2003a) were also associated with higher fall-risk. Fallers also displayed significantly lower stride frequency than non-fallers (0.86 ± 0.07 versus 0.97 ± 0.08) and shorter stride lengths (0.86 ± 0.26 m versus 1.28 ± 0.17 m) (Auvinet et al. 2003), while step lengths less than 60cm were also observed in high fall-risk groups (Menz et al. 2003a).

Other more complex accelerometer-derived variables related to greater fall-risk included reduced stride symmetry and regularity (Auvinet et al. 2003), greater gait instability and ML variability (Toebes et al. 2012) and lower correlations between arm and leg accelerations (Caby et al. 2011). Lower average vertical and ML accelerations at the lumber spine and AP accelerations at the ankle during walking were also observed in high fall-risk individuals (Itoh et al. 2012).

Sensor data was also used to extract temporal variables for sit-stand-sit transitions, and when segmented into phases, a longer sit-to-stand duration was found to be associated with greater fall-risk for single performances (de Bruin et al. 2007, Weiss et al. 2011) and mean durations calculated from FTSS performance (Doheny et al. 2011, Najafi et al. 2002). Fallers also displayed decreased jerk in both the AP (Weiss et al. 2011) and ML (Doheny et al. 2011) directions compared to non-fallers i.e. they produced a slower rate of change of acceleration during sit-to-stand. Other parameters relating to acceleration amplitudes (Narayanan et al. 2010, Weiss et al. 2011) and frequencies (Doheny et al. 2011) during sit-stand-sit transitions were linked to greater fall-risk in single studies only.
Six of the seven studies examining the TUG formed falls prediction models based on a number of sensor variables. Narayanan et al. (2010) did not include any TUG variables in their prediction model. Logistic regression models based on a combination of gyroscope-derived and demographic variables were found to retrospectively discriminate between fallers and non-fallers with greater accuracy (mean 76.8%) than BBS scores (mean 61.4%) or TUG times (mean 60.6%) in three groups: males, females aged <75 years and females aged ≥75 years (Greene et al. 2010). Predictive classifier models for the same groups, also based on demographic and sensor data combined; prospectively identified fallers with a mean accuracy of 79.7% (Greene et al. 2012a). Logistic regression was also used to develop a simple model combining three accelerometer-derived measures (standard deviation, jerk during sit-to-stand, and mean step duration) which correctly classified the faller status of 88% of participants, compared to 63% for TUG time via stopwatch (Weiss et al. 2011). Marschollek et al. (2009) included sensor-derived gait variables from the TUG e.g. step length, step duration, number of steps, as well as overall energy expenditure and frequency-based variables to form a classification tree prediction model. This model improved the accuracy of faller status classification to 90%, compared to 83.6% for clinical assessments alone. A separate classification tree model comprised of spectral density-related variables extracted from accelerometer TUG data predicted falls with 80% accuracy (Marschollek et al. 2011a). Similarly, kinematic energy and pelvic sway during walking were used in another decision tree model to classify individuals with high fall-risk scores with 90.5% accuracy (Gietzelt et al. 2009).

4.4 Discussion

The results of this review confirm that SBFRA has great potential to assist and improve the capacity to identify those at risk of falling in clinical practice. The time and cost-related advantages of wireless inertial sensors over other methods that objectively measure balance and gait e.g. force platforms or three-dimensional motion analysis systems are evident. However, further discussion of some key points relating to the collection and analysis of sensor data, and the methodological characteristics of current evidence is warranted to inform aspects of study design and SBFRA data analysis to be included in this research.
4.4.1 Sensor Data

In most studies of standing balance reviewed, greater body “sway” was associated with higher fall-risk. Unfortunately, the precise parameters used to describe this entity known as “sway” were not consistent across studies. Winter (2009, pp.127-130) described this issue of confusion surrounding the term “sway”, as it leads readers to erroneously infer that displacement of the body’s centre of mass or centre of gravity is being described when this may not be the case. Doheny et al. (2012b) provided the closest sensor-based estimate of “sway” according to this definition, since they calculated displacement of the sensor placed on the lower back at the approximate level of the body’s centre of mass. Their results indicated that sensor-derived measures of standing sway could significantly discriminate between fallers and non-fallers. However, calculating displacement or “sway” in this manner – by double integration of the acceleration signal obtained from the sensor – requires significant data processing to correct for the inherent measurement errors which are magnified by integration, and further magnified when integrating twice. It is perhaps for this reason that four studies quantified “sway” as the RMS of sensor acceleration, since it is more easily calculated and less error-prone than displacement. These studies noted significantly higher RMS values among fallers than non-fallers in standing under a range of conditions (Doheny et al. 2012a, Doheny et al. 2012b, Greene et al. 2012b, O'Sullivan et al. 2009). A disadvantage of using RMS acceleration is that it is less intuitively understood by researchers and clinicians alike, particularly when mislabelled as “sway”. Since it represents the combined absolute accelerations of the body’s centre of mass (CoM), RMS acceleration may be more accurately described as a measure of postural instability. The evidence reviewed shows that CoM displacement and RMS acceleration are both valid as sensor-derived variables for fall-risk estimation, with higher values for both equating to higher fall-risk. However, for the readers’ benefit, researchers should ensure that these and other sensor-derived variables are clearly described and not mislabelled using existing terminology.

Aside from static balance tests, sensor data was gathered from a broad selection of dynamic functional tasks, many of which are valid clinical fall-risk assessment tools in their own right. For example, FTSS performances are timed by clinicians to measure functional capacity and lower limb power, while the quality of the performance may be observed (Buatois et al. 2008, Zhang et al. 2013). The results of this review show that sensor data can be used to segment sit-stand-sit transitions, which can provide a clinically meaningful way of objectively quantifying performance aside from timing.
alone, such as highlighting difficulty in rising to a stand or controlling the descent to sitting. Instrumenting quick and simple fall-risk assessment measures such as this would be a highly feasible way to integrate sensor-based assessment into practice, and could provide improved objectivity and accuracy in fall-risk assessment without increasing clinicians’ workloads.

Similarly, the studies reviewed indicate that sensors may be highly useful as a convenient means of performing objective gait analysis to detect and monitor gait-related fall-risk factors. Overall, the sensor data obtained demonstrated that fallers tend to have slower walking speeds, yet take more steps and take longer to complete each phase of gait. They also have more variable gait patterns that are less symmetrical and coordinated. These fall-risk-related gait features have been identified in clinical literature previously (Kelsey et al. 2010, Quach et al. 2011, Verghese et al. 2009), but with the caveat that a cost-effective and user-friendly means of measuring them would be required before they could be routinely assessed with accuracy in practice (Persad et al. 2010). The findings of this review suggest that wireless inertial sensors may be the solution to this issue.

What is not clear from the current evidence is whether it is more effective and feasible to develop complex fall-risk classification models based on a single instrumented task, or to extract selected variables from a range of instrumented tasks. For example, as a composite task consisting of many subtasks, the TUG presents the opportunity to gather rich sensor data in a short time-frame, while also serving as a useful predictor of falls in its own right (Shumway-Cook et al. 2000). It is clear from the evidence reviewed that the most common and effective use of this data is the formation of falls classification models based on the analysis of many variables extracted from TUG performance. To make these models transferable to clinical practice, a number of algorithms which take factors like gender, age and comorbidities into account would need to be developed, similar to the separate models described by Greene et al. (2010). The alternative approach – developing a model composed of selected variables from performances on a battery of fall-risk assessments tasks – was adopted by Narayanan et al. (2010). This method created a model that was highly correlated with a validated clinical measure of fall-risk, the Physiological Profile Assessment. This approach more closely reflects actual practice, where decisions on fall-risk are based on multiple assessment criteria to gain a comprehensive clinical picture of clients and their capabilities (Persad et al. 2010). Although it may seem more reasonable and acceptable from a clinician’s
perspective to use sensor-based assessments in this manner to augment clinical
decision-making, a prospective study comparing both methods to actual falls incidence
would be required to determine which method has superior predictive value.

4.4.2 Study Design

The majority of studies reviewed were cross-sectional, with only three studies adopting
a prospective design (Greene et al. 2012a, Marschollek et al. 2011a, Schwesig et al. 2013). Cross-sectional studies are useful for identifying sensor features that can
discriminate between fallers and non-fallers based on falls history. Prospective studies
are required to determine the predictive value of sensor-based assessments, an issue
identified by Howcroft et al. (2013).

A wide variety of methods were used to classify fall-risk among participants, from falls
history to results of clinical fall-risk assessment tools, singly or combined to form a
composite fall-risk score. This reflects actual clinical practice, where a range of fall-risk
screening and assessment tools are available to clinicians, and are often combined as
part of a comprehensive assessment (Persad et al. 2010). However, for research
purposes, this variation renders it challenging to compare the magnitude of fall-risk
between participants in different studies, particularly in studies where the fall-risk
criteria used are not well-described. From the perspective of clinicians, future studies
which classify fall-risk using clearly defined standards such as records of falls or results
of clinical assessment tools, and apply these as comparators for sensor-based
assessments, would provide relevant and easily-interpreted evidence of the value of
SBFRA.

The broad range of settings noted in this review indicates the potential to adapt SBFRA
for use in many environments, particularly in clinical and community settings, as
explored in Chapter 3. However, this broad range of settings in which the studies
reviewed were performed also means a range of populations were included, from
community-dwelling older adults to hospital inpatients and nursing home residents.
Therefore, caution must be taken when generalising the findings to all populations,
since sensor-derived variables associated with fall-risk among individuals with marked
balance and mobility impairments e.g. hospital inpatients or nursing home residents,
may not be observed among community-dwelling older adults with higher levels of
functional mobility. Similarly, features of postural control in populations with
neurological conditions are markedly different to those without (Nardone and Schieppati 2010) e.g. in quiet standing, some individuals with Parkinson’s disease may show reduced body sway due to rigidity (Horak et al. 1992), while individuals with hemiparesis due to stroke may show asymmetrical standing sway patterns (Dickstein and Abulaffio 2000) with poor repeatability (Helbostad et al. 2004). Further research identifying population-specific sensor-based fall-risk variables and thresholds is required to improve the clinical utility of current findings.

4.4.3 Limitations
Although a broad search strategy and thorough screening process were carried out, there is a chance that some relevant articles not available in the databases searched may have been omitted. Also, since this is a rapidly-growing area of research, it is likely that further relevant studies have been published since the literature search took place. Despite these limitations, this review provides a comprehensive picture of the currently available evidence in the field of SBFRA.

4.5 Chapter Summary
The literature review contained in this chapter achieved its aims to address the identified learning needs in relation to the applications of SBFRA in clinical research. The extensive evaluation and synthesis of evidence produced many valuable findings to inform further study design and data analysis.

In terms of study design, most studies reviewed utilised cross-sectional designs which are appropriate for determining the capacity of SBFRA methods to classify individuals based on falls history or clinical fall-risk assessment results. Ensuring that both the population being studied and the methods of classifying fall-risk in this population are clearly defined is essential for further studies, as these were the primary methodological limitations noted in the studies reviewed.

As regards sensor data analysis, it was found that a range of static and dynamic tasks could be assessed using wireless inertial sensors to provide an array of potentially meaningful variables. Common variables from the literature to consider for inclusion in further SBFRA analyses include acceleration RMS and frequency-related variables obtained from standing balance assessments, variables related to gait speed, step count
and gait variability, and a broad array of variables derived from TUG performance. Gait was not assessed in the feasibility study (Chapter 3), but the results of this review suggest that a test of gait should be included in further fall-risk assessment batteries in this research. Since such a large number of sensor-derived variables have been found to successfully classify fall-risk in older populations, both as stand-alone variables and as components in more complex classification models, it will also be necessary to examine both single variables and combinations of relevant variables in future analyses.

Overall, the findings of this chapter highlight the evident requirement for well-designed and clearly described clinically-oriented SBFRA research in specific older populations. The following chapter will describe the study design and methodological features of the main study undertaken in the current research, which aims to address this requirement and build upon the knowledge obtained and described thus far in order to answer our research questions.
CHAPTER 5. MAIN STUDY DESIGN AND METHODOLOGY
5.1 Introduction

Since the main purpose of this research was to explore the clinical meaningfulness of sensor-based fall-risk assessment (SBFRA) in community-dwelling older adults, it was deemed necessary to conduct a study of two groups from this population who were distinct in their levels of fall-risk in order to obtain data reflecting a variety of individuals on the fall-risk spectrum. The first – hereafter referred to as the ‘High-Risk group’ – studied older adults who were identified as being at risk of falling or had a history of falls, and had been referred to a falls prevention intervention by a healthcare professional. The second group studied healthy older adults who did not have a history of falls and had never been identified as being at risk of falling, and will therefore be referred to as the ‘Low-Risk group’. The ability to distinguish between older adults who are at high or low levels of fall-risk is essential in clinical practice, so that appropriate falls prevention interventions can be targeted towards those who require them (Voermans et al. 2007).

The decision to adopt this study design was largely based on feasibility, organisational and ethical constraints. Theoretically, a single randomised study including individuals at varying levels of fall-risk would be the ideal methodology to examine the abilities of sensor-based assessments to differentiate between varying levels of fall-risk and, as a secondary purpose, to assess changes in fall-risk over time in response to an intervention. However, patient access to community falls prevention interventions within the Health Service Executive (HSE) is predominantly via referral from a healthcare practitioner who has identified the individual as having a history or risk of falls, or has self-reported concerns about balance and/or falls. Therefore, individuals on HSE waiting lists for such services are largely at high risk of falling, which would not allow us to adequately explore variations in fall-risk using the sensor data obtained. Equally, randomisation was not deemed feasible within this organisational structure, nor would it be appropriate from an ethical perspective, since those referred to falls prevention services are in need of intervention. Falls prevention programmes are proven to be effective in preventing future falls (Gillespie et al. 2012), therefore such individuals should not be denied or delayed access to these services for research purposes, nor should limited public health service resources be devoted to providing services to those not requiring them.
This chapter will describe the main study undertaken to answer the research questions described in Chapter 1, including detailed accounts of the participant eligibility criteria, recruitment processes, and the assessment protocols for each group. A brief description of the general sensor-based assessment method also will be included, although more in-depth details of the precise protocols, sensor data processing and analysis methods adopted for the specific static and dynamic tasks assessed will be described in subsequent chapters. All assessments described were carried out by the author, unless otherwise stated.

5.2 Ethics Committee Approval

Approval was obtained from each of the relevant ethics committees prior to the commencement of data collection. For the High-Risk group, approval was obtained from both the Clinical Research Ethics Committee of the Cork Teaching Hospitals and the HSE Mid-Western Regional Hospital Scientific Research Ethics Committee (Appendices I and J respectively). Separate approval was also obtained from the Education and Health Sciences Research Ethics Committee at the University of Limerick for the Low-Risk group (Application Reference: EHSREC11-12).

5.3 High-Risk Group

5.3.1 Study Design

A longitudinal observational design was employed for the High-Risk group. This arm of the study was carried out in collaboration with physiotherapists employed by the HSE in three centres: North Lee and South Lee Primary, Community and Continuing Care (PCCC) Services, Cork and St. Joseph’s Hospital, Ennis, Co. Clare. The High-Risk group was composed of community-dwelling older adults identified as being at risk of falling and who were referred to and participating in standardised primary care falls prevention interventions in these centres. Cross-sectional data on fall-risk and falls-related psychosocial variables were gathered at two distinct time-points before and immediately after the six-week falls prevention intervention, in order to fulfil requirements of our primary and secondary research questions.
5.3.2 Content of the Falls Prevention Intervention
High-Risk group participants took part in a six-week community falls prevention intervention provided by the HSE. The interventions were matched in design and based on the evidence for optimal falls prevention, as described in Chapter 3. They consisted of a weekly group exercise and education session in the local community hospital or primary care centre and a home exercise programme (HEP). A sample of the group exercise class content and progressions are provided in Appendix K. The contents of the HEPs were based on the Otago Exercise Programme and were individually prescribed based on assessment findings and progress in group sessions. The educational component of the interventions covered topics such as common risk factors for falls, home safety and falls prevention strategies in the community, exercise adherence strategies, and when possible included input from members of the multidisciplinary team, typically occupational therapy and occasional podiatry and nursing/pharmacy input. An exercise and falls incidence calendar was also provided to participants to record days on which they exercised and/or on which a fall occurred during the intervention. For these purposes, a fall was be defined as “an unexpected event in which the participant comes to rest on the ground, floor or lower level” (Lamb et al. 2005). These calendars were completed as a standard component of the intervention to encourage exercise adherence and awareness of fall-risk behaviours.

5.3.3 Participants
Thirty-eight participants were recruited to the High-Risk group. This sample size was in line with initial estimates of 30-40 participants, which were based on the timeline for completion of this research and the estimated number of participants that would be recruited from each repetition of the intervention. This number of participants also compares favourably to some previously published studies in the area of sensor-based fall-risk assessment (Weiss et al. 2011, Doheny et al. 2011, Itoh et al. 2012).

Eligibility criteria were chosen in line with those required for participation in the falls prevention intervention and represented a high level of fall-risk for the chosen population. Inclusion criteria were as follows: aged 65 or over; community-dwelling; history of falls, near-falls or fear of falling in the previous 12 months; independently mobile with or without an aid; independent in transfers; willing and able to participate in group exercise; medical clearance from family doctor/consultant.
Exclusion criteria were: severe visual or cognitive impairment; currently undergoing investigations for cause(s) of fall(s); hip surgery in the previous three months; active alcohol dependency; uncontrolled cardiovascular conditions; severe breathlessness or dizziness; unmanaged pain or acute systemic illness. In addition, participants with a current neurological diagnosis which affected balance and mobility e.g. Parkinson’s disease were excluded from participating in the study, but were eligible to participate in the intervention. All participants provided written informed consent prior to participation.

5.3.4 Recruitment Procedure

Participants in the High-Risk group were recruited from the waiting lists of standardised primary care falls prevention interventions in three centres, two in Cork city and one in Ennis, Co. Clare. Individuals who met the inclusion criteria and were referred to the ‘Steady On’ falls prevention intervention at St. Joseph’s Hospital, Ennis or the ‘Steady Up’ intervention in the North/South Lee PCCC catchment areas were invited to participate in the High-Risk group. These interventions operated an open referral system i.e. referrals were accepted from medical consultants, general practitioners (GPs), public health nurses, and other allied health professionals. Medical clearance was obtained from GPs for all participants on referral to the intervention. Once cleared to take part, an initial multifactorial assessment was carried out by a member of the HSE Physiotherapy team prior to commencing the intervention, as per usual practice. A letter of invitation to participate in the study, an information sheet and consent form was given to individuals at this assessment (Appendices L, M and N respectively). Individuals interested in participating in the study return their signed consent forms to their Physiotherapist after that initial assessment. These Physiotherapists thus acted as gatekeepers to the study, since they assessed eligibility to participate in the intervention and also to the study. The contact details of participants who provided consent and were cleared to take part in the intervention were then passed on to the investigator so that an appointment for the High-Risk group assessment could be arranged.

5.3.5 Assessment Protocol

Participants in the High-Risk group underwent a fall-risk assessment prior to commencing the intervention (High-Risk Pre-Intervention) and repeated this same
assessment one week after the final exercise class in the intervention (High-Risk Post-Intervention). The protocol first included a basic assessment in which general demographic and medical history information was recorded, including age, one-year falls history and related injuries if applicable, walking aid usage, number of current medications and the presence or absence of diagnosed osteoporosis. This assessment also included a number of standardised assessment tools. The questionnaire-based assessment tools used were:

- **Modified Falls Efficacy Scale (MFES)** – A measure of falls-related efficacy. The MFES has been shown to demonstrate high internal consistency (Cronbach's alpha = 0.95) and excellent test-retest reliability (intra-class correlation coefficient = 0.93) in high and low fall-risk community-dwelling older adults (Hill et al. 1996), and has been recommended for use in falls research by the Prevention of Falls Network Europe (ProFaNE) consensus (Lamb et al. 2005).

- **Falls Behavioural Scale for the Older Person (FaB)** – A questionnaire measuring engagement in fall-risk behaviours, which has been shown to be valid and reliable, demonstrating high internal consistency (Cronbach's alpha = 0.84) and test-retest reliability (intra-class correlation coefficient = 0.94) (Clemson et al. 2003, Clemson et al. 2008).

- **Geriatric Depression Scale – 15-items (GDS)** - A measure of depression, specifically designed for use among older adults, and has been used to identify depression as a risk factor for falls previously (Whooley et al. 1999). The 15-item version of the GDS has been shown to be a reliable and highly sensitive screening tool for major depression in older adults (Almeida and Almeida 1999).

- **EuroQol EQ-5D-3L quality of life instrument** – A brief general measure of health-related quality of life (Rabin and de Charro 2001). Studies have demonstrated good validity and test-retest reliability, although its responsiveness may be limited where large changes in quality of life are not expected (Haywood et al. 2005). The EQ-5D-3L is also recommended for use in falls prevention research by the ProFaNE consensus statement (Lamb et al. 2005).

- **Physical Activity Scale for the Elderly (PASE)** – A brief, feasibly-implemented measure of self-reported physical activity levels among older adults, based on recall of participation in a variety of activities over the week prior to administration (Washburn et al. 1993). The PASE has been found to display adequate levels of validity and reliability (Dinger et al. 2004, Forsén et al. 2010)
and exhibits comparable psychometric properties to other self-report physical activity assessment tools for older adults (Harada et al. 2001).

Assessments of balance and functional mobility were also included. These were as follows:

- **Standing balance tests**: Participants stood unsupported for 10 seconds in each of three progressively more challenging conditions – normal stance width, eyes open; normal stance width, eyes closed; feet together, eyes open. This procedure will be described in detail in Chapter 7.

- **Five times sit-to-stand test (FTSS)**: As used in the feasibility study and described in Section 3.2.3.1. The FTSS is a valid measure of functional strength and balance performance (Lord et al. 2002) and has adequate test-retest reliability in community-dwelling older adults (Tiedemann et al. 2008).

- **Timed Up and Go test (TUG)**: Also as used in the feasibility study and described in Section 3.2.3.1. The TUG is a valid and reliable measure of functional balance and mobility in older adults (Podsiadlo and Richardson 1991, Steffen et al. 2002, Wrisley and Kumar 2010). Further details of this procedure will be provided in Chapter 7.

- **A 5 metre walk test (5m walk)**: A 5m walk at participants’ usual gait speed incorporating a rolling start and stop was included to measure gait speed, since gait speed is a quick, reliable and sensitive measure of functional capacity and fall-risk in older adults (Graham et al. 2008a, Peel et al. 2012). Further details of the procedure adopted will also be provided in Chapter 7.

The Berg Balance Scale (BBS) (Berg 1989b) was completed by a primary care team Physiotherapist as part of the team’s existing, standard pre- and post-intervention assessment. Participants’ BBS scores at both time points were shared with the author to provide an additional measure of functional balance while avoiding repetition of the instrument for participants. As described in Chapter 2, Section 2.6.1, the BBS is a valid and reliable assessment tool which – despite its potential ceiling effect in populations without marked balance and mobility impairments – is widely used in both research and clinical practice (Bogle Thorbahn and Newton 1996).
5.4 Low-Risk Group

5.4.1 Study Design
The Low-Risk group attended a single assessment session of approximately 60 minutes duration, thus this arm of the study was cross-sectional in design. Participants were not provided with any intervention prior to this assessment, but were provided with the results of their assessments and information on healthy ageing and falls prevention upon completion of the study (Appendices O and P).

5.4.2 Participants
Thirty-six participants were initially recruited to the Low-Risk group, as this was in line with the estimated sample size of the High-Risk group. Three participants did not conform to the inclusion/exclusion criteria following assessment, leaving thirty-three participants in the Low-Risk group in total.

Since the aim for this group was to collect data from healthy, low fall-risk older adults, inclusion criteria were as follows: aged 65 or over; community-dwelling; no history of falls in the previous 12 months; not previously identified by a healthcare professional as being at risk of falling; never referred to or participated in a falls prevention intervention; independently mobile with or without an aid; independent in transfers.

Exclusion criteria were: severe visual or cognitive impairment; hip surgery in the previous three months; active alcohol dependency; uncontrolled angina, hypertension or arrhythmias; severe breathlessness or dizziness; unmanaged pain or acute systemic illness; current neurological diagnosis affecting balance or mobility. All participants provided written informed consent prior to participation.

5.4.3 Recruitment Procedure
Participants in the Low-Risk group were recruited via written advertisement in local newspapers, community noticeboards, through local Active Retirement Ireland groups and through other local sports and social clubs and societies in the surrounding areas of the University of Limerick, including Limerick City and County, North Tipperary and East Clare (Appendix Q).
5.4.4 Assessment Protocol

The assessment was similar to that of the High-Risk group, and took place in a single assessment session at the University of Limerick, Ireland. Demographic and medical history data were gathered initially, specifically age, height, weight, one-year falls history and related injuries (to check for eligibility), walking aid usage, current medications and the presence or absence of diagnosed osteoporosis. Participants then completed the BBS as a measure of balance capabilities. Then, participants completed the same questionnaires as used in the High-Risk group:

- Modified Falls Efficacy Scale
- Falls Behavioural Scale
- 15-item Geriatric Depression Scale
- EuroQol EQ-5D-3L quality of life instrument
- Physical Activity Scale for the Elderly

Balance and mobility tests were then performed as for the High-Risk group and described in Section 5.3.5.

Figure 5.1. Flow diagram illustrating the assessment and intervention schedule for participants in both groups.
5.5 Sensor-Based Assessment Methods

5.5.1 Instrumentation and Procedure
The functional balance and mobility assessments were performed while wearing a single Shimmer2R device (Shimmer, Dublin, Ireland) with tri-axial accelerometer, gyroscope and magnetometer sensors. This device (dimensions 5.6 x 7.14 x 1.85cm, approximately 57g) was worn over clothes on a belt and positioned at the midline at the level of the second sacral vertebra, as this location provides an approximate reflection of the position of the body’s centre of mass. The decision to use a single sensor and the choice of location were informed by the experiences and findings of the feasibility study (Chapter 3) in combination with the procedures noted in the literature on SBFRA (Chapter 4). Data was streamed to a laptop via Bluetooth for all assessments, and the data files obtained were stored under coded identities with no personal information that would allow participants to be identified. The sensor-based assessment set-up is illustrated in Figure 5.2.

![Figure 5.2. Sensor-based fall-risk assessment data collection set-up.](image)

Static and dynamic balance and mobility assessments were chosen for inclusion in the SBFRA. The static tasks performed were standing balance trials under three conditions,
as mentioned in Section 5.3.5. The dynamic tasks chosen for SBFRA were the TUG and the 5m walk test. These tests were selected because they are valid, reliable, and feasible to perform in home or community settings, as noted in Chapter 3, and they provide opportunities to gather meaningful sensor data according to the findings of previous research, as discussed in Chapter 4. Figure 5.3 illustrates the sensor position and orientation used during the data collection process. Further details on the static and dynamic SBFRA procedures will be provided in Chapter 8.

![Sensor position and orientation](image)

**Figure 5.3.** Sensor position and orientation of axes used throughout data collection and analysis.

### 5.6 Chapter Summary

This chapter has provided details of the study design and methodologies used to address our primary and secondary research questions, including reasoning and justification for the chosen methods. The results obtained from the study described will now be reported and discussed in the following chapters.
CHAPTER 6. CLINICAL ASSESSMENTS OF FACTORS RELATED TO FALL-RISK IN TWO GROUPS OF COMMUNITY-DWELLING OLDER ADULTS
6.1 Introduction

Chapter 5 has described in detail the design of the current research and the data collection procedures adopted. The data collected can be divided into distinct categories, as listed in Chapter 1: clinical fall-risk assessment data, and static and dynamic sensor-based data. This chapter will present the results of the first of those data sets – the clinical assessments of fall-risk undertaken by both the High-Risk and Low-Risk groups. As described in the previous chapter, these clinical assessment tools measure fall-risk via functional balance task performance and also via a range of falls-related behavioural and psychosocial outcome measures. This is in line with recommendations that fall-risk assessment in clinical practice should be multifactorial (American Geriatrics Society and British Geriatrics Society 2011, Close and Lord 2011, Persad et al. 2010).

The primary aim of this chapter is to present and discuss the clinical fall-risk assessment results for each group and to examine how these assessments differ between these two distinct groups. To achieve this, the fall-risk profiles of each group presented by these clinical assessments will be considered in relation to each other and to current literature. The implications of these results for the sensor-based assessments of fall-risk will also be considered as, in line with our primary research question, these clinical assessment results will provide context for the sensor-based assessment results. It is anticipated that the High-Risk group will exhibit results which indicate a significantly higher level of fall-risk than the Low-Risk group across most, if not all, measures.

A secondary aim of this chapter is to present and discuss the fall-risk profile of the High-Risk group before and after participation in a community-based falls prevention intervention, as part of our secondary research question. It is anticipated that some changes in the selected functional, behavioural and psychosocial fall-risk measures will be detected following intervention, and that these changes will reflect a reduction in fall-risk following intervention.

6.2 Statistical Analysis

Statistical analysis was carried out using IBM SPSS Statistics for Windows Version 20 (IBM Corp., Armonk, USA). An alpha level of 0.05 was used for all statistical tests. Assessment results for the High-Risk group were compared to those of the Low-Risk
group using appropriate parametric and non-parametric tests, according to the distributions of the data. Chi-squared tests were used to compare the proportions of females and individuals who used walking aids between groups. Age and EQ-5D-3L visual analogue scale (VAS) were normally distributed in both groups and so were compared using independent samples t-tests. All other variables were compared using Mann-Whitney tests. To compare pre and post-intervention changes in the High-Risk group, paired-samples t-tests were used for normally distributed variables and Wilcoxon Signed Ranks tests were used for variables not following a normal distribution.

### 6.3 Results

#### 6.3.1 Participant Summaries

As seen in Table 6.1, participants in the High-Risk group were older ($p=0.002$), experienced more falls ($p<0.001$), and used more medications ($p<0.001$) than the Low-Risk group. Age ranges for both groups were similar. A higher proportion of the High-Risk group used walking aids ($p<0.001$), while the Low-Risk group had a higher proportion of females ($p=0.030$).

In the High-Risk group, six participants dropped out of the intervention and a further two participants were unable to fully complete the post-intervention assessment. The proportion of females was slightly higher post-intervention as five of the eight participants who dropped out were male.

**Table 6.1.** Characteristics of participants in the High-Risk and Low-Risk groups.

<table>
<thead>
<tr>
<th></th>
<th>High-Risk Intervention (n=38)</th>
<th>Pre-Intervention</th>
<th>High-Risk Intervention (n=30)</th>
<th>Post-Intervention</th>
<th>Low-Risk (n=33)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>78 (67, 91)</td>
<td>77.5 (67, 91)</td>
<td>74 (67, 86)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Females (%)</td>
<td>65.8</td>
<td>73.3</td>
<td>87.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Falls in past year</td>
<td>2 (0, 6)</td>
<td>2 (0, 6)</td>
<td>0 (0, 0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medications</td>
<td>5 (2, 11)</td>
<td>6 (2, 10)</td>
<td>3 (0, 12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walking aid use (%)</td>
<td>57.9</td>
<td>53.3</td>
<td>6.1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Values presented as median (maximum, minimum), except percentages. Asterisks denote significant differences between groups, *$p<0.05$, **$p<0.001$. 

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6.3.2 Clinical Assessments

Most variables differed significantly between the High-Risk group and the Low-Risk group; both Pre- and Post-Intervention (Table 6.2). As regards the balance and mobility assessments, median Berg Balance Scale (BBS) scores among the Low-Risk group were close to the maximum of 56, whereas the High-Risk group scored significantly lower and also exhibited a much wider range of scores. The High-Risk group also performed more poorly and with greater variability than the Low-Risk group on the Time Up and Go test (TUG), Five Times Sit-to-Stand test (FTSS) and gait speed measures. Significant differences between groups were also noted on behavioural and psychosocial measures, namely the Geriatric Depression Scale (GDS), Falls Behavioural Scale for the Older Person (FaB), Modified Falls Efficacy Scale (MFES), Physical Activity Scale for the Elderly (PASE) and EQ-5D-3L, the exception being EQ-5D Pain and Anxiety scores. Note in Table 6.2 that the EQ-5D-3L health states sub-scores and VAS scores are presented separately, rather than as a summary index, in order to determine the specific health-related quality of life domains in which differences were observed.

Following intervention, significant increases in BBS scores, TUG times, FaB scores, and PASE scores were noted in the High-Risk group. The mean difference in TUG time was 1.9s (standard deviation = 4.4s), and the differences in time ranged from a 8.3s decrease to a 10.3s increase. The percentage of participants who failed the FTSS decreased at follow-up due to drop-outs, since three participants who failed the FTSS at the Pre-Intervention assessment did not complete the intervention.
Table 6.2. Clinical fall-risk assessment results in the High-Risk and Low-Risk groups.

<table>
<thead>
<tr>
<th>Variable (units)</th>
<th>High-Risk Pre-Intervention</th>
<th>High-Risk Post-Intervention</th>
<th>$p$ Pre v Post</th>
<th>Low-Risk</th>
<th>$p$ Pre v Low</th>
<th>$p$ Post v Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBS (score/56)</td>
<td>41.5 (26, 55)</td>
<td>47.0 (27, 54)</td>
<td>0.003</td>
<td>53.0 (40, 56)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TUG (s)</td>
<td>14.8 (5.9, 47.9)</td>
<td>15.9 (5.8, 47.8)</td>
<td>0.032</td>
<td>8.6 (6.1, 22.8)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>FTSS (s)</td>
<td>22.2 (8.9, 53.3)</td>
<td>20.9 (9.2, 56.3)</td>
<td>0.551</td>
<td>13.1 (9.4, 28.2)</td>
<td>0.001</td>
<td>0.017</td>
</tr>
<tr>
<td>FTSS Failure (%)</td>
<td>18.4%</td>
<td>13.3%</td>
<td>0.569</td>
<td>0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gait Speed (m/s)</td>
<td>0.74 (0.18, 1.54)</td>
<td>0.81 (0.28, 1.37)</td>
<td>0.432</td>
<td>1.28 (0.61, 1.67)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>FaB (score/4)</td>
<td>3.31 (1.80, 3.81)</td>
<td>3.42 (2.04, 3.89)</td>
<td>0.024</td>
<td>2.58 (1.92, 3.73)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>GDS (score/15)</td>
<td>3 (0, 13)</td>
<td>3 (0, 12)</td>
<td>0.914</td>
<td>1 (0, 8)</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>MFES (score/10)</td>
<td>8.0 (3.6, 9.9)</td>
<td>8.5 (4.1, 10.0)</td>
<td>0.380</td>
<td>10.0 (7.4, 10.0)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>PASE (score)</td>
<td>62.8 (9.7, 137.5)</td>
<td>67.4 (33.6, 179.7)</td>
<td>0.021</td>
<td>136.8 (33.6, 215.5)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>EQ-5D-3L (score/3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mobility</td>
<td>2 (1, 2)</td>
<td>2 (1, 2)</td>
<td>0.102</td>
<td>1 (1, 2)</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Self-Care</td>
<td>1 (1, 2)</td>
<td>1 (1, 2)</td>
<td>0.705</td>
<td>1 (1, 2)</td>
<td>0.014</td>
<td>0.024</td>
</tr>
<tr>
<td>Usual Activities</td>
<td>2 (1, 3)</td>
<td>2 (1, 2)</td>
<td>0.414</td>
<td>1 (1, 2)</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Pain</td>
<td>2 (1, 3)</td>
<td>2 (1, 3)</td>
<td>1.000</td>
<td>2 (1, 3)</td>
<td>0.621</td>
<td>0.952</td>
</tr>
<tr>
<td>Anxiety/Depression</td>
<td>1 (1, 3)</td>
<td>2 (1, 2)</td>
<td>0.527</td>
<td>1 (1, 2)</td>
<td>0.197</td>
<td>0.174</td>
</tr>
<tr>
<td>VAS (score/100)</td>
<td>70 (10, 100)</td>
<td>72.5 (30, 90)</td>
<td>0.293</td>
<td>80 (50, 100)</td>
<td>&lt;0.001</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Note. Values are presented as median (minimum, maximum), except $p$-values. BBS=Berg Balance Scale; TUG=Timed Up and Go test; FTSS=Five Times Sit-to-Stand test; FaB=Falls Behavioural Scale for Older Adults; GDS=15-item Geriatric Depression Scale; MFES=Modified Falls Efficacy Scale; PASE=Physical Activity Scale for the Elderly; VAS=Visual Analogue Scale.
6.4 Discussion

6.4.1 Comparison of Fall-Risk between Groups

As anticipated, the High-Risk group differed significantly from the Low-Risk group on most clinical assessments of fall-risk. Considering the overall findings, it is apparent that the High-Risk group is at a higher risk of falling and displays many typical functional, behavioural and psychosocial characteristics associated with an increased level of fall-risk. Similar patterns of findings have been shown in numerous previous studies (Shin et al. 2009, Viccaro et al. 2011, Hedman et al. 2013, Olivares et al. 2011).

6.4.1.1 Functional Balance Performance

Low-Risk group participants outperformed the High-Risk group on all task performance-based measures and, in keeping with these results, also reported less difficulty with activities of daily living which are linked to functional performance. This bodes well for the discriminatory capacities of the sensor-based assessments of static and dynamic task performances which follow in Chapters 8 and 9 respectively, as they will aim to quantify task performance in greater objective detail, which may provide even more accurate and meaningful fall-risk information.

The Low-Risk group scored close to maximum on the BBS, a measure of functional balance, as would be expected for community-dwelling adults in this age group (Steffen et al. 2002). Many among the High-Risk group scored below the proposed BBS fall-risk cut-off score of 45 (Berg et al. 1992). Performance on the BBS alone may not be an entirely accurate predictor of fall-risk (Muir et al. 2008), but if more sensitive and specific fall-risk criteria are used (i.e. BBS scores lower than 51 combined with a history of falls) the profile of the High-Risk group still indicates an elevated level of fall-risk (Shumway-Cook et al. 1997).

The Low-Risk group exhibited TUG times in line with reference values for their age group (Bohannon 2006b), while the High-Risk group showed great variation in their performances, with median times that were indicative of increased fall-risk (Shumway-Cook et al. 2000, Alexandre et al. 2012). Similarly, FTSS performances also indicated moderate fall-risk in the High-Risk group, according to a cut-off time of 15 seconds (Buatois et al. 2008, Buatois et al. 2010), while the Low-Risk group’s times were as expected for their age group (Bohannon 2006a). Both FTSS time and ability to complete the test differed between groups, with High-Risk group participants recording
more test failures as well as longer times, which echoes previous findings among high fall-risk groups (Chan et al. 2007, Graafmans et al. 1996, Kelsey et al. 2010).

Equally, gait speed among the Low-Risk group was within the ‘normal’ range of 1.0 to 1.3m/s, as defined by Quach et al. (2011), and was significantly faster than the High-Risk group. Median High-Risk group gait speed was also slightly slower than reference values for their age and gender (Bohannon 2008), and was in the ‘mildly abnormal’ range of 0.6 to 1.0m/s (Quach et al. 2011). Since a gait speed of less than 1m/s can be used as an indicator of the need for intervention to reduce fall-risk (Fritz and Lusardi 2009), these results suggest that the High-Risk group were appropriately referred to the intervention.

6.4.1.2 Behavioural and Psychosocial Outcomes

The two groups also differed significantly on behavioural and psychosocial measures associated with fall-risk. In line with previous research showing the protective effects of physical activity (PA) in relation to falls (Thibaud et al. 2012), the Low-Risk group reported higher PA levels than the High-Risk group. High-Risk group participants were roughly as active as would be expected for their age and gender, since a preliminary normative PASE score for such a group is approximately 62.3 ± 50.7 (New England Research Institutes 1991). However, normative scores do not indicate the extent to which these participants meet recommended PA guidelines (Nelson et al. 2007), therefore it is possible that these participants are not engaging in the sufficient amount and/or type of PA to lessen their risk of falling, especially since PASE scores are greatly influenced by light intensity PA such as household tasks.

As well as being less active, High-Risk group participants reported less engagement in fall-risk behaviours than Low-Risk participants, a characteristic which has been shown previously using the FaB (Clemson et al. 2004). This suggests that the Low-Risk group may not have felt the need to engage in protective behaviours to the same extent as the High-Risk group due to their higher physical performance capacity (Delbaere et al. 2010a). This proposition is supported by the high falls-related self-efficacy scores noted among the Low-Risk group. The lower falls efficacy noted among High-Risk participants would be expected in this study, since self-reported fear of falling was a possible reason for referral to the intervention. The difference in falls efficacy between the High and Low-Risk groups in this study is similar to previous findings between falls clinic patients and healthy older adults (Hill et al. 1996).
Greater levels of disability, poorer health status and self-perceived health, and lower PA levels are all risk factors for depression among older adults in the community (Cole and Dendukuri 2003, Strawbridge et al. 2002), which may explain the higher depression scores noted among the High-Risk group, who exhibited these traits. Higher levels of depression, poorer self-perceived health and lower falls-related self-efficacy have also been noted in community-dwelling older adults who report fear of falling and PA restriction due to this fear (Dias et al. 2011). Therefore, the High-Risk group may have – or be at risk of developing – a similar negative pattern of thinking and behaviour. Referral to the group exercise and education programme was appropriate for this group of individuals, as this type of intervention can improve balance confidence, reduce activity avoidance (Bula et al. 2011) and possibly improve depressive symptoms (Sjosten et al. 2008).

6.4.2 Effects of Intervention
While clear and apparent differences were noted between the two groups, the effects of the intervention on the selected clinical outcomes were less clear.

6.4.2.1 Functional Balance Performance
Some beneficial effects on measures of functional balance performance were noted. For example, a statistically significant increase in BBS scores of 6.5 points was observed, and this change is likely to be clinically significant also, given that the minimum detectable change for scores in this range is between 4 and 5 points (Donoghue and Stokes 2009). However, FTSS times did not change significantly following intervention, and the change in the percentage of participants who failed the test can be attributed solely to drop-outs. Equally, gait speed did not change significantly and, while it remained within a range which is normal for females aged 80 years and over (Seino et al. 2014), it also remained at a level which is associated with limited community ambulation (Fritz and Lusardi 2009).

Although TUG times appeared to increase post-intervention, closer inspection of the distribution of the differences revealed that the changes varied greatly between participants and results were skewed by relatively large increases in TUG time post-intervention in some participants. Also, the standard error of measurement for TUG time is approximately 5.5% (Wang et al. 2009), which equates to approximately 0.83s
for a 15s TUG performance. Considering this fact, the recorded change of approximately one second in TUG time following intervention may not be clinically meaningful in our sample, despite being statistically significant. It must also be noted that recording only the time taken to complete the TUG or 5m walk overlooks the quality and safety of the performance. For example, an individual may record a TUG time within normal limits, but exhibit unsteadiness when turning and poor lower limb power and control when sitting. Although their time would indicate low fall-risk, the quality of the performance would suggest otherwise. Thus, the analysis of the sensor-based assessments of these dynamic tasks in Chapter 7 may present methods to detect and quantify aspects of performance strategy and movement quality.

6.4.2.2 Behavioural and Psychosocial Outcomes

As regards the behavioural and psychosocial impacts of the intervention, self-reported PA levels increased slightly following intervention, which can be largely attributed to the addition of the group and home exercise component of the intervention to the participants’ usual activity levels. PA among the High-Risk group was mainly composed of household activities and some walking, as has been observed in previous studies (Chad et al. 2005, Chan et al. 2007), thus adding structured exercise sessions significantly increased overall PA levels. Although total PA remained low in comparison to PASE scores reported in similar studies (Quach et al. 2011, Liu-Ambrose et al. 2004), the change in PA behaviour achieved following intervention may still be beneficial, since reduced sedentary time and increased exercise participation can reduce fall-risk (Shin et al. 2009, Ribom et al. 2009).

Unlike some previous studies (Filiatrault et al. 2013, Tinetti et al. 1994, Zijlstra et al. 2007), no significant improvement in falls efficacy was noted following intervention. However, pre-intervention MFES scores may be considered high enough to represent a lack of fear of falling (Chamberlin et al. 2005), thus large changes may not be reasonable to expect. The intervention also did not affect depression scores, similar to many previous falls prevention studies (Sjösten et al. 2008). This may be due to the intensity and duration of the exercise, which was undertaken for balance and mobility training purposes, rather than according to recommendations for effective treatment of depression (Dunn et al. 2005, National Collaborating Centre for Mental Health 2010, Blumenthal et al. 2012). The slight improvement in self-rated health which was noted on the EQ-5D VAS following intervention was not statistically significant, and also
may not be considered clinically significant considering the minimally important differences reported in literature for other patient populations ranges from approximately 4 to 15 points (Pickard et al. 2007, Coteur et al. 2009).

Older adults who experience a fall often do not alter their behaviour to prevent further falls (Boyd and Stevens 2009). Participants in the High-Risk group showed greater awareness of risks and engaged in more protective behaviours following intervention, based on increased FaB scores, which suggests that participants heeded the falls prevention advice offered in during the education component of the intervention (described in Chapter 5, Section 5.3.2). This echoes the findings of a previous pilot study (Gopaul and Connelly 2012). Altered behaviour patterns may cause concern that participating in the falls prevention intervention could increase fear of falling and thus activity restriction, which in turn could lead to further declines in physical capacity and ultimately increased fall-risk – the “vicious circle” of fear of falling (Filiatrault et al. 2013). However, when considered in tandem with the relatively high levels of falls efficacy and the slight increase in PA observed, it is reasonable to conclude that the intervention in this case improved safety awareness actions without negatively impacting on other fall risk-related behavioural and psychosocial factors.

6.5 Limitations

Due to the considerable array of risk factors and other constructs that have been related to fall-risk (Tinetti et al. 1988, Voermans et al. 2007, Kwan et al. 2011, Chang and Ganz 2007), it is not possible to state that the clinical assessment carried out for all participants was entirely comprehensive. Although the selected assessment tools were carefully considered (as discussed in Chapters 2, 3 and 6) it is possible that other relevant differences between the groups exist, or that other changes occurred as a result of the intervention that were not detected using the chosen set of assessment tools. For example, falls efficacy, which was measured in this research, is a related but slightly different construct to fear of falling (Moore and Ellis 2008). While the MFES was chosen as a measure which was designed to reflect both constructs (Hill et al. 1996), and considerable evidence supports its use (Lamb et al. 2005), it does not necessarily offer a full representation of the complex relationships between fear of falling, efficacy and activity (Scheffer et al. 2008). However, the chosen clinical assessment tools
offered as broad an assessment of multifactorial fall-risk factors as was feasible to conduct within a reasonable assessment timeframe.

The short time-frame for the intervention limits the possibility of achieving and detecting changes in the selected fall-risk measures, since only six weeks separated the pre- and post-intervention assessments. As discussed in Chapter 4, a large body of evidence shows that exercise interventions that aim to reduce falls incidence should be considerably longer than six weeks in duration. Although some changes have been noted in short interventions, these changes may be short-term effects. Thus a further limitation is the lack of longer-term follow-up assessments of the High-Risk group to determine the long-term effects of the intervention. Since exploring changes in this group following intervention was a secondary aspect of this research, it was deemed to be outside the scope of this study to devote considerable time and resources to a longer-term intervention and follow-up period. As described in Chapter 4, the intervention duration was established by the collaborating service providers prior to the design of this research. As regards a longer follow-up period, a single assessor carried out all assessments, thus it was not possible to schedule repeat assessments within the time-frame for completion of this research. Considering the short-term benefits observed in this study, further research focusing on evaluating this type of intervention in greater detail (e.g. monitoring adherence, participant satisfaction, cost-benefit analyses etc.), including the long-term effects, is recommended.

Six participants dropped out of the High-Risk group, which limited the number of data sets available for evaluating the effects of the falls prevention intervention. This is a relatively high rate of dropouts for such a short intervention, considering that an attrition rate of approximately 10% can be expected in community falls prevention programmes over twelve months (Nyman and Victor 2012). Since four of the six dropouts and the two further incomplete post-intervention assessments were due to health reasons, it may be the case that some participants were inappropriately referred to the falls prevention programme or their health deteriorated while on the waiting list, leading to a higher attrition rate than expected.
6.6 Chapter Summary

The findings of the selected clinical fall-risk assessments showed that the High-Risk group fit the profile of a group of older adults with an elevated risk of falling, while the Low-Risk group exhibited characteristics which confirmed their low-risk status, being healthy, physically active and displaying high levels of balance, mobility and falls efficacy. All measures of task performance differed significantly between the groups. This suggests that further sensor-based analysis of task performance may also be useful to distinguish between groups based on their level of fall-risk. These results also show that referral to the falls prevention intervention was appropriate for the High-Risk group. The falls prevention intervention undertaken had beneficial effects on balance performance and behavioural factors related to fall-risk over the short intervention period, however a long-term follow-up would be required to determine if these benefits can be maintained or further improvements could be achieved over time. No changes were noted in timed task performance-based measures of fall-risk following intervention. The following chapters will therefore analyse the sensor data obtained for these tasks – first static, then dynamic – with the aim of quantifying the quality of task performance and potentially detecting changes which may go unnoticed using timing or observation alone.
CHAPTER 7. SENSOR-BASED ASSESSMENTS OF STATIC AND DYNAMIC BALANCE IN COMMUNITY-DWELLING OLDER ADULTS
7.1 Introduction
Chapter 5 described the functional tasks included in the sensor-based fall-risk assessment (SBFRA) procedure used in this research to assess participant’s balance and mobility. As described in Chapter 1, the tasks evaluated can be categorised as static or dynamic: static referring to the assessments of standing balance, and dynamic referring to the Timed Up and Go test (TUG) and 5 metre walk test (5m walk) tasks. This chapter will describe the sensor data collection procedures, analysis methods, results and discussions for both the static and dynamic tasks assessed. Sections 7.2 to 7.5 will focus on the static aspect i.e. the standing balance tasks, while Sections 7.6 to 7.9 will focus on the dynamic tasks.

7.2 Sensor-Based Assessment of Static Task Performance
Standing balance tasks are frequently used in research and clinical practice as indicators of steady state balance performance capacity (Huxham et al. 2001). In clinical settings, standing balance tasks are often included in functional balance assessment tools, such as the Berg Balance Scale (BBS), with the aim of detecting the presence or absence of balance impairment. Variations of standing balance tasks are used in systems/physiological assessment tools, such as the Mini-BESTest (Franchignoni et al. 2010), to pose challenges to an individual’s postural control systems and thus aid in determining the systems/physiological factors which are limiting balance performance. For example, the support surface may be altered by reducing an individual’s base of support or standing on a compliant surface such as foam; the sensory context may be altered by closing the eyes (Mancini and Horak 2010).

A range of methods exist to objectively evaluate standing balance performance for fall-risk assessment: kinetic or force-related variables can be obtained via force plates; kinematic variables which describe the spatial and temporal characteristics of movement via three-dimensional optical motion analysis systems or inertial sensors, or muscle activation measures via electromyography (Visser et al. 2008). Research has confirmed that many of these methods can accurately detect balance impairments (Baloh et al. 1998), identify fallers (Melzer et al. 2004, Whitney et al. 2006) and predict future falls incidence (Piirtola and Era 2006). While a vast number of possible variables can be examined, the common aim is to quantify the minute movements used by the human
body to maintain upright posture, and to identify characteristics of these movements which indicate impaired balance and thus increased risk of falling (Muir et al. 2010b).

The potential effectiveness of using wireless inertial sensors to achieve this aim by objectively assessing standing balance has been discussed in Chapter 4. In the same chapter it was noted that, while a number of sensor-derived variables have been found to discriminate between individuals of varying levels of fall-risk, some identified variables do not consistently do so (e.g. spectral edge frequency (SEF) variables), some variables are poorly or inconsistently defined between different studies (e.g. “sway”, as described in Chapter 4), no consensus on the optimal array of variables for use in sensor-based assessments of standing balance has been established and the clinical relevance of the selected variables has often not been considered.

Therefore, the following sections will examine the sensor-based assessments of standing balance undertaken by participants in both the High-Risk and Low-Risk groups as objective tests of static balance performance and indicators of fall-risk. The primary aim is to identify variables that can be extracted from sensor-based standing balance assessments which can differentiate between the High-Risk and Low-Risk groups and to discuss the clinical meaning and relevance of these variables. As part of this aim, comparisons between variables in three separate standing conditions will also be made to explore the responses of each group to varying standing balance challenges, as high and low fall-risk individuals may react differently to such challenges (Chapter 2). Variables that are found to distinguish between groups will then be further analysed in Chapter 8 to determine the value they present compared to clinical fall-risk assessments, in line with the overarching primary research question.

A secondary aim – in keeping with our secondary research question – is to examine changes in the selected sensor-based variables before and after participation in a falls prevention intervention, and to discuss whether any differences observed may reflect positive or negative changes in standing balance performance. This will provide an indication of potentially useful variables which may be used to evaluate standing balance performance over time and to assess outcomes in clinical practice.
7.3 Sensor-Based Assessment of Static Tasks: Methods

For details of the study designs, recruitment strategies and participant inclusion and exclusion criteria, the reader is referred to Chapter 5. This section will focus on the data collection procedures, data processing and statistical analysis techniques. All data processing was carried out using MATLAB Version 7.9.0.529 (R2009b) (The Mathworks Inc., Natick, USA).

7.3.1 Standing Balance Task Protocols

As described in Chapter 5, sensor data was recorded using a single Shimmer2R sensor with tri-axial accelerometer, gyroscope and magnetometer functions (Shimmer, Dublin, Ireland). The sensor was worn on a belt over the participants’ clothing and positioned at the midline at the level of the second sacral vertebra, as this location provides an approximate reflection of the position of the body’s centre of mass. Sensor data were streamed to a laptop via Bluetooth, and recorded for 10 seconds under each of the following three unsupported standing conditions:

1. Standing in normal stance width, with eyes open (Stand)
2. Standing in normal stance width, with eyes closed (EC)
3. Standing with feet together with eyes open (FT)

Data collection was carried out in the same order for all participants in both High-Risk and Low-Risk groups, as part of the overall assessment described in Chapter 5. The testing sequence used was selected as it presents increasingly difficult test conditions, similar to the sequences used in the modified Romberg test (Agrawal et al. 2011) and Clinical Test of Sensory Interaction and Balance (Shumway-Cook and Horak 1986). Sensor data was sampled at a minimum sampling frequency of 50Hz for all trials, which is comparable to sampling rates used in video analysis of activities such as walking and is a sufficiently high rate to allow low-pass filtering at recommended cut-off frequencies for standing and walking activities (Bartlett 2007, p.53, p.136).

A number of variables were derived from accelerometer data in order to obtain measures of body movement during the standing balance tasks. The selected variables, justification for their selection and details of the processes used to extract them from accelerometer data will be described in the following sections.
7.3.2 Data Processing: Sway Angle Variables

First, the accelerometer signals for each axis were filtered using an 8th-order low-pass Butterworth filter with a cut-off frequency of 2Hz to reduce noise while preserving the low frequency features in the signals. This type of digital low-pass filtering is widely used in human movement analysis, with cut-off frequencies of 4Hz to 8Hz common in sports biomechanics and lower cut-off frequencies for slow activities, which informed the choice of filter in this analysis of standing (Bartlett 2007, pp.135-137).

As illustrated in Chapter 5 (Figure 5.3), the sensor was positioned for every data collection episode such that the x-axis primarily represented vertical accelerations, the y-axis primarily represented medio-lateral (ML) accelerations and the z-axis primarily represented antero-posterior (AP) accelerations. However, accelerometer measurements are comprised of actual accelerations due to movement of the device as well as a constant acceleration due to gravity. Since the axes of a body-worn accelerometer cannot be consistently accurately aligned to the true vertical, AP and ML axes throughout a task, acceleration due to gravity will be decomposed along the sensing axes to varying extents depending on the angle of tilt of the device (Moe-Nilssen 1998a). If the angle of tilt of the device relative to the true horizontal plane is known, the “true” horizontal accelerations of the body in standing can be calculated by correcting for this sensor tilt (Moe-Nilssen and Helbostad 2002). Correcting for sensor tilt using this method makes two assumptions (Moe-Nilssen 1998a):

- The mean measured acceleration due to body movement over a measured period is equal to 0, and
- The tilt of the sensor remains constant throughout the measured period.

Although this method is widely used to correct acceleration data for sensor tilt, to our knowledge no previous studies have investigated this angle of tilt in greater detail. The assumption that the tilt of the sensor is constant over the measured time period may be reasonable when averaging over the entire period, but small changes in the instantaneous tilt of the sensor will occur as an individual sways while standing. Hence, it was decided to investigate the tilt angle of the body-worn sensor and variables related to this tilt angle to determine if these variables are related to fall-risk status i.e. do they differ between High-Risk and Low-Risk groups in this study. The term “sway angle” will be used throughout this study to describe the angle of the measured acceleration vector on a given sensor axis relative to the true horizontal plane.
Thus, ML and AP sway angle values were calculated as the angles of deviation between the horizontal plane – perpendicular to the constant gravity vector – and the measured acceleration vectors in the ML (frontal plane) and AP (sagittal plane) directions respectively (Figure 7.1). Sway angle (θ in Figure 7.1) was measured in degrees. Mean ML and AP sway angle was calculated for each participant in each standing condition, as was standard deviation, minimum, maximum, range and interquartile range of the sway angle values obtained, as measures of sway angle variability (Appendix R).

Figure 7.1. The relationships between the measured acceleration on a single axis of a tilted accelerometer and the true vertical and horizontal accelerations. “Sway angle”, represented by θ, is the angle of tilt of the accelerometer’s sensing axis relative to true horizontal (perpendicular to the gravity vector). Adapted from Moe-Nilssen and Helbostad (2002).
7.3.3 Data Processing: Acceleration-Related Variables

The second set of variables, those relating to the averaged properties of the acceleration signals obtained, was selected for two main reasons. Firstly, these selected variables indicate the overall magnitudes and frequencies of the actual accelerations measured during standing, whereas measures of “sway angle” do not. Secondly, they allow comparisons to be made with previous studies of sensor-based standing balance assessment (Doheny et al. 2012a, Doheny et al. 2012b, Greene et al. 2012b, O’Sullivan et al. 2009), which facilitates interpretation of the findings in this study.

The raw acceleration data for each axis was first band-pass filtered using a 4th order Butterworth filter with normalised cut-off frequencies of 0.1 to 5Hz (Greene et al. 2012b). The AP and ML acceleration data was then corrected for sensor tilt angle using the method described in the previous section (Moe-Nilssen and Helbostad 2002). The root of the sum of the squares (RSS) of the acceleration signals obtained for all three axes was calculated to obtain a scalar which represents the magnitude of the acceleration vector.

The root-mean-square (RMS) acceleration values for the ML, AP and RSS signals of each 10s standing trial period were calculated, since RMS acceleration values have been identified in numerous SBFRA studies as useful measures of postural instability (Doheny et al. 2012a, Doheny et al. 2012b, Greene et al. 2012b, O’Sullivan et al. 2009), as discussed in Chapter 4, Section 4.3.3.2. A sample plot of the RSS acceleration signal obtained from a High-Risk group participant in the Stand condition is provided in Figure 7.2, with the RMS value marked.
Figure 7.2. Sample plot of RSS acceleration signal in the Stand condition for a High-Risk group participant, with RMS value marked by the solid horizontal red line (0.0295g).

Spectral edge frequency (SEF) was also calculated for the ML, AP and RSS data by using a fast Fourier transformation to obtain the power spectral density of each acceleration signal. SEF was defined here as the frequency below which 95% of the power spectrum of the signal was contained (Doheny et al. 2011, Doheny et al. 2012a, Greene et al. 2012b). Figure 7.3 illustrates a sample power spectral density plot, with the SEF value marked.
Figure 7.3. Sample power spectral density plot of the RSS acceleration signal for a High-Risk group participant in the EC condition. The SEF of the signal is marked by the red line (4.346Hz).

The MATLAB code used to obtain all acceleration-related variables described in this section is presented in Appendix S. It was expected that RMS values would be higher among the High-Risk group than the Low-Risk group, since RMS trunk accelerations are greater in older adults than young adults (Moe-Nilssen and Helbostad 2002) and in older fallers compared to non-fallers (Doheny et al. 2012a, Greene et al. 2012b). It was also expected that RMS values would increase with increasing standing task complexity, while SEF values can be expected to decrease (O'Sullivan et al. 2009, Doheny et al. 2012a).

7.3.4 Data Processing: Acceleration Signal Optima

The sway angle and acceleration-related variables described in the previous sections relate to each 10s standing trial as a whole. It was hypothesised that subtle differences in patterns of movement may be overlooked if considering such variables only, since
they present averages over the trial period rather than examining specific events within the trial. Therefore, further analysis was carried out to detect the changes in acceleration that occurred throughout the standing trial and to examine the nature of these changes.

An algorithm was developed by a supervisor of this research (PvdV) in collaboration with the author, who contributed to defining the purpose of the algorithm and the variables of interest to be extracted. This algorithm detected peaks and troughs in the acceleration signals (henceforth referred to as ‘optima’) by searching for changes in the sign of the derivative of the signal within specified timeframes. Peak detection algorithms are widely used in sensor-based gait analysis (Zijlstra and Hof 2003) and in sensor-based fall detection research (Bourke et al. 2007), but are less frequently applied to standing balance assessments. Once the optima were detected, a number of variables of potential interest were extracted. In the absence of previous evidence utilising this data processing method for this precise purpose, these variables were decided upon via discussion between the author and supervisors. The variables selected for analysis were:

- The number of optima detected over the 10-second trial: This was extracted as a simple frequency-related variable, since frequency of postural sway may be a marker of fall-risk in older adults (Williams et al. 1997).
- The mean inter-optima acceleration amplitude (expressed in g): This was chosen as an indicator of postural control, since it describes the magnitude of the distinct accelerations of the body’s centre of mass that occur while maintaining standing balance (Winter 1995).
- The maximum inter-optima acceleration amplitude (expressed in g): Identifying the largest amplitude accelerations that occurred within standing balance trials was considered to be of interest since these events signify large, sudden corrections in the position of the body’s centre of mass, which may indicate challenges to maintaining postural control.
- The mean inter-optima jerk (expressed in g/s): Jerk, defined as the derivative of acceleration with respect to time, provides an indication of the smoothness of movement and has been proposed as a marker of the ability of an individual to control motion and maintain postural stability (Mancini et al. 2011).

The minimum inter-optima acceleration amplitude was also extracted initially, but the value was zero for all data files, thus it was not considered for analysis.
The optima detection and variable extraction algorithm was applied to AP and ML acceleration signals which were low-pass filtered as described in Section 7.3.2 and corrected for sensor tilt as described in Section 7.3.3. Figure 7.4 displays a sample plot of AP and ML acceleration signals with the detected optima marked. The MATLAB code used – which contains the data processing, optima detection algorithm and variable extraction processes – is provided in Appendix T.

![Sample plot of ML and AP acceleration signals](image)

**Figure 7.4.** Sample plot of ML and AP acceleration signals in the Stand condition for a High-Risk group participant. ML optima are marked by red triangles; AP optima are marked by blue circles.

### 7.3.5 Statistical Analysis

Statistical analysis was carried out using IBM SPSS Statistics for Windows Version 20.0 (IBM Corp., Armonk, USA). An alpha level of 0.05 was used for all statistical tests. To identify variables that differed significantly between groups, High-Risk group data from pre-intervention and post-intervention assessments were compared to the Low-Risk group’s data using independent samples t-tests or Mann-Whitney U tests as appropriate for the given data distributions. Comparisons between the various standing
conditions were also made within each group using repeated-measures ANOVAs or Friedman’s Tests for normally and abnormally distributed data respectively, followed by paired t-tests or Wilcoxon signed ranks tests for pairwise comparisons as appropriate. The extracted variables were also compared in the High-Risk group before and after participation in the six-week falls prevention intervention using paired-samples t-tests for normally distributed variables and Wilcoxon Signed Ranks tests for variables not following a normal distribution.

7.4 Static Tasks: Results
Table 7.1 describes the characteristics of participants in each group at each assessment time, as previously reported in Chapter 6, Table 6.1 and reproduced here for the reader’s convenience. As seen in Table 7.1, the High-Risk group were older, experienced more falls, and used more medications than the Low-Risk group. Also, more High-Risk group participants used walking aids. Participants in the Low-Risk group ranged in age from 67 to 86 years, and in the High-Risk group from 67 to 91 years.

Table 7.1. Characteristics of participants in the High-Risk and Low-Risk group.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Intervention (n=38)</th>
<th>Pre- Intervention</th>
<th>High-Risk Intervention (n=30)</th>
<th>Post-</th>
<th>Low-Risk (n=33)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>78 (67, 91)</td>
<td>77.5 (67, 91)</td>
<td>74 (67, 86) *</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Females (%)</td>
<td>65.8</td>
<td>73.3</td>
<td>87.9 *</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Falls in past year</td>
<td>2 (0, 6)</td>
<td>2 (0, 6)</td>
<td>0 (0, 0) **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medications</td>
<td>5 (2, 11)</td>
<td>6 (2, 10)</td>
<td>3 (0, 12) **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walking aid use (%)</td>
<td>57.9</td>
<td>53.3</td>
<td>6.1 **</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. Values are median (maximum, minimum), with the exception of percentages. Asterisks denote significant differences between groups, * = p<0.05, ** = p<0.001.

7.4.1 Sway Angle
As shown in Table 7.2, no significant differences between High-Risk and Low-Risk groups were noted for any of the selected sway angle variables.

Measures of ML sway angle variability – standard deviation (SD), range, inter-quartile range (IQR) – changed significantly (p<0.05) under different standing conditions in
both groups, with ML variability highest under the FT condition in both High-Risk and Low-Risk groups.

As regards the secondary aim of this study, mean ML sway angle was seen to decrease significantly in the High-Risk group following intervention in the Stand (median difference=0.428°, \( p=0.011 \)), EC (median difference=0.411°, \( p=0.004 \)) and FT conditions (median difference=0.025°, \( p=0.014 \)). Although trends towards reduced sway angle variability measures (SD, range, IQR) can be seen for the EC condition following intervention, none of the reductions were statistically significant. AP sway angle SD and IQR values were significantly higher in the EC condition than in Stand Pre-Intervention, but did not differ Post-Intervention.
Table 7.2. AP and ML sway angle measures in each group under each standing balance condition.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre (°)</th>
<th>High-Risk Post (°)</th>
<th>p (Pre v Post)</th>
<th>Low-Risk (°)</th>
<th>p (Pre v Low)</th>
<th>p (Post v Low)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>-3.037 (13.573)</td>
<td>1.549 (17.993)</td>
<td>0.163</td>
<td>2.334 (11.347)</td>
<td>0.085</td>
<td>0.693</td>
</tr>
<tr>
<td>AP EC</td>
<td>-2.180 (13.715)</td>
<td>2.827 (18.185)</td>
<td>0.171</td>
<td>2.015 (11.919)</td>
<td>0.192</td>
<td>0.828</td>
</tr>
<tr>
<td>AP FT</td>
<td>-2.670 (14.501)</td>
<td>2.632 (18.945)</td>
<td>0.339</td>
<td>1.570 (11.910)</td>
<td>0.216</td>
<td>0.910</td>
</tr>
<tr>
<td>ML Stand</td>
<td>1.610 (3.422)</td>
<td>0.236 (3.077)</td>
<td>0.011</td>
<td>1.402 (2.901)</td>
<td>0.654</td>
<td>0.172</td>
</tr>
<tr>
<td>ML EC</td>
<td>1.707 (3.466)</td>
<td>0.189 (3.099)</td>
<td>0.004</td>
<td>1.365 (2.749)</td>
<td>0.571</td>
<td>0.119</td>
</tr>
<tr>
<td>ML FT</td>
<td>1.636 (3.443)</td>
<td>0.361 (3.258)</td>
<td>0.014</td>
<td>1.293 (2.806)</td>
<td>0.474</td>
<td>0.248</td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>0.540 (0.332)</td>
<td>0.631 (0.417)</td>
<td>0.721</td>
<td>0.561 (0.375)</td>
<td>0.981</td>
<td>0.367</td>
</tr>
<tr>
<td>AP EC</td>
<td>0.841 (0.783) *</td>
<td>0.641 (0.383)</td>
<td>0.107</td>
<td>0.581 (0.216)</td>
<td>0.192</td>
<td>0.954</td>
</tr>
<tr>
<td>AP FT</td>
<td>0.644 (0.315)</td>
<td>0.612 (0.290)</td>
<td>0.349</td>
<td>0.653 (0.302)</td>
<td>0.627</td>
<td>0.573</td>
</tr>
<tr>
<td>ML Stand</td>
<td>0.282 (0.222)</td>
<td>0.275 (0.198)</td>
<td>0.510</td>
<td>0.281 (0.143)</td>
<td>0.328</td>
<td>0.535</td>
</tr>
<tr>
<td>ML EC</td>
<td>0.353 (0.388)</td>
<td>0.312 (0.244)</td>
<td>0.721</td>
<td>0.279 (0.140)</td>
<td>0.871</td>
<td>0.908</td>
</tr>
<tr>
<td>ML FT</td>
<td>0.464 (0.272) † ‡</td>
<td>0.429 (0.315) † ‡</td>
<td>0.393</td>
<td>0.439 (0.332) † ‡</td>
<td>0.571</td>
<td>0.989</td>
</tr>
<tr>
<td>Range</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>2.355 (1.252)</td>
<td>2.873 (1.718)</td>
<td>0.510</td>
<td>2.586 (1.644)</td>
<td>0.706</td>
<td>0.390</td>
</tr>
<tr>
<td>AP EC</td>
<td>3.664 (3.636)</td>
<td>2.936 (1.759)</td>
<td>0.417</td>
<td>2.807 (1.257)</td>
<td>0.595</td>
<td>0.908</td>
</tr>
<tr>
<td>AP FT</td>
<td>2.943 (1.275)</td>
<td>2.841 (1.279)</td>
<td>0.688</td>
<td>3.041 (1.561)</td>
<td>0.982</td>
<td>0.602</td>
</tr>
<tr>
<td>ML Stand</td>
<td>1.525 (1.079)</td>
<td>1.499 (0.822)</td>
<td>0.265</td>
<td>1.847 (1.320)</td>
<td>0.680</td>
<td>0.877</td>
</tr>
<tr>
<td>ML EC</td>
<td>1.805 (1.599)</td>
<td>1.676 (1.078)</td>
<td>0.370</td>
<td>1.823 (1.287) *</td>
<td>0.238</td>
<td>0.319</td>
</tr>
<tr>
<td>ML FT</td>
<td>2.499 (1.621) † ‡</td>
<td>2.156 (1.244) † ‡</td>
<td>0.894</td>
<td>2.638 (3.075) ‡</td>
<td>0.439</td>
<td>0.966</td>
</tr>
<tr>
<td>IQR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>0.755 (0.556)</td>
<td>0.869 (0.552)</td>
<td>0.721</td>
<td>0.744 (0.637)</td>
<td>0.869</td>
<td>0.272</td>
</tr>
<tr>
<td>AP EC</td>
<td>1.042 (0.656) *</td>
<td>0.848 (0.497)</td>
<td>0.381</td>
<td>0.763 (0.318)</td>
<td>0.083</td>
<td>0.897</td>
</tr>
<tr>
<td>AP FT</td>
<td>0.883 (0.518)</td>
<td>0.782 (0.357)</td>
<td>0.453</td>
<td>0.873 (0.453)</td>
<td>1.000</td>
<td>0.422</td>
</tr>
<tr>
<td>ML Stand</td>
<td>0.361 (0.286)</td>
<td>0.342 (0.164)</td>
<td>0.581</td>
<td>0.333 (0.132)</td>
<td>0.248</td>
<td>0.910</td>
</tr>
<tr>
<td>ML EC</td>
<td>0.484 (0.541) *</td>
<td>0.378 (0.232)</td>
<td>0.804</td>
<td>0.336 (0.097)</td>
<td>0.355</td>
<td>0.908</td>
</tr>
<tr>
<td>ML FT</td>
<td>0.582 (0.349) † ‡</td>
<td>0.595 (0.510) † ‡</td>
<td>0.734</td>
<td>0.466 (0.169) † ‡</td>
<td>0.355</td>
<td>0.662</td>
</tr>
</tbody>
</table>

Note. Values presented are means (SD), except p-values. AP=Antero-posterior; ML=Medio-lateral; EC=Eyes closed; FT=Feet together; SD=Standard deviation; IQR=Interquartile range. Significant differences from Pre- to Post-Intervention and between High-Risk and Low-Risk groups are in bold. *=Significant difference between Stand and EC (p<0.05); †= Significant difference between EC and FT (p<0.05); ‡= Significant difference between Stand and FT (p<0.05).
### 7.4.2 Acceleration-Related Variables

In Table 7.3, when comparing the results between groups, higher SEF values were observed among the Low-Risk group than the High-Risk group Pre-Intervention for the AP direction in all standing conditions (Stand median 4.541Hz versus 4.395Hz, \( p=0.001 \); EC median 4.395Hz versus 4.297Hz, \( p=0.017 \); FT median 4.443Hz versus 4.346Hz, \( p=0.009 \)) and for RSS in the EC condition only (\( p=0.007 \)). These findings were altered following intervention, where no significant differences in SEF values were noted between groups.

When examining the findings between various standing conditions, both the High-Risk group Pre-Intervention and the Low-Risk group exhibited higher RMS ML and RSS acceleration values in FT compared to Stand, and in EC compared to Stand, with the only exception being RMS RSS. In the High-Risk group, ML SEF was lower for FT than Stand Pre- and Post-Intervention, and was also lower than EC Pre-Intervention.

As regards the effects of the intervention, SEF values in the FT condition increased Post-Intervention for AP (median 4.346Hz versus 4.443Hz, \( p=0.006 \)) and RSS (median 4.248Hz versus 4.321Hz, \( p=0.025 \)), while ML and RSS RMS values were higher in FT than Stand Pre-Intervention, but not Post-Intervention.
Table 7.3. AP, ML and RSS acceleration variables in each group under each standing condition.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre</th>
<th>High-Risk Post</th>
<th>p Pre v Post</th>
<th>Low-Risk</th>
<th>p Pre v Low</th>
<th>Post v Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS (g)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>0.008 (0.007, 0.011)</td>
<td>0.008 (0.005, 0.010)</td>
<td>0.315 0.008 (0.007, 0.010)</td>
<td>0.982 0.662</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP EC</td>
<td>0.010 (0.008, 0.014)</td>
<td>0.009 (0.007, 0.013) *</td>
<td>0.358 0.009 (0.007, 0.012)</td>
<td>0.267 0.817</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP FT</td>
<td>0.009 (0.008, 0.012)</td>
<td>0.009 (0.007, 0.011)</td>
<td>0.975 0.010 (0.008, 0.012)</td>
<td>0.652 0.310</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML Stand</td>
<td>0.006 (0.005, 0.007)</td>
<td>0.007 (0.006, 0.009)</td>
<td>0.098 0.006 (0.006, 0.008)</td>
<td>0.145 0.622</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML EC</td>
<td>0.007 (0.005, 0.010) *</td>
<td>0.007 (0.005, 0.009)</td>
<td>0.770 0.008 (0.007, 0.009) *</td>
<td>0.221 0.050</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML FT</td>
<td>0.009 (0.007, 0.012) † ‡</td>
<td>0.008 (0.006, 0.010)</td>
<td>0.644 0.008 (0.007, 0.011) ‡</td>
<td>0.773 0.455</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS Stand</td>
<td>0.014 (0.011, 0.016)</td>
<td>0.013 (0.011, 0.016)</td>
<td>0.770 0.014 (0.011, 0.016)</td>
<td>0.738 0.746</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS EC</td>
<td>0.015 (0.011, 0.020)</td>
<td>0.015 (0.012, 0.016)</td>
<td>0.524 0.015 (0.013, 0.016) *</td>
<td>0.917 0.874</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS FT</td>
<td>0.015 (0.013, 0.019) ‡</td>
<td>0.015 (0.012, 0.017)</td>
<td>0.813 0.016 (0.014, 0.018) ‡</td>
<td>0.661 0.147</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEF (Hz)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>4.395 (4.248, 4.492)</td>
<td>4.419 (4.334, 4.553)</td>
<td>0.359 4.541 (4.443, 4.590)</td>
<td>0.001 0.055</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP EC</td>
<td>4.297 (4.199, 4.443)</td>
<td>4.395 (4.199, 4.565)</td>
<td>0.244 4.395 (4.346, 4.492) *</td>
<td>0.017 0.925</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP FT</td>
<td>4.346 (4.248, 4.443)</td>
<td>4.443 (4.297, 4.553)</td>
<td>0.006 4.443 (4.346, 4.529)</td>
<td>0.009 0.904</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML Stand</td>
<td>4.541 (4.443, 4.590)</td>
<td>4.541 (4.443, 4.639)</td>
<td>0.273 4.541 (4.456, 4.590)</td>
<td>0.528 0.782</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML EC</td>
<td>4.541 (4.443, 4.590)</td>
<td>4.541 (4.443, 4.590)</td>
<td>0.752 4.492 (4.443, 4.590)</td>
<td>0.802 0.838</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML FT</td>
<td>4.443 (4.395, 4.541) † ‡</td>
<td>4.492 (4.395, 4.553) ‡</td>
<td>0.268 4.492 (4.443, 4.590)</td>
<td>0.125 0.295</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS Stand</td>
<td>4.297 (4.150, 4.395)</td>
<td>4.297 (4.199, 4.395)</td>
<td>0.189 4.346 (4.162, 4.443)</td>
<td>0.078 0.321</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS EC</td>
<td>4.248 (4.102, 4.346)</td>
<td>4.346 (4.077, 4.395)</td>
<td>0.795 4.395 (4.297, 4.431)</td>
<td>0.007 0.066</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSS FT</td>
<td>4.248 (4.150, 4.346)</td>
<td>4.321 (4.150, 4.407)</td>
<td>0.025 4.297 (4.126, 4.395)</td>
<td>0.156 0.745</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Values presented are medians (IQR), except p-values. AP=Antero-posterior; ML=Medio-lateral; EC=Eyes closed; FT=Feet together; RMS=Root-mean-square; SEF=Spectral edge frequency. Significant differences from Pre- to Post-Intervention and between the High-Risk and Low-Risk groups are in bold. *=Significant difference between Stand and EC conditions (p<0.05); †= Significant difference between EC and FT conditions (p<0.05); ‡= Significant difference between Stand and FT conditions (p<0.05).
7.4.3 Acceleration Signal Optima

Table 7.4 displays the results for the analyses of the optima of the AP and ML acceleration signals for each of the three standing balance conditions. As regards differences between groups, the number of optima detected within the 10s FT standing trial was significantly higher among the High-Risk group Pre-Intervention than the Low-Risk group in the ML direction (median 29.00 versus 27.00, \( p=0.02 \)). In the Stand condition, mean inter-optima ML jerk (median 0.018 g/s versus 0.013g/s, \( p=0.002 \)) and ML acceleration amplitude (median 0.012g versus 0.009g, \( p=0.013 \)) were both greater among the Low-Risk group than the High-Risk group Pre-Intervention.

When comparing the responses of participants to the various standing conditions, a clear pattern can be observed across both groups, whereby inter-optima mean jerk, mean acceleration amplitude and maximum acceleration amplitude in the ML direction are all greatest in the FT condition. In the AP direction, mean and maximum inter-optima amplitudes and jerk are greatest in the EC condition in both groups, although this pattern was not consistently significant in the High-Risk group Post-Intervention.

No significant changes were noted following intervention in any of the acceleration signal optima variables.
Table 7.4. AP and ML peak-to-peak variables in each group under each standing balance condition.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre (°)</th>
<th>High-Risk Post (°)</th>
<th>P (Pre v Post)</th>
<th>Low-Risk (°)</th>
<th>p (Pre v Low)</th>
<th>p (Post v Low)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Optima</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AP Stand</td>
<td>23.00 (20.00, 28.00)</td>
<td>23.00 (19.75, 26.00)</td>
<td>0.323</td>
<td>24.00 (21.25, 27.75)</td>
<td>0.445</td>
<td>0.132</td>
</tr>
<tr>
<td>AP EC</td>
<td>23.00 (20.00, 27.00)</td>
<td>23.00 (19.50, 27.00)</td>
<td>0.894</td>
<td>24.50 (21.25, 27.75)</td>
<td>0.369</td>
<td>0.377</td>
</tr>
<tr>
<td>AP FT</td>
<td>26.00 (23.00, 29.00) †</td>
<td>23.00 (21.00, 28.00)</td>
<td>0.160</td>
<td>25.00 (23.00, 27.00)</td>
<td>0.525</td>
<td>0.237</td>
</tr>
<tr>
<td>ML Stand</td>
<td>28.00 (24.75, 30.25)</td>
<td>26.00 (24.75, 28.00)</td>
<td>0.084</td>
<td>26.50 (24.25, 31.00)</td>
<td>0.773</td>
<td>0.159</td>
</tr>
<tr>
<td>ML EC</td>
<td>30.00 (25.00, 32.00)</td>
<td>28.00 (25.50, 30.00)</td>
<td>0.150</td>
<td>27.75 (24.25, 31.00)</td>
<td>0.790</td>
<td>0.285</td>
</tr>
<tr>
<td>ML FT</td>
<td>29.00 (26.00, 31.00)</td>
<td>27.00 (25.75, 29.50)</td>
<td>1.000</td>
<td>27.00 (23.25, 28.75)</td>
<td><strong>0.020</strong></td>
<td>0.073</td>
</tr>
</tbody>
</table>

| Mean          |                   |                    |                |              |               |               |
| AP Stand       | 0.016 (0.013, 0.021) | 0.019 (0.013, 0.024) | 0.697          | 0.017 (0.015, 0.020) | 0.592          | 0.652          |
| AP EC          | 0.019 (0.014, 0.028) * | 0.021 (0.017, 0.024) | 0.489          | 0.022 (0.018, 0.026) * | 0.317          | 0.321          |
| AP FT          | 0.017 (0.014, 0.025) † | 0.021 (0.015, 0.028) | 0.139          | 0.020 (0.017, 0.024) ‡ | 0.100          | 0.869          |
| ML Stand       | **0.013 (0.010, 0.016)** | 0.016 (0.010, 0.021) | 0.222          | 0.018 (0.013, 0.019) | **0.002**      | 0.375          |
| ML EC          | 0.016 (0.011, 0.023) * | 0.017 (0.011, 0.022) | 0.475          | 0.019 (0.016, 0.020) | 0.288          | 0.502          |
| ML FT          | 0.020 (0.013, 0.028) †† | 0.020 (0.014, 0.026) †† | 0.984          | 0.021 (0.018, 0.026) †† | 0.286          | 0.139          |

| Jerk (g/s)     |                   |                    |                |              |               |               |
| ML Stand       | 0.009 (0.007, 0.013) | 0.012 (0.008, 0.015) | 0.265          | **0.012 (0.009, 0.015)** | **0.013**      | 0.612          |
| ML EC          | 0.011 (0.008, 0.018) * | 0.012 (0.009, 0.015) | 0.393          | 0.013 (0.010, 0.018) | 0.399          | 0.333          |
| ML FT          | 0.015 (0.011, 0.021) †† | 0.014 (0.011, 0.019) †† | 0.781          | 0.015 (0.013, 0.018) †† | 0.316          | 0.215          |

| Amplitude      |                   |                    |                |              |               |               |
| ML Stand       | 0.021 (0.018, 0.028) | 0.025 (0.017, 0.042) | 0.482          | 0.019 (0.015, 0.027) | 0.268          | 0.205          |
| ML EC          | 0.031 (0.021, 0.052) * | 0.029 (0.019, 0.037) | 0.122          | 0.024 (0.020, 0.036) * | 0.087          | 0.874          |
| ML FT          | 0.026 (0.018, 0.038) † | 0.027 (0.021, 0.035) | 0.453          | 0.033 (0.020, 0.044) ‡ | 0.211          | 0.517          |

| Maximum        |                   |                    |                |              |               |               |
| ML Stand       | 0.014 (0.010, 0.018) | 0.015 (0.008, 0.017) | 0.787          | 0.015 (0.012, 0.019) | 0.263          | 0.345          |
| ML EC          | 0.015 (0.010, 0.024) † | 0.017 (0.011, 0.021) | 0.721          | 0.016 (0.012, 0.020) | 0.518          | 0.942          |
| ML FT          | 0.019 (0.016, 0.035) ‡ | 0.022 (0.017, 0.030) ‡† | 0.558          | 0.020 (0.017, 0.026) ‡† | 0.953          | 0.789          |

Note. Values presented are median (IQR), except p-values. AP=Antero-posterior; ML=Medio-lateral; EC=Eyes closed; FT=Feet together; SD=Standard deviation; IQR=Interquartile range. Significant differences from Pre- to Post-Intervention and between the High-Risk and Low-Risk groups are in bold. *=Significant difference between Stand and EC (p<0.05); †= Significant difference between EC and FT (p<0.05); ‡= Significant difference between Stand and FT (p<0.05).
### 7.5 Sensor-Based Assessment of Static Tasks: Discussion

#### 7.5.1 Between-Groups Comparisons

The primary aim of this chapter was to identify variables derived from sensor-based standing balance assessments that differed between the High-Risk and Low-Risk groups assessed. Our findings were mixed in this regard. Sway angle variables were analysed under the premise that they could provide simple, easily interpreted and reasonably accurate quantifiers of standing balance performance. However, no differences in variables related to sway angle were noted between groups under any condition, thus these variables cannot be used to distinguish between these high and low fall-risk groups.

To interpret these findings, it is necessary to consider the meaning of the variables selected and the aspects of standing balance performance that they represent. The mean sway angle variable – as calculated in this study – indicates the mean orientation of the sensor relative to the true horizontal plane over the course of the standing trial. Considering the sensor placement, this could be thought of as a broad indicator of lumbar spine/pelvis position in standing. Measures of sway angle variability were considered also, since these variables reflect the changes in lumbo-pelvic orientation of participants in standing. It was hypothesised that such measures of changes in orientation might be related to postural sway, which if increased in standing is associated with poorer postural control and increased fall-risk (Lord et al. 2003, Lajoie and Gallagher 2004, Maki et al. 1994). The lack of any significant differences in these variables between groups indicates that sway angle may not be a useful indicator of standing balance performance in relation to fall-risk. Lumbo-pelvic posture and biomechanics are complex (Nordin and Frankel 2001, pp.256-285), therefore a simplistic approach as taken in this study may not accurately reflect this complexity. Also, it is unclear if lumbo-pelvic posture is relevant in fall-risk assessment, although some evidence suggests that thoracic posture can be useful as a marker of fall-risk (Kado et al. 2007, O'Brien et al. 1997). Perhaps future research investigating sway angle using a thoracic sensor placement could identify a use for sway angle variables, but in the present study it is clear that other sensor-derived variables must be explored.

Differences in the frequency content of acceleration signals during standing were noted between groups. Specifically, AP SEF was greater among the Low-Risk group than the High-Risk group Pre-Intervention in all standing conditions, as was RSS SEF in the EC
condition. Considering that SEF values decrease as tasks become more challenging to postural control (Doheny et al. 2012a), this may indicate that the High-Risk group found all standing conditions more challenging than the Low-Risk group.

Notably, none of the averaged ML sway angle or acceleration-related variables discriminated between groups in this study, in contrast to previous studies showing that fallers and those at risk of future falls sway at a higher amplitude and frequency than non-fallers, particularly in the ML direction (Lajoie and Gallagher 2004, Maki et al. 1994, Melzer et al. 2004, Piirtola and Era 2006, Buatois et al. 2006). However, mean inter-optima ML acceleration amplitude and jerk were significantly greater among the Low-Risk group than the High-Risk group in the Stand condition in this study. The identification of these variables as potential classifiers of fall-risk in community-dwelling older adults is a novel finding of this study. Although this may appear to oppose the previous findings mentioned, those previous studies were based on displacement of the body’s centre of pressure, rather than acceleration of the centre of mass, as measured in this study. Thus, they are not directly comparable since they are different variables and related to slightly different constructs (Winter 1995).

In a study which used a more similar SBFRA methodology to that adopted in this study, trunk accelerometer-derived jerk in standing was found to be lower in individuals with multiple sclerosis than in healthy controls (Mancini et al. 2012a), which was proposed to indicate slower postural control responses in those with multiple sclerosis. It is therefore possible that the lower inter-optima jerk and acceleration amplitude values observed among the High-Risk group represent slower and less efficient responses to the constant minor changes in centre of mass position that occur in standing. This finding would further explain why none of the ML variables which were averaged over the 10s trial period detected differences between groups, since averaging may conceal these small fluctuations.

7.5.2 Effects of Varied Standing Conditions between and within Groups

The responses of both groups to the varied standing conditions were largely similar, although some specific differences were noted. In both groups, measures of ML sway angle variability differed significantly between standing conditions, being greatest in the FT condition. These findings were echoed by the higher mean ML and resultant RMS
acceleration values also noted in this condition in both groups. Inter-optima ML amplitude and jerk values were also highest in the FT condition, compared to EC and Stand, for all participants. These findings are in line with previous research which shows that reducing stance width increases the velocity and fluctuation of body position in standing, particularly in the ML direction (Day et al. 1993).

However, the High-Risk group showed decreased ML SEF values in the FT condition compared to other conditions, whereas the Low-Risk group did not. Although it was an isolated difference between groups, this may indicate that the High-Risk group found the FT condition more difficult than the Low-Risk group, since lower SEF values are seen in more challenging standing tasks (Doheny et al. 2012a). Perhaps other, more challenging standing balance tasks may have been required to consistently distinguish between those at high or low risk of falling. Such challenges could be achieved via further reductions in base of support (BoS), manipulations of the sensory context or the addition of a cognitive dual-task, as these methods have been shown to enable fall-risk classification elsewhere (Muir et al. 2010a, Shumway-Cook and Woollacott 2000).

Restricting visual input affected sensor-based measures of standing balance performance to varying extents in both groups. Results were not consistent, although some trends towards increased sway angle variability and RMS values, and decreased SEF values were noted, which would suggest that participants found standing with eyes closed marginally more difficult than quiet standing. This would be expected, since humans typically derive about one-third of their orientation information from vision during eyes-open quiet stance (Peterka 2002) and restricting vision has previously been shown to increase velocity and variability of body sway (Day et al. 1993). Still, the findings of this study suggest that FT was the most challenging standing condition for all participants and that reducing the BoS provided a greater challenge to the maintenance of postural stability in both groups than limiting visual input. The older adults in this study may not have found the EC condition overly challenging due to the occurrence of sensory re-weighting, a term which refers to an adaptive reduction in reliance on vision for postural control over time, since vision typically declines or becomes less reliable with advancing age (Balasubramaniam and Wing 2002, Peterka 2002).

Anxiety may also have played a role in participants’ postural control responses with eyes closed. Looking at RSS values, amplitude (RMS) was similar or lower for EC than
FT and frequency (SEF) was similar or higher. Similar changes in amplitude and frequency have been noted to characterise the more conservative postural control responses which have been observed in both young and older adults under conditions of perceived ‘threat’ or increased anxiety (Adkin et al. 2000, Brown et al. 2006, Davis et al. 2009). Participants in this study may also have adapted their responses due to increased anxiety when asked to close their eyes.

In previous studies using similar sensor-based methods to ours, combined AP and ML jerk (Mancini et al. 2011) and both AP and ML accelerations were found to be greater during eyes closed standing than with eyes open in healthy older adults (Moe-Nilssen and Helbostad 2002). In this study, AP jerk and amplitudes were greater with eyes closed than in quiet standing, but no consistent significant differences were seen in the ML direction. These more apparent postural control responses can be expected in the AP direction, in keeping with the biomechanics of an ‘ankle strategy’ of postural control (Winter 1995). Also, participants in the previous studies stood with a fixed stand width of 10cm (Moe-Nilssen and Helbostad 2002, Mancini et al. 2011), whereas in this study participants stood at their usual, comfortable stance width, which may have offered a wider BoS and a potentially greater degree of stability. This may explain why the ML differences were less pronounced in this study.

### 7.5.3 Effects of Intervention

Although posturography has been used to evaluate therapeutic outcomes (Mancini and Horak 2010, Visser et al. 2008) and wireless inertial sensors have been proposed to be useful for this purpose (Howcroft et al. 2013), few studies have actually implemented sensor-based assessment techniques to evaluate the outcomes of interventions, hence the exploratory nature of this aspect of our secondary research question. One study compared force plate and accelerometer measures to evaluate the use of ankle or hip strategies for postural control among older adults following a short inpatient rehabilitation period (Lindemann et al. 2012), but to our knowledge there are no published studies which evaluate the effects of a falls prevention intervention using accelerometers. This may be due to the poor body of evidence examining the psychometric properties (e.g. validity, reliability, sensitivity to change) of various accelerometer-based methods. Some evidence suggests that measuring RMS trunk accelerations in standing is reliable in healthy adults (Moe-Nilssen 1998c) and can
distinguish between fallers and non-fallers regardless of the time of day at which testing occurs (Doheny et al. 2012a), but may exhibit poor repeatability in frail older people or individuals with hemiparesis (Helbostad et al. 2004). This could limit the applicability as an outcome measure in these populations, but features of reliability still need to be established in other clinical populations and for other sensor variables.

Between-groups results indicated that higher AP and RSS SEF values are associated with the Low-Risk group, thus the increase in these measures in the FT condition following intervention may reflect beneficial changes following intervention. Considering that the falls prevention programme included a number of exercises which challenged balance specifically by reducing the BoS, as recommended (Sherrington et al. 2011), it is reasonable to expect that High-Risk group participants would improve their performance on a task where the BoS is reduced, in accordance with the principle of training specificity (Reilly et al. 2009).

Trends towards reductions in sway angle variability measures (SD, range and IQR) were also noted following intervention, particularly for the AP direction in the EC condition, but none of these reductions were statistically significant. However, these AP sway angle values were significantly higher with EC than in normal standing Pre-Intervention, but did not differ from them Post-Intervention. This suggests a potential improvement in EC standing balance following intervention. Although the intervention did not include specific balance exercises with limited visual input, the balance training exercises challenged the vestibular and somatosensory systems via reduced support, the use of compliant surfaces or the addition of head turns to tasks for those who were capable. Such training should improve the performance of these balance control systems, thus when sensory re-weighting leads to greater reliance on these systems in visually restricted conditions (Peterka 2002), the decline in balance performance should in theory be less marked. Currently used outcome measures in research and clinical practice tend to assess balance without differentiating between the underlying systems limiting performance, which makes it challenging to confirm this theory based on current evidence and findings (Pasma et al. 2014), although improvements in eyes-closed sway variables have been reported previously following interventions that do not include specific vision-restricted training (Young et al. 2011, Rogers et al. 2001, Jessup et al. 2003). In further studies, it would be useful to use assessment methods which discriminate between the various balance control systems, as this would allow more
efficient training by targeting weaker systems and would provide valuable information on the training effects obtainable on the various systems which influence balance.

7.6 Sensor-Based Assessment of Dynamic Task Performance

The following sections will address the sensor data obtained during dynamic fall-risk assessment tasks for both the High-Risk and Low-Risk groups, namely the 5 metre walk test (5m walk) and the Timed Up and Go test (TUG). This work is both timely and relevant, as a large quantity of research using wearable inertial sensors to analyse human mobility performance has emerged in the recent past (Muro-de-la-Herran et al. 2014). Section 7.7 will focus on the precise details of the assessment protocols for each test of task performance and will then go on to describe in detail the data processing and analysis methods. The results obtained for each test will be presented, followed by an in-depth discussion of these results. In keeping with our primary research question, the emphasis will be on identifying sensor-based variables which differ between the High-Risk and Low-Risk groups, as well as the functional meaning of these variables and their relevance to clinical practice. As per our secondary research question, any changes noted in the High-Risk group following intervention will be reported and discussed.

7.7 Sensor-Based Assessment of Dynamic Tasks: Methods

This section will describe in detail the assessment protocols for the tests of dynamic task performance undertaken – the 5m walk test and the TUG – as well as the data processing and analysis procedures used for the sensor data obtained.

7.7.1 5m Walk Test Protocol

The 5m walk test was performed at participants’ self-selected usual gait speed. An 8m path on a level surface was marked using tape in the laboratory (for the Low-Risk group) or primary care centre (for the High-Risk group). Some participants in the High-Risk group completed the 5m walk test in their homes if adequate space was available. A 1.5m rolling start and stop was employed, thus gait was timed and sensor data
recorded for the middle 5m section of the 8m path. Each participant performed two recorded 5m walk trials.

A 5m distance was selected as this was deemed the maximum distance over which it was feasible to conduct the test in the various settings. Although 6m or 10m walk tests are more commonly used, the distance does not necessarily influence the gait speed results obtained (Graham et al. 2008b). Also, distances of 5m or less have been used previously to obtain gait speed measures which distinguished between fallers and non-fallers (Chu et al. 2005, Shumway-Cook et al. 2005).

### 7.7.2 5m Walk Data Processing

Sensor data was recorded for each 5m walk at a minimum sampling frequency of 50Hz. Data processing was carried out using MATLAB Version 7.9.0.529 (R2009b) (The Mathworks Inc., Natick, USA). Accelerometer data was filtered using a second-order low-pass Butterworth filter with a normalised cut-off frequency of 6Hz, as is commonly used for human movement data analysis (Bartlett 2007, p.153).

The main variables of interest extracted from the accelerometer data were gait speed, step count, mean step time and step time variability (defined as the standard deviation of the mean step time). Cadence, measured in steps per min (steps/min), was also calculated based on the step count and the time recorded. Accelerometer-derived measures of gait speed, step time and cadence have previously been found to show excellent reliability and repeatability (Senden et al. 2009).

The code used to process the data and extract these variables can be found in Appendix U. For each variable, the mean value obtained over the two 5m walk trials was used as the value for each participant. Gait speed in metres per second (m/s) was calculated by dividing the length of the walk (i.e. 5 metres) by total time taken to complete the walk.

Step count was obtained based on the square root of the sum of the squared (RSS) low-pass filtered acceleration signals for each axis. The RSS acceleration signal was calculated to obtain a single signal to characterise gait during the 5m walk. Figure 7.5A shows the low-pass filtered acceleration signals obtained for each axis during a sample 5m walk from a participant in the Low-Risk group. Figure 7.5B shows the RSS acceleration signal for the same 5m walk which – as is evident from the repetitious nature of the signal obtained – enables gait cycles to be identified with ease. As Figure
7.5B also shows, steps were counted using a peak detection method, similar to that described in Section 7.3.4. Peak detection algorithms have previously been used in sensor-based gait analysis (Zijlstra and Hof 2003), although in the current study peaks were detected in the RSS acceleration signal, rather than from the acceleration signal on a single axis. While Zijlstra and Hof (2003) were aiming to detect initial contact of the foot in order to determine left and right step parameters, the aim of the current analysis was to achieve consistent successful step detection across a range of participants of varying gait characteristics. As Figure 7.6 shows, individuals with flexed trunk postures and/or asymmetrical gait patterns can present challenges to step detection if the method is based on data from one axis only, since such features of gait affect both sensor orientation and measured accelerations. While using a combined RSS signal does not readily allow estimation of when specific events occur during gait, it nullifies the influence of sensor orientation or tilt and it facilitated consistent successful peak detection across the range of individuals encountered in this study, as demonstrated in Figures 7.5B and 7.6B. As long as a step is consistently measured from the occurrence of one event in the gait cycle to the occurrence of the same event on the contralateral side in that cycle (Whittle 2007), the spatio-temporal gait variables of interest in this study i.e. step count, cadence, mean step time and step time variability, will remain unchanged regardless of which event in the gait cycle is chosen to mark these start and end points.

Individual step times were determined as the time between successive peaks, as identified from the RSS acceleration signal. Mean step time was then calculated as the mean of all steps identified in a given 5m walk trial. Step time variability was defined as the standard deviation of step times in a single trial for each participant, as described by Menz et al. (2003b).
Figure 7.5. A. Sample graph showing low-pass filtered signals from all three accelerometer axes during a 5m walk trial for a Low-Risk group participant. B. Sample graph for the same participant showing the root of the sum of the squared acceleration signals for the same 5m walk trial. A red ‘X’ marks each peak which was detected and used to calculate the selected step variables.
Figure 7.6. A. Sample graph showing low-pass filtered signals from all three accelerometer axes during a 5m walk trial for a High-Risk group participant. B. Sample graph for the same participant showing the root of the sum of the squared acceleration signals for the same 5m walk trial. A red ‘X’ marks each peak which was detected and used to calculate the selected step variables.
7.7.3 TUG Test Protocol

The TUG was performed in a laboratory for the Low-Risk group and in a local primary care centre for the High-Risk group. Some High-Risk group participants completed the TUG in their homes if sufficient space and a suitable chair were available. The TUG protocol adopted was in line with previously published descriptions of the test (Podsiadlo and Richardson 1991, Bohannon 2006b). Participants began seated in a standard armchair (approximate seat height of 46cm, arm height 65cm) with their back against the chair and their arms resting on the armrests. Participants were instructed, on the word “go”, to get up and walk at a safe and comfortable pace to a marker on the floor three meters away, turn, return to the chair and sit down again. Participants wore their usual footwear for the test. No physical assistance was provided, but participants could use their usual walking aid if required. For the High-Risk group, if a walking aid was used at the Pre-Intervention assessment it was also used Post-Intervention. Participants walked through the test once to ensure they were familiar with the procedure. Sensor data was then recorded for the second trial, which was timed using a stopwatch also.

7.7.4 TUG Data Processing

A wide range of methods of instrumenting the TUG and analysing the subsequent data have been published previously, and such methods have been used to successfully detect performance characteristics associated with Parkinson’s disease (Zampieri et al. 2010, Mancini et al. 2012b, Palmerini et al. 2013), to quantify mobility deficits (Salarian et al. 2010, Mellone et al. 2012), and to classify participants’ levels of fall-risk (Greene et al. 2012a, Greene et al. 2010, Zakaria et al. 2013) and frailty (Greene et al. 2014). Most studies have focused on segmenting the overall TUG performance into specific phases, such that the characteristics of the selected phases can be analysed (Weiss et al. 2011, Higashi et al. 2008).

The main aim of the TUG sensor data analysis in this study was to segment the TUG and examine the specific phases identified, primarily in terms of their temporal characteristics. The overall TUG times noted in this study differentiated between the High-Risk and Low-Risk groups, but the slight increase in TUG time Post-Intervention was both unexpected and perhaps not clinically meaningful (Chapter 6). It was hypothesised that:
1. TUG phase times and sensor-derived variables for selected phases could be used to further distinguish between the High-Risk and Low-Risk groups, and that

2. Analysis of the TUG phases could quantify the change in TUG performance within the High-Risk group in a clinically meaningful manner.

Accelerometer and gyroscope data collected during the TUG was analysed using as-yet unpublished software created by Dr. Alan Bourke (affiliated to École Polytechnique Fédérale de Lausanne, Switzerland at that time) who created the code to process the data with collaboration from the author of this thesis to define the aims of the analysis and the desired variables to extract. The software firstly corrected all accelerometer and gyroscope data for sensor tilt. It then allowed the TUG to be segmented manually via the selection of specific points in the signals. Eight different points were selected based on the accelerometer and gyroscope signals, as presented in Figure 7.7, according to the following criteria:

- **P1**: Start of the TUG. The start of the recorded signals, since the beginning of the recording and the instruction to the participant to begin the TUG were simultaneous.
- **P2**: End of the sit-to-stand transition before walking. This was selected based on the RSS accelerometer signal and the gyroscope signals, as all signals plateaued when a standing position was reached.
- **P3**: Start of the mid-way turning point. The initiation of the turn was denoted by a marked change in the slope of the angle data obtained from the integrated gyroscope signal, as observed prior to the six-second marker in the lowermost graph in Figure 7.7.
- **P4**: End of the mid-way turning point and the start of the return walk. When the angle signal used to select P6 reached a plateau, the turn was considered to have ended.
- **P5**: Start of the turn before sitting. Similar to P6, this was selected as the beginning of the change in slope of the gyroscope angle signal during/after the return walk phase.
- **P6**: End of the turn. This was marked at the point at which the gyroscope angle signal returned to its starting value.
- **P7**: Start of the stand-to-sit. This was selected using a combination of almost all signals, as this event initiates a notable change in slope of the RSS, AP and vertical accelerometer signals, along with a marked change in angular velocity.
• **P8:** End of the stand-to-sit. This was determined as being the point at which the participant became stationary at the end of the trial, which indicated that the stand-to-sit transition, and thus the TUG itself, was complete.

As seen in Figure 7.7, the order of P6 and P7 may be reversed, as the turning and sitting movements at the end of the TUG may overlap if participants use a composite turn-and-sit strategy, rather than executing distinct turning and sitting phases.

**Figure 7.7.** Sample TUG data for accelerometer and gyroscope sensors obtained for a High-Risk group participant. The uppermost graph presents the accelerometer signals for each axis. The second graph from the top presents the RSS acceleration signal, including the manually-selected time points used to segment the TUG. The third graph from the top presents angular velocity signals obtained from each axis of the gyroscope. The lowermost graph shows the angle signal obtained by integrating the gyroscope signal and correcting for signal drift.
Based on these points selected in the TUG, times for specific phases of the task were calculated as presented in Table 7.5.

### Table 7.5. Phase durations and ratios extracted from TUG performance.

<table>
<thead>
<tr>
<th>Phase Name</th>
<th>Description</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>SensorTUG</td>
<td>Total TUG time, as per the sensor-based time-points</td>
<td>P8 – P1</td>
</tr>
<tr>
<td>STS1</td>
<td>Time for the sit to stand</td>
<td>P2 – P1</td>
</tr>
<tr>
<td>Walk1</td>
<td>Time for the first walk</td>
<td>P3 – P2</td>
</tr>
<tr>
<td>Turn</td>
<td>Time for the turn</td>
<td>P4 – P3</td>
</tr>
<tr>
<td>Walk2</td>
<td>Time for the second walk</td>
<td>P5 – P4</td>
</tr>
<tr>
<td>TotalTurnSit</td>
<td>Time from the start of the turn to the end of the sit</td>
<td>P8 – P5</td>
</tr>
<tr>
<td>STS2</td>
<td>Stand to sit time</td>
<td>P8 – P7</td>
</tr>
<tr>
<td>EndTurntoStartSit</td>
<td>Time from end of the turn to the start of the sit. This number can be negative since the sit can start before the turn finishes, depending on the strategy adopted by the participant.</td>
<td>P6 – P7</td>
</tr>
<tr>
<td>STS2:TotalTurnSit</td>
<td>Ratio of the end of the turn to the start of the sit in proportion to the whole turn to sit movement</td>
<td>(P8-P7)/(P8-P5)</td>
</tr>
<tr>
<td>WTW :Total</td>
<td>Ratio of walk-turn-walk to total TUG time</td>
<td>(P4 – P2)/(P8 – P1)</td>
</tr>
</tbody>
</table>

The two ratios were novel inclusions in the TUG analysis of this study, and were included as they were hypothesised to be potentially useful as simple indicators of performance strategy, a concept which is easily observed but not so easily quantified. For example, a high $STS2:TotalTurnSit$ ratio would indicate a composite turn-and-sit performance, as opposed to a distinct turn followed by a distinct stand-to-sit phase. A high $WTW:Total$ ratio would indicate that an individual spent a great proportion of time on the walking aspects of the test, and may require further examination for gait impairments or specific difficulty in turning.

For the $Turn$ phase, acceleration and angular velocity mean, variance, minimum and maximum were also extracted as measures of the smoothness or steadiness of the $Turn$ phase. Difficulty turning has been observed during the TUG in older adults and those at risk of falling (Thigpen et al. 2000, Leigh Hollands et al. 2010), and previous studies
have used sensor-derived variables to quantify turn performance (Herman et al. 2014, Weiss et al. 2013) and to distinguish between fallers and non-fallers based on this data (Greene et al. 2010).

7.7.5 Statistical Analysis

Statistical analysis was performed using IBM SPSS Statistics for Windows Version 20.0 (IBM Corp., Armonk, USA). The distributions of the data were assessed for normality, and parametric or non-parametric tests were used for subsequent analyses depending on the distributions observed. To compare the High-Risk and Low-Risk groups, independent-samples t-tests or Mann-Whitney U-tests were used. Significance for all tests was assumed at $p<0.05$. Within the High-Risk group, paired-samples t-tests or Wilcoxon signed ranks tests were used to compare pre- and post-intervention data.

7.8 Dynamic Tasks: Results

The characteristics of the participants in each group have been presented previously in Table 7.1.

7.8.1 5m Walk Test

Complete data sets for the 5m walk test were obtained for 33 participants in the Low-Risk group and 29 participants in the High-Risk group. Dropouts in the High-Risk group occurred due to withdrawals from the falls prevention intervention, as described in Chapter 6, and one additional participant’s sensor data was lost due to technical error. The majority of 5m walk data was not normally distributed; hence descriptive statistics and test results are reported as appropriate for such data.

As displayed in Table 7.6, all selected gait variables differed significantly between the High-Risk and Low-Risk groups. Low-Risk participants walked significantly faster and exhibited a higher cadence than High-Risk participants. They also showed shorter step times and less step time variability than the High-Risk group. Mean acceleration amplitudes in the ML and AP directions, as well as RSS accelerations, were significantly greater among the Low-Risk group. There were no significant intervention effects noted in the High-Risk group on any of the selected variables.
Table 7.6. Sensor-derived gait variables extracted from the 5m walk tests.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre-Intervention</th>
<th>High-Risk Post-Intervention</th>
<th>( p )</th>
<th>Low-Risk</th>
<th>( p )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(m/s)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gait Speed</td>
<td>0.77 (0.18, 1.54)</td>
<td>0.83 (0.28, 1.37)</td>
<td>0.509</td>
<td>1.28 (0.61, 1.67)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Step Count (number)</td>
<td>10.5 (6.0, 21.5)</td>
<td>10.0 (6.0, 22.0)</td>
<td>0.085</td>
<td>8.0 (6.0, 15.5)</td>
<td>&lt;0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>96.0 (74.8, 120.1)</td>
<td>96.3 (73.9, 117.0)</td>
<td>0.284</td>
<td>118.8 (101.8, 160.3)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Mean Step Time (s)</td>
<td>0.60 (0.50, 0.75)</td>
<td>0.60 (0.48, 0.78)</td>
<td>0.666</td>
<td>0.49 (0.39, 0.58)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Step Time Variability (s)</td>
<td>0.04 (0.02, 0.14)</td>
<td>0.04 (0.02, 0.10)</td>
<td>0.814</td>
<td>0.02 (0.01, 0.06)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>ML RMS Accel (g)</td>
<td>0.06 (0.00, 0.10)</td>
<td>0.06 (0.04, 0.11)</td>
<td>0.543</td>
<td>0.08 (0.05, 0.16)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>AP RMS Accel (g)</td>
<td>0.08 (0.04, 0.14)</td>
<td>0.08 (0.04, 0.22)</td>
<td>0.329</td>
<td>0.11 (0.06, 0.20)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>RSS RMS Accel (g)</td>
<td>1.01 (0.99, 1.05)</td>
<td>1.01 (0.99, 1.04)</td>
<td>0.094</td>
<td>1.03 (0.99, 1.06)</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Note. Data presented are medians (minimum, maximum). AP=Antero-posterior; ML=Medio-lateral; RMS=Root-mean-square; RSS=Root-sum-square; Accel=Acceleration.

7.8.2 Timed Up and Go Test

Results for the selected TUG variables for the High-Risk and Low-Risk groups are presented in Table 7.7. Only TUG data from the Pre-Intervention assessment of the High-Risk group was compared to the Low-Risk group, as an equipment fault resulted in a large amount of missing gyroscope data for the Post-Intervention assessments. Since the gyroscope signals were used to segment the TUG and selected gyroscope-derived variables were also analysed during the Turn phase, it was not deemed possible to perform meaningful analysis on the affected data sets. However, the fact that Pre- and Post-Intervention data could not be compared does not interfere with our primary research question, as this is focused on the ability to differentiate between the groups.

As seen in Table 7.7 a large number of variables differed significantly between groups. As regards the temporal variables selected, the High-Risk group took longer than the Low-Risk group to complete the total TUG as well as most distinct TUG phases. The ratio of the STS2 phase in relation to the TotalTurnSit movement was also significantly
higher among the Low-Risk group than the High-Risk group. It is also notable that the sensor-derived TUG times are greater than the manually-timed TUG. As illustrated in Figure 7.8, both measures are highly correlated ($R^2=0.978$), which shows that the sensor-derived times were consistently longer than the manually-timed results.

Figure 7.8. Plot illustrating correlation between manual and sensor-derived TUG times.
Table 7.7. Selected temporal, accelerometer and gyroscope-derived TUG variables for each group.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre (n=30)</th>
<th>High-Risk Post (n=18)</th>
<th>Low-Risk (n=30)</th>
<th>p (Pre v Low)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual-timed TUG (s)</td>
<td>14.8 (5.9, 40.0)</td>
<td>19.1 (7.6, 47.8)</td>
<td>8.7 (6.1, 22.8)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Sensor TUG (s)</td>
<td>16.02 (5.81, 40.58)</td>
<td>20.01 (10.25, 46.92)</td>
<td>10.1 (5.1, 23.7)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>STS1(s)</td>
<td>2.06 (0.46, 7.16)</td>
<td>2.74 (1.22, 4.32)</td>
<td>1.59 (1.00, 2.93)</td>
<td>0.004</td>
</tr>
<tr>
<td>Walk1(s)</td>
<td>3.87 (1.24, 11.19)</td>
<td>5.24 (1.12, 15.09)</td>
<td>1.64 (0.49, 4.70)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Turn (s)</td>
<td>3.02 (1.59, 8.32)</td>
<td>3.89 (2.05, 9.98)</td>
<td>2.22 (1.44, 4.26)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Walk2 (s)</td>
<td>2.53 (0.64, 9.41)</td>
<td>3.85 (0.83, 9.29)</td>
<td>1.49 (0.36, 4.95)</td>
<td>0.005</td>
</tr>
<tr>
<td>TotalTurnSit (s)</td>
<td>4.31 (0.93, 11.76)</td>
<td>5.89 (3.83, 11.52)</td>
<td>2.71 (1.69, 6.82)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>STS2 (s)</td>
<td>2.89 (0.42, 8.30)</td>
<td>2.98 (1.46, 8.37)</td>
<td>1.94 (1.35, 4.06)</td>
<td>0.021</td>
</tr>
<tr>
<td>EndTurntoStartSit (s)</td>
<td>-1.51 (-5.40, 0.18)</td>
<td>-1.66 (-8.27, 1.44)</td>
<td>-1.25 (-2.12, -0.48)</td>
<td>0.312</td>
</tr>
<tr>
<td>WalkTurnWalk : Total</td>
<td>0.58 (0.44, 0.75)</td>
<td>0.57 (0.42, 0.73)</td>
<td>0.56 (0.46, 0.67)</td>
<td>0.312</td>
</tr>
<tr>
<td>STS2 : TotalTurnSit</td>
<td>0.54 (0.24, 0.93)</td>
<td>0.51 (0.23, 1.00)</td>
<td>0.76 (0.54, 1.08)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAccelMeanX (g)</td>
<td>-0.01 (-0.60, 0.37)</td>
<td>-0.05 (-0.16, 0.10)</td>
<td>-0.08 (-0.19, 0.43)</td>
<td>0.056</td>
</tr>
<tr>
<td>TAccelMeanY (g)</td>
<td>0.02 (-0.14, 0.09)</td>
<td>0.03 (-0.10, 0.13)</td>
<td>0.00 (-0.11, 0.06)</td>
<td>0.554</td>
</tr>
<tr>
<td>TAccelMeanZ (g)</td>
<td>-0.01 (-0.21, 0.00)</td>
<td>-0.01 (-0.03, 0.00)</td>
<td>-0.02 (-0.12, 0.00)</td>
<td>0.005</td>
</tr>
<tr>
<td>TAccelVarX (g²)</td>
<td>0.01 (0.00, 0.06)</td>
<td>0.01 (0.00, 0.02)</td>
<td>0.03 (0.01, 0.06)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAccelVarY (g²)</td>
<td>0.01 (0.00, 0.07)</td>
<td>0.01 (0.00, 0.02)</td>
<td>0.02 (0.01, 0.07)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAccelVarZ (g²)</td>
<td>0.01 (0.00, 0.05)</td>
<td>0.01 (0.00, 0.04)</td>
<td>0.04 (0.01, 0.13)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAccelMaxX (g)</td>
<td>0.23 (-0.37, 0.86)</td>
<td>0.20 (0.08, 0.35)</td>
<td>0.39 (0.13, 1.22)</td>
<td>0.020</td>
</tr>
<tr>
<td>TAccelMaxY (g)</td>
<td>0.29 (-0.10, 0.56)</td>
<td>0.25 (0.11, 0.56)</td>
<td>0.44 (0.17, 0.81)</td>
<td>0.001</td>
</tr>
<tr>
<td>TAccelMaxZ (g)</td>
<td>0.33 (0.16, 1.13)</td>
<td>0.34 (0.16, 1.10)</td>
<td>0.67 (0.32, 1.09)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAccelMinX (g)</td>
<td>-0.35 (-1.23, 0.18)</td>
<td>-0.31 (-0.74, -0.05)</td>
<td>-0.50 (-1.03, -0.12)</td>
<td>0.002</td>
</tr>
<tr>
<td>TAccelMinY (g)</td>
<td>-0.31 (-1.70, -0.13)</td>
<td>-0.23 (-0.58, -0.07)</td>
<td>-0.41 (-1.15, -0.20)</td>
<td>0.045</td>
</tr>
<tr>
<td>TAccelMinZ (g)</td>
<td>-0.25 (-0.49, -0.13)</td>
<td>-0.19 (-0.46, -0.12)</td>
<td>-0.38 (-0.89, -0.19)</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Table 7.7 continued.

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Risk Pre</th>
<th>High-Risk Post</th>
<th>Low-Risk</th>
<th>P (Pre v Low)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TAngVelMeanX (°/s)</td>
<td>0.20 (-5.85, 4.51)</td>
<td>0.17 (-2.91, 5.06)</td>
<td>0.30 (-7.95, 9.01)</td>
<td>0.828</td>
</tr>
<tr>
<td>TAngVelMeanY (°/s)</td>
<td>0.36 (-6.89, 8.38)</td>
<td>0.60 (-4.76, 4.53)</td>
<td>1.39 (-5.47, 12.40)</td>
<td>0.197</td>
</tr>
<tr>
<td>TAngVelMeanZ (°/s)</td>
<td><strong>57.89 (21.88, 104.73)</strong></td>
<td>44.37 (17.55, 81.33)</td>
<td><strong>80.06 (42.92, 112.87)</strong></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAngVelVarX (°/s²)</td>
<td><strong>105.62 (35.66, 824.97)</strong></td>
<td>98.07 (30.40, 1253.58)</td>
<td><strong>352.32 (65.91, 684.34)</strong></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>TAngVelVarY (°/s²)</td>
<td><strong>181.87 (30.35, 2123.88)</strong></td>
<td>105.70 (18.99, 1940.22)</td>
<td><strong>332.74 (81.10, 5628.96)</strong></td>
<td>0.012</td>
</tr>
<tr>
<td>TAngVelVarZ (°/s²)</td>
<td><strong>824.88 (176.66, 5603.52)</strong></td>
<td>748.99 (153.55, 2336.89)</td>
<td><strong>1377.18 (353.63, 5270.16)</strong></td>
<td>0.022</td>
</tr>
<tr>
<td>TAngVelMaxX (°/s)</td>
<td><strong>28.80 (16.36, 112.28)</strong></td>
<td>22.07 (14.53, 102.76)</td>
<td><strong>47.32 (25.33, 98.42)</strong></td>
<td>0.001</td>
</tr>
<tr>
<td>TAngVelMaxY (°/s)</td>
<td>41.56 (15.79, 231.84)</td>
<td>29.74 (13.10, 129.53)</td>
<td>45.45 (20.30, 246.20)</td>
<td>0.263</td>
</tr>
<tr>
<td>TAngVelMaxZ (°/s)</td>
<td><strong>123.51 (61.62, 244.37)</strong></td>
<td>103.41 (44.69, 173.10)</td>
<td><strong>153.08 (84.88, 263.88)</strong></td>
<td>0.001</td>
</tr>
<tr>
<td>TAngVelMinX (°/s)</td>
<td>-33.05 (-127.15, -15.78)</td>
<td>-28.75 (-106.04, -18.05)</td>
<td><strong>-45.03 (-74.33, -17.21)</strong></td>
<td>0.011</td>
</tr>
<tr>
<td>TAngVelMinY (°/s)</td>
<td>-44.59 (-162.97, -16.71)</td>
<td>-31.31 (-116.32, -11.94)</td>
<td><strong>-49.21 (-263.68, -19.50)</strong></td>
<td>0.375</td>
</tr>
<tr>
<td>TAngVelMinZ (°/s)</td>
<td><strong>-6.36 (-51.16, 21.03)</strong></td>
<td>-13.17 (-44.94, 5.75)</td>
<td><strong>-0.46 (-64.72, 20.02)</strong></td>
<td>0.010</td>
</tr>
</tbody>
</table>

Note. Data are presented as median (minimum, maximum). Significant differences between groups are presented in bold.
Figure 7.9 presents the TUG phase times as percentages of the total sensor TUG times, to provide an alternative view of the relative contributions of each phase to the total performances. This illustrates that Walk1 took a disproportionate amount of time to complete among the High-Risk group in comparison to their Low-Risk counterparts.

![TUG Phase Times as % of Total TUG Time](image)

### Figure 7.9. Stacked bar chart displaying TUG phase times as percentages of total sensor TUG times for the High-Risk and Low-Risk groups.

Many of the accelerometer and gyroscope-derived variables for the Turn phase also differed significantly between groups, as displayed in Table 7.7. Measures of variance in acceleration and angular velocity on all axes were higher among the Low-Risk group than High-Risk participants. Many of the minimum and maximum acceleration and angular velocity variables selected were also significantly greater among the Low-Risk group, which – in keeping with the greater variance – indicates a wider range of amplitudes for both measures in this group.
7.9 Sensor-Based Assessment of Dynamic Tasks: Discussion

7.9.1 5m Walk Test: Sensor-Based Gait Analysis

As expected, mean gait speed in the Low-Risk group was similar to reference values for healthy adults of a similar age (Bohannon and Williams Andrews 2011) – including accelerometer-derived reference values (Auvinet et al. 2002) – whereas the High-Risk group was significantly slower. Gait speed results between groups have previously been discussed in Chapter 6, Section 6.4.1, and so will not be discussed further here.

Although gait speed is a highly valuable clinical measure in older adults (Studenski et al. 2011, Middleton et al. 2014), the sensor data obtained allowed differences in gait between groups to be examined in greater depth than via speed alone. Results demonstrated that the Low-Risk group achieved their faster gait speed by taking faster steps and covering the 5m distance in fewer steps, as indicated by the shorter mean step time and lower step count over 5m respectively. These characteristics resulted in a higher cadence among Low-Risk participants i.e. they took more steps per minute than High-Risk participants. Lower cadence in the High-Risk group suggests a more conservative gait pattern, since the longer gait cycle at a lower cadence is achieved by lengthening the stance phase and the time spent in double limb support, thereby reducing the single limb support proportion of the gait cycle and thus reducing the dynamic balance demands of gait (Whittle 2007, p.97).

Step time variability was higher among the High-Risk group than among the Low-Risk group, which is consistent with previous research showing that step and stride time variability increases with increasing fall-risk (Menz et al. 2003a, Callisaya et al. 2011, Hausdorff et al. 2001). The actual step time variability values obtained for the High-Risk group are comparable to those obtained by Menz et al. (2003c) among older adults, while the values obtained for the Low-Risk group are similar to those observed among healthy young adults (Menz et al. 2003c), which further illustrates the extent of the low level of fall-risk among the Low-Risk group in this study.

The higher RMS values noted among the Low-Risk group for ML, AP and RSS accelerations are also as expected, since RMS acceleration values increase with increasing gait speed (Menz et al. 2003b, Moe-Nilssen 1998b). Previous studies have also found higher RMS accelerations during walking in younger adults compared to older adults (Menz et al. 2003c, Mazza et al. 2008), which again shows that the Low-
Risk group’s gait shares further characteristics with a low fall-risk population. The lower RMS values noted in the High-Risk group may also be considered as an indicator of elevated fall-risk, as lower acceleration amplitudes have been found in older adults who perform poorly on assessments of balance and mobility (Ishigaki et al. 2011).

From a clinical perspective, the overall gait analysis findings may appear slightly counter-intuitive. It may be expected that step time variability would be lower among the High-Risk group, since they appear to adopt a more conservative gait pattern in terms of speed, cadence and acceleration amplitudes. However, gait variability – despite being a valid marker of fall-risk (Hausdorff et al. 2001, Lord et al. 1996, Verghese et al. 2009) – should not be confused with gait stability. Stability is the capacity to respond to perturbations, and is distinct from gait variability (Dingwell and Marin 2006). Gait variability has been noted to increase as gait becomes slower in both younger (Jordan et al. 2007, Dingwell and Marin 2006) and older adults (Kang and Dingwell 2008). However, local dynamic stability has been found to increase at slower gait speeds, despite greater gait variability (Kang and Dingwell 2008, Dingwell and Marin 2006). This suggests that reducing gait speed is a strategy which aims to make gait more stable, rather than less variable, which would explain why older adults tend to slow their gait when presented with challenging conditions to avoid trips and falls (Menz et al. 2003b, Pavol et al. 2001, Uemura et al. 2011). Although gait stability was not measured in this study, it must be considered as a potential influence on overall gait patterns since the relationships between gait stability, variability, speed and fall-risk are complex and remain unclear (Bruijn et al. 2009).

### 7.9.2 Sensor-Based TUG Analysis

As observed in Chapter 6, Section 6.4.1, the Low-Risk group’s total TUG times were within the bounds of reference values for their age group (Bohannon 2006b), while the High-Risk group’s times were indicative of increased fall-risk (Shumway-Cook et al. 2000, Alexandre et al. 2012), regardless of the timing method. However, sensor-derived TUG times were consistently slightly longer than the manually-timed TUG. The difference between the sensor and manual TUG times must be explained by the endpoints chosen for each method, since the stopwatch and sensor recording started simultaneously. The manually-timed TUG ended once the participant sat on the chair at the end of the test, whereas the sensor-based test was considered to have finished when
the participant was at rest at the end of the TUG (i.e. the point at which the signal plateaued), in order to facilitate consistent end-point selection. Thus, the sensor-derived time was slightly longer since it also included time spent moving into a resting position after chair contact.

The TUG was segmented in 5 main phases in this study, all of which differed significantly in duration between groups: STS1, Walk1, Turn, Walk2 and TurnSit. These phases are similar to those adopted in previous studies of instrumented TUG performance, and have been used to successfully classify fall-risk (Zakaria et al. 2013, Tmaura et al. 2013), frailty (Galan-Mercant and Cuesta-Vargas 2014), and disability (Weiss et al. 2013) in older adults, and mobility impairments in individuals with hemiplegia (Higashi et al. 2008) and Parkinson’s disease (Zampieri et al. 2010). The clinical relevance of analysing the performance of each phase of the TUG is that it may be used to highlight specific areas of difficulty in task performance (e.g. walking, turning, sit-to-stand transitions) on an individual basis, and thus to inform subsequent interventions (Tmaura et al. 2013, Zakaria et al. 2013).

In this study, the Walk1 phase was identified as taking a disproportionate amount of time to complete for the High-Risk group. Sit-to-walk has been identified as a challenging postural transition for older adults, since they tend to take longer to complete the transition, delay the initiation of gait and begin gait with shorter step lengths and lower step velocities when compared to healthy younger adults (Buckley et al. 2009, Lockhart et al. 2012). These shorter and slower initial steps, coupled with the poorer gait performance of the High-Risk group noted in the 5m walk test, may explain the disproportionately poor performance of the High-Risk group during the Walk1 phase in comparison to the Low-Risk group.

A novel element of the TUG phase times analysis in this study was the exploration of ratios between certain TUG phases. The lower ratio of STS2:TotalTurnSit seen in the High-Risk group indicates that these participants adopted a different strategy to perform this task than Low-Risk participants. Their tendency to perform a more distinct turn followed by a stand-to-sit, as opposed to a more fluid turning and sitting movement, echoes the changes in stand-to-walk noted previously, where older adults did not merge the tasks to the same extent as healthy younger adults (Buckley et al. 2009). A longer duration of the turn-to-sit phase has previously been noted in people with early untreated Parkinson’s disease (Salarian et al. 2010), but this loss of fluidity in the
*TotalTurnSit* phase is a novel marker identified in this study to characterise the performance of community-dwelling adults at risk of falling.

The more in-depth analysis of the *Turn* phase revealed that acceleration and angular velocity variance and amplitude ranges were significantly lower among the High-Risk group compared to the Low-Risk group, which again suggests a more conservative strategy in this phase on the part of higher-risk participants. The lower ranges of yaw (x-axis) and roll (z-axis) angular velocity seen in the High-Risk group are consistent with the slower *Turn* phase observed, and have been seen previously in high fall-risk older adults (Zakaria et al. 2013, Greene et al. 2010), as well as frail older adults (Galan-Mercant and Cuesta-Vargas 2014) and those with instrumental activities of daily living disability (Weiss et al. 2013). It is likely that the High-Risk group favoured a more stable, but slower ‘step turn’ strategy, whereas the Low-Risk group were comfortable using a ‘spin turn’, which involves a faster pivot on the stance foot (Hase and Stein 1999). This slower ‘step turn’ strategy has been noted as a useful and easily observed clinical marker of turning difficulty in older adults and those at risk of falling or with low balance confidence (Thigpen et al. 2000, Leigh Hollands et al. 2010, Fuller et al. 2007). Clinically, the ability of sensor-based TUG analysis to quantify turn performance during the TUG, stand-to-sit strategy and segmented phase times may add great value to conducting this quick test of mobility, as it could offer clinicians multiple markers of mobility performance and fall-risk in one simple tool, aside from total TUG time alone.

### 7.10 Limitations

Many results from our sensor-based static and dynamic task analyses successfully discriminated between the High-Risk and Low-Risk groups and provided clinically-meaningful quantitative descriptors of task performance. Despite this, there were also some limitations.

The issue of multiplicity must be considered as a limitation to the statistical methods applied (Berry 2007), since the use of multiple single comparisons via t tests and/or non-parametric tests increases the probability of detecting statistically significant differences between the High-Risk and Low-Risk groups. However, making adjustments to counteract this type I error increases the risk of type II error (Rothman
1990). Given that the primary aim of this chapter was to identify any sensor-based variables that differed between the High-Risk and Low-Risk groups, and to consider their clinical relevance, it was considered more advantageous to risk identifying some irrelevant variables than overlooking potentially meaningful variables. Also, analysis of the fall-risk classification accuracy of all variables identified will be carried out in Chapter 8, which may assist in ruling out any potentially irrelevant variables included based on the results obtained in this chapter.

A single waist-mounted sensor was used in this study. A multi-sensor system could be used to extract additional features which may be relevant to measuring balance and thus create more accurate fall-risk classification models (Greene et al. 2012b). However, a single sensor is more feasible to operate, as discussed in Chapter 3, and has been shown to be useful in assessing fall-risk based on standing balance previously (Doheny et al. 2012a, Doheny et al. 2012b, Greene et al. 2012a, O'Sullivan et al. 2009).

As mentioned in Chapter 6, the short-term nature of the falls prevention programme limited the prospects of detecting large changes in the High-Risk group following intervention, as per our secondary research question. However, positive neural effects of training on postural control have been noted in young adults after only four weeks of balance training at a similar frequency and intensity to this intervention (Granacher et al. 2011), thus some beneficial training effects can still be expected in an intervention of this duration.

The use of more challenging standing balance tasks may have better discriminated between groups, but as found in the feasibility study (Chapter 3), many participants may not have been able to attempt single leg stance and may have been unsafe attempting tandem stance. This would have limited the ability of the assessor to gather sensor data safely for such conditions in this study, but may be possible to implement in future work where more than one assessor is available. Also, as mentioned previously, the methods used to assess standing balance in this study did not allow differentiation between the underlying systems which govern balance performance, as is the case in much research and clinical practice (Pasma et al. 2014).

As regards dynamic tasks, the sheer quantity of data generated and potential variables that may be extracted from 5m walk and TUG performances means that it is neither possible nor feasible to perform exhaustive data analysis. For example, although the
prioritisation of the Turn phase for in-depth analysis was clearly justified by the results obtained in the current study, the sit-to-stand and stand-to-sit phases have also previously been found to contain useful data for classifying frailty and fall-risk in older adults (Galan-Mercant and Cuesta-Vargas 2014, Weiss et al. 2011), thus other potentially relevant variables may have been overlooked given the selective nature of the analysis. Similarly, gait stability may have been a useful additional variable to extract, since reduced stability is associated with increased risk of falling (Lockhart and Liu 2008, Toebes et al. 2012). However, the small number of gait cycles recorded over the 5m walk test is not optimal for calculating measures of gait stability (Bruijn et al. 2009, Hamacher et al. 2011). Recent research has shown that at least 15 bouts of eight strides are required to obtain valid measurements of gait stability (van Schooten et al. 2014). Thus, a longer walk test with a greater number of repetitions should be used in future research where gait stability is a variable of interest.

Finally, gait variability in the 5m walk was calculated as the standard deviation of the mean step time for each 5m walk trial. Pooling left and right step times in this way can introduce asymmetry as a confounding factor, thus limiting the meaningfulness of step time variability (Lord et al. 2011). However, accelerometer-based measurement of gait variability, calculated as the standard deviation of distinct left and right step times, has also previously been found to show low repeatability and poor reliability (Senden et al. 2009). Therefore, separating left and right step times may not have solved this potential issue. Although gait variability is commonly based on standard deviation, many other methods exist. Perhaps using a more robust parameter than standard deviation – which is readily influenced by outliers – may be advisable in future research to ensure reliability and repeatability (Chau et al. 2005).

7.11 Chapter Summary

As per the primary aim of this chapter, a range of variables derived from sensor-based assessments of static and dynamic task performance were noted to distinguish between the high and low fall-risk groups in this study. For the assessments of standing balance specifically, these variables were AP and RSS acceleration SEF, as well as inter-optima jerk and acceleration amplitude in the ML direction. Selected variables were also found to distinguish between standing balance task conditions. In more challenging standing balance conditions, greater sway angle variability, overall and inter-optima acceleration
amplitudes and inter-optima jerk were noted, as was lower acceleration SEF. Some changes in selected accelerometer variables suggested improvements in AP postural control with eyes closed and with reduced base of support following intervention. The inclusion of more challenging standing balance tasks may have been necessary to elicit more detectable differences between groups, or changes following intervention.

From two simple tests of dynamic task performance, a number of sensor-derived temporal and kinematic variables were observed to provide meaningful markers of gait and mobility performance that are characteristic of a community-dwelling older adult’s level of fall-risk. Although the analysis of the dynamic task data was selective in nature, and therefore could not identify an exhaustive list of relevant variables, a highly useful array of meaningful sensor-based gait and mobility variables were obtained. The sensor-based variables which were found to differ between the high and low fall-risk groups in this chapter will be further examined in Chapter 8 to determine their precise capacity to classify individuals based on their level of fall-risk, thereby indicating their relevance to clinical practice.
CHAPTER 8. CLASSIFYING FALL-RISK USING CLINICAL AND SENSOR-BASED METHODS
8.1 Introduction

In Chapters 6 and 7 a number of clinical and sensor-based variables that differed between the high and low fall-risk groups in this study were identified. This partially answers our primary research question, as it is clear from these findings that sensor-based variables can distinguish between groups of community-dwelling older adults based on their level of fall-risk.

However, to determine whether these sensor-based fall-risk assessment (SBFRA) variables can be used as clinically meaningful markers of fall-risk, it is necessary to compare the clinical and sensor-based variables identified in terms of their abilities to classify individuals as being at high or low risk for falls. This ability to classify individuals as being at a high or low level of fall-risk is vital in clinical practice, since identifying those who are at risk for falls enables clinicians to provide timely and appropriate falls prevention interventions.

First, this chapter will present the statistical methods used and the rationale for their usage. The results will initially focus on comparing the fall-risk classification properties of each of the significant clinical and sensor-derived variables identified in the preceding chapters. Then, the optimal selection of variables for classifying individuals as being at high risk for falls will be determined using classification and regression trees (CRTs). The CRTs will be developed using clinical variables, sensor-derived variables and a combination of both in order to compare the classification properties of SBFRA to clinical assessments and to determine if SBFRA can be used to augment clinical assessment findings.

8.2 Methods

The statistical methods used in this chapter were selected based on the statistical advice of Dr. Jean Saunders, a statistician based in the Statistical Consulting Unit at the University of Limerick. All statistical analyses were performed using IBM SPSS Statistics for Windows Version 20.0 (IBM Corp., Armonk, USA).
8.2.1 Characteristics of Sample and Criteria for Classification

Although participants were recruited and assessed as two separate groups up to this point of the thesis, the statistical methods used in this chapter consider all participants as a single sample (n=71). Data for the High-Risk group from the Pre-Intervention assessments only were included in the analyses in this chapter, since this was the High-Risk participants’ first assessment and thus avoids the potential confounding influence of a learning effect at the Post-Intervention assessment. Also, a more complete data set for the High-Risk group was available for the Pre-Intervention assessment, which enabled a larger number of participants to be included in the classification analyses. The purpose of treating the two groups as one sample is to determine the capacity of the selected variables – or combinations of variables – to classify participants as being at risk of falling when presented with a range of participants of low and high levels of fall-risk i.e. both groups together. Using a dichotomous method of classifying fall-risk has its limitations, since fall-risk is a complex, multifactorial construct. Individuals may present with various fall-risk factors to varying extents, thus creating a spectrum of fall-risk rather than distinct categories. However, the statistical methods adopted in this chapter were chosen to reflect the type of decisions which face clinicians in practice, namely deciding whether a client is at risk of falling and in need of intervention (High-Risk) or not (Low-Risk).

Classification accuracy was determined based on membership of the High-Risk group i.e. ‘group’ was chosen as the dependent variable. As per the inclusion criteria described in Chapter 5, participants in the High-Risk group had either experienced one or more self-reported falls in the previous 12 months – according to the ProFaNE definition of a fall described in Chapter 1 (Lamb et al. 2005) – or were considered to be at risk or afraid of falling by a healthcare practitioner. As such, the High-Risk group in this study represents a range of older adults, from very high-risk individuals with a history of multiple falls, to lower risk individuals who may have sustained a single fall or have begun to exhibit declining balance and mobility. Basing classification accuracy on such an inclusive category could lead to misleadingly high levels of accuracy for the classification models which are to be obtained. Equally, selection bias may also increase classification accuracy, since participants were recruited according to the criteria chosen to define the High-Risk and Low-Risk groups. Classification based on falls history over the previous 12 months was considered as a potential alternative dependent variable by which to classify participants while minimising these limitations, but was rejected as
this would overlook participants who had not experienced a fall in this time-frame despite displaying clear risk factors for falls, such as marked impairments in balance and mobility or fear of falling and/or activity restriction. Thus, despite the limitations noted, the inclusion criteria for the High-Risk group were deemed to be a more accurate reflection of fall-risk status.

8.2.2 Determining the Classification Accuracy of Single Variables

First, all variables found to significantly differ between the High-Risk and Low-Risk groups at any time-point were identified from the clinical variables described in Chapter 6 and the sensor-derived variables in Chapter 7. The full list of these variables will be presented in Section 8.3, Table 8.1.

Then, taking all participants included in the main study as a whole (n=71), receiver operator characteristic (ROC) curves were plotted for each significant variable to determine its accuracy in classifying participants from the full sample as being members of the High-Risk group. ROC curves are widely used in clinical research to measure the accuracy of diagnostic tests or predictive models (Zou et al. 2007). The ROC curve is a plot of the sensitivity of the test on the y-axis versus ‘one minus the specificity’ of the test on the x-axis, for a range of threshold values of the test in question. Since the ROC curve illustrates accuracy across a range of threshold values, it can be highly useful when examining tests for which optimal thresholds or cut-off values are not established (Fan et al. 2006), as is the case for the sensor-derived variables obtained in the current study.

For each significant clinical and sensor-based variable identified in Chapters 7, 8 and 9, the area under the ROC curve (AUC) was calculated based on the nonparametric assumption as an indicator of the average discriminative power of the variable across the range of threshold values obtained (Faraggi and Reiser 2002). The AUC ranges from 0.5, which indicates a discriminative value no better than chance, to a maximum of 1, which represents perfect discrimination. For this study, variables with AUC values >0.9 are considered to have excellent discriminative value and those in the range of 0.7-0.9 are considered to be moderate in value (Fischer et al. 2003).

In this study, the AUC represents the overall probability that the selected variable is higher for a participant in the High-Risk group than for a Low-Risk group participant.
across all cut-off values. Therefore, AUC is an indicator of discriminative power, not an indicator of the actual probability that an individual is classified correctly based on the selected variable at the optimal cut-off value. Thus, the sensitivity, specificity, overall classification accuracy, and positive and negative predictive values at the optimal cut-off value were also examined for the three top-performing clinical and sensor-derived variables, as indicators of their classification properties. The optimal cut-off value for each variable was selected as the point on the ROC curve closest to the point (0, 1) (Akobeng 2007b). These variables all displayed AUC values approximately $\geq 0.9$ i.e. excellent discriminative value. The definitions and methods used to calculate these key classification properties are described below (Akobeng 2007a, Lalkhen and McCluskey 2008, Alberg et al. 2004).

- **Sensitivity**: The ability of the variable to correctly identify participants who were in the High-Risk group.

  \[\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}\]

  Where ‘true positives’ refers to those classified as being in the High-Risk group who were actually in the High-Risk group, and ‘false negatives’ refers to those classified as not being in the High-Risk group who were actually in that group.

- **Specificity**: The ability of the variable to correctly identify participants who were not in the High-Risk group.

  \[\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}\]

  Where ‘true negatives’ refers to participants who were classified as not being in the High-Risk group and were not actually in that group, and ‘false positives’ refers to those who were classified as being in the High-Risk group but were not actually in that group.

- **Accuracy**: The overall probability that a participant will be correctly classified by the selected variable.

  \[\text{Accuracy} = \frac{(\text{True Positives} + \text{True Negatives})}{\text{Total number of participants}}\]

- **Positive Predictive Value (PPV)**: The proportion of participants classified as being in the High-Risk group who actually are in that group.
PPV = True Positives / (True Positives + False Positives)

- **Negative Predictive Value (NPV)**: The proportion of participants classified as not being in the High-Risk group who are not in that group.

\[ NPV = \frac{\text{True Negatives}}{(\text{True Negatives} + \text{False Negatives})} \]

Considering the definitions provided and the methods of calculation, it can be seen that sensitivity, specificity and accuracy are properties related to the test variable itself, whereas PPV and NPV are also determined by the prevalence of fall-risk in the sample. From a practical standpoint, PPV and NPV are highly meaningful to clinicians because they indicate the probability that a positive assessment result for high fall-risk represents an actual risk of falling for a patient. Thus, these properties were used to examine the ability of the selected clinical and sensor-derived variables to correctly classify participants who are at high risk of falls and those who are not, and to facilitate comparisons between the two types of assessment variables.

### 8.2.3 Classification and Regression Tree Models

CRT analysis is a method of classifying or segmenting a given population into easily-defined, clinically-meaningful subgroups whose members share similar health-related characteristics. As such, CRT methods are becoming increasingly recognised for use in the public health domain (Lemon et al. 2003). Three CRT models were created using three distinct categories of variables: CRT1 used clinical variables only; CRT2 used sensor-derived variables only; CRT3 used both clinical and sensor-derived variables combined. Three separate trees were created for the following reasons:

- To compare the classification accuracy of clinical and sensor-based assessments, by comparing CRT1 versus CRT2
- To examine whether or not sensor-derived variables can be used to improve the classification accuracy of clinical assessments, based on the results of CRT3

The CRT method used specified a minimum parent node size of 5 and a minimum child node size of 3. Tenfold cross-validation was also implemented, which partitions the data into sets on which the model is tested, to ensure the most accurate model is selected (Schaffer 1993). This same classification tree development methodology has been successfully used previously in the field of SBFRA, but using different clinical and
sensor-derived variables, among a different population (geriatric clinic inpatients) and with a smaller sample size than the current study (Marschollek et al. 2011a).

The overall classification accuracy, sensitivity, specificity, positive and negative predictive values of each CRT model were calculated to facilitate comparisons in classification properties between clinical and sensor-derived variables, and to determine whether the sensor-derived variables could be used to augment or improve the accuracy of clinical assessments. CRTs were chosen for this purpose as they present easily interpreted, meaningful results and the findings may be readily transferred to clinical practice (Lemon et al. 2003).

8.3 Results
A sample ROC curve for the gait speed variable is presented in Figure 8.1 to illustrate how optimal cut-off values were determined for each variable. In this figure, the point of intersection of the dotted red lines indicates the optimal cut-off value for gait speed (1.02m/s), since this point is closest to (0, 1) and represents the best possible combination of sensitivity and specificity for this variable. Points further to the right on this curve would be more sensitive but much less specific, and vice versa for points to the left of the chosen value. Figure 8.1 also demonstrates that the AUC for gait speed is large – with a value of 0.906 – which indicates that this variable has an excellent capacity to discriminate between participants based on their level of fall-risk.
Figure 8.1. Sample ROC curve for the gait speed variable. The diagonal dashed line indicates an AUC of 0.5, with a classification accuracy equivalent to chance. The optimal cut-off value is located at the point of intersection of the vertical and horizontal dotted red lines (1.02m/s), where the sensitivity = 86.5% and the specificity = 84.8% (note that the x-axis values are 1-specificity).

8.3.1 Comparing Single Variables: Clinical versus Sensor-Derived

Table 8.1 presents the AUC values for all clinical and sensor-derived variables that differed significantly between the High-Risk and Low-Risk groups. The sensor-derived variables are separated according to the tasks to which they relate: static, 5m walk and TUG (both timings and variables related to the turn phase). In Table 8.1, the variables which exhibited excellent discriminative capacity (defined as an AUC value ≥0.9 approx.) are marked in bold. The clinical variables meeting this criterion are BBS score, gait speed and PASE score, while the sensor-derived variables are mean step time and cadence during the 5m walk test and the variance of z-axis (antero-posterior) acceleration during the turn phase of the TUG.
Table 8.1. AUC values for all clinical and sensor-derived variables that differed significantly between High-Risk and Low-Risk groups.

<table>
<thead>
<tr>
<th>Clinical</th>
<th>AUC</th>
<th>Static</th>
<th>AUC</th>
<th>AUC</th>
<th>AUC</th>
<th>AUC</th>
<th>AUC</th>
<th>AUC</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.681</td>
<td>AP Stand</td>
<td>0.735</td>
<td>Step Count</td>
<td>0.790</td>
<td>Sensor TUG</td>
<td>0.844</td>
<td>TAcelMeanZ</td>
<td>0.713</td>
</tr>
<tr>
<td>Medications</td>
<td>0.757</td>
<td>SEF</td>
<td>Cadence</td>
<td>0.954</td>
<td>STS1</td>
<td>0.719</td>
<td>TAcelVarX</td>
<td>0.815</td>
<td></td>
</tr>
<tr>
<td>1-Year Fall History</td>
<td>0.882</td>
<td>AP EC SEF</td>
<td>0.675</td>
<td>Mean Step Time</td>
<td>0.961</td>
<td>Walk1</td>
<td>0.869</td>
<td>TAcelVarY</td>
<td>0.840</td>
</tr>
<tr>
<td>BBS</td>
<td>0.916</td>
<td>AP FT SEF</td>
<td>0.683</td>
<td>Step Time</td>
<td>0.830</td>
<td>Turn</td>
<td>0.771</td>
<td>TAcelVarZ</td>
<td>0.895</td>
</tr>
<tr>
<td>TUG</td>
<td>0.837</td>
<td>RSS EC SEF</td>
<td>0.702</td>
<td>Variability</td>
<td>Walk2</td>
<td>0.713</td>
<td>TAcelMaxX</td>
<td>0.679</td>
<td></td>
</tr>
<tr>
<td>FTSS</td>
<td>0.856</td>
<td>ML Stand</td>
<td>0.732</td>
<td>ML RMS Accel</td>
<td>0.724</td>
<td>TotalTurnSit</td>
<td>0.838</td>
<td>TAcelMaxY</td>
<td>0.745</td>
</tr>
<tr>
<td>Gait Speed</td>
<td>0.906</td>
<td>Jerk</td>
<td>AP RMS Accel</td>
<td>0.807</td>
<td>STS2</td>
<td>0.676</td>
<td>TAcelMaxZ</td>
<td>0.826</td>
<td></td>
</tr>
<tr>
<td>FaB</td>
<td>0.855</td>
<td>ML Stand</td>
<td>0.688</td>
<td>RSS RMS Accel</td>
<td>0.779</td>
<td>STS2:TotalTurnSit</td>
<td>0.782</td>
<td>TAcelMinX</td>
<td>0.736</td>
</tr>
<tr>
<td>GDS</td>
<td>0.758</td>
<td>Amplitude</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>TAcelMinY</td>
<td>0.654</td>
</tr>
<tr>
<td>MFES</td>
<td>0.892</td>
<td>ML FT No.</td>
<td>0.598</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>TAcelMinZ</td>
</tr>
<tr>
<td>PASE</td>
<td>0.904</td>
<td>of Optima</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Variables with excellent discriminative capacity (AUC ≥0.9 approx.) are presented in bold. AUC = area under the curve; TUG = Timed up and go test; BBS = Berg Balance Scale; FaB = Falls Behavioural Scale for the Older Person; GDS = Geriatric Depression Scale; MFES = Modified Falls Efficacy Scale; PASE = Physical Activity Scale for the Elderly; VAS = Visual analogue scale; AP = antero-posterior; SEF = Spectral edge frequency; EC = eyes closed; FT = feet together; RSS = root sum square; ML = medio-lateral; RMS = root mean square; STS = sit-to-stand; T = Turn; Accel = Acceleration; Var = Variance; Min = Minimum; Max = Maximum; AngVel = Angular Velocity.
To further compare the relative classification properties of each set of variables, the best-performing variables identified in Table 8.1 were examined in greater detail. These variables are those with AUC values approximately ≥0.9 and represent the three best-performing clinical and sensor-derived variables. The optimal cut-off values for fall-risk classification in our sample for these variables are presented in Table 8.2. For each variable, the sensitivity, specificity, PPV and NPV at the chosen cut-off value is also presented. It can be seen that the single most accurate variable for classifying participants as being in the High-Risk group is cadence, measured in steps per minute and obtained from sensor-derived step count during the 5m walk test. In this sample, a cadence of ≤109.3 steps per minute exhibits equally excellent sensitivity, specificity, PPV and NPV in classifying participants as being at high risk of falling.

Table 8.2. Optimal cut-off values, with corresponding sensitivity and specificity, for the clinical and sensor-derived variables which exhibited excellent discriminative capacity based on AUC values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Clinical Variables</th>
<th>Sensor-Derived Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BBS</td>
<td>Cadence</td>
</tr>
<tr>
<td></td>
<td>Gait Speed</td>
<td>Mean Time</td>
</tr>
<tr>
<td></td>
<td>PASE</td>
<td>Step</td>
</tr>
<tr>
<td>AUC</td>
<td>0.916</td>
<td>0.954</td>
</tr>
<tr>
<td></td>
<td>0.906</td>
<td>0.961</td>
</tr>
<tr>
<td>Cut-Off Value</td>
<td>≤49.5&lt;sup&gt;a&lt;/sup&gt;</td>
<td>≤116.2&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>≤1.02&lt;sup&gt;b&lt;/sup&gt;</td>
<td>≤109.3&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>86.8%</td>
<td>90.9%</td>
</tr>
<tr>
<td></td>
<td>86.5%</td>
<td>87.9%</td>
</tr>
<tr>
<td></td>
<td>92.1%</td>
<td>90.9%</td>
</tr>
<tr>
<td></td>
<td>81.8%</td>
<td>80.0%</td>
</tr>
<tr>
<td></td>
<td>84.6%</td>
<td>81.5%</td>
</tr>
<tr>
<td></td>
<td>84.6%</td>
<td>82.1%</td>
</tr>
<tr>
<td></td>
<td>84.4%</td>
<td>80.7%</td>
</tr>
<tr>
<td>PPV</td>
<td>84.6%</td>
<td>84.6%</td>
</tr>
<tr>
<td></td>
<td>84.6%</td>
<td>89.3%</td>
</tr>
<tr>
<td></td>
<td>90.9%</td>
<td>88.2%</td>
</tr>
<tr>
<td>NPV</td>
<td>84.4%</td>
<td>84.4%</td>
</tr>
<tr>
<td></td>
<td>89.3%</td>
<td>90.9%</td>
</tr>
</tbody>
</table>

Note. AUC=Area under the curve; PPV=Positive Predictive Value; NPV=Negative Predictive Value; TAccelVarZ = Acceleration Signal Variance on the z-axis (AP) during the Turn phase of the Timed Up and Go test; Units for cut-off values are as follows: <sup>a</sup> = points on an ordinal rating scale; <sup>b</sup> = metres per second; <sup>c</sup> = steps per minute; <sup>d</sup> = seconds; <sup>e</sup> = g<sup>2</sup>; PPV = positive predictive value; NPV = negative predictive value.
8.3.2 Classification and Regression Trees to Classify High Fall-Risk

Three separate CRT models were created: CRT1 was comprised of clinical assessment variables only (Figure 8.2); CRT2 was comprised of sensor-derived variables only (Figure 8.3); and CRT3 was created using all clinical and sensor-derived variables (Figure 8.3 also). The classification properties of each CRT model are displayed in tables accompanying each Figure: CRT1 in Table 8.3, CRT2 and CRT3 in Table 8.4. These tables display the overall accuracy, sensitivity, specificity, PPV and NPV for each CRT model. As displayed in Figure 8.3, the same CRT model was created when both clinical and sensor-derived variables were eligible for inclusion in the model as when sensor-derived variables only were included. This indicates that the most accurate classification was obtained using sensor-derived variables only, and that the results of the clinical assessment tools did not improve the capacity of these sensor-derived variables to classify participants as being at high risk of falls.
Figure 8.2. CRT1, which was created based on clinical assessment tool variables only.

Table 8.3. Classification properties of CRT1, with 2x2 table used to calculate properties.

<table>
<thead>
<tr>
<th>CRT1 (Clinical Variables Only)</th>
<th>High-Risk?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted No</td>
</tr>
<tr>
<td>Accuracy</td>
<td>95.8%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>94.7%</td>
</tr>
<tr>
<td>Specificity</td>
<td>97.0%</td>
</tr>
<tr>
<td>PPV</td>
<td>97.3%</td>
</tr>
<tr>
<td>NPV</td>
<td>94.1%</td>
</tr>
<tr>
<td>Observed No</td>
<td>32</td>
</tr>
<tr>
<td>Observed Yes</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
</tr>
</tbody>
</table>

Note. CRT1 = Classification and regression tree 1; PPV = Positive predictive value; NPV = Negative predictive value.
Figure 8.3. The model which represents both CRT2, created using sensor-derived variables only, and CRT3, which used a combination of clinical and sensor-derived variables.

Table 8.4. Classification properties of CRT2 and CRT3, including 2x2 table.

| CRT2 (Sensor-Derived Only) and CRT3 (Clinical and Sensor-Derived Variables) |
|-----------------------------|-----------------------------|-----------------------------|
| Accuracy | 95.8% | High-Risk? | Predicted No | Predicted Yes | Total |
| Sensitivity | 92.1% | Predicted No | 33 | 0 | 33 |
| Specificity | 100.0% | Observed No | 3 | 35 | 38 |
| PPV | 100.0% | Observed Yes | 36 | 35 | 71 |
| NPV | 91.7% | Predicted Yes | 36 | 35 | 71 |

Note. CRT = Classification and regression tree; PPV = Positive predictive value; NPV = Negative predictive value.
As shown in Figure 8.2, CRT1 classifies participants based on one-year falls history, gait speed, TUG time and FTSS time. Having had one or more falls in the past year and a gait speed of ≤0.6m/s classified 89.5% (34 out of 38) of the high risk participants correctly. CRT2 and CRT3 both classify participants based on cadence and the spectral edge frequency of the acceleration signal in the antero-posterior direction during quiet standing (Figure 8.3). Tables 10.3 and 10.4 indicate excellent overall classification accuracy which was the same for all CRT models (95.8%). CRT1 displayed similar sensitivity (94.7%) and specificity (97%) values, whereas CRT2 and CRT3 were marginally less sensitive (92.1%) but displayed 100% specificity. All CRT models showed PPVs and NPVs of over 90%.

8.4 Discussion

In order to interpret the results of this chapter in a clinically-meaningful way it is necessary to consider the implications of the classification properties calculated for determining levels of fall-risk in practice. A highly sensitive test for fall-risk is a necessity in practice, since an assessment that incorrectly overlooks individuals who are actually at risk would be undesirable for both the clinician and the individual, considering the potential consequences of falls described in Chapter 1. Equally, specificity should also be high for fall-risk assessment tools, as a highly sensitive test with low specificity could result in many who are at low risk being incorrectly classified as high-risk. From a health service provision standpoint, this could lead to inappropriate referral to falls prevention interventions, unnecessarily long waiting lists and inefficient use of services.

The decision to use CRTs over multiple logistic regression models was made for a number of practical reasons relating to the clinical applicability of each method. Firstly, CRTs are more easily interpreted than logistic regression models as they do not contain complex algorithms (Stel et al. 2003a). Secondly, multiple logistic regression techniques may be less easily applied to inform clinical decision-making, since they are mostly used to estimate the average effect of a variable, accounting for other factors, on a specific dependent variable (Lemon et al. 2003). This means that such regression techniques consider the implication for the “average” individual in the sample, but do not consider subgroups with specific features. For example, in Figure 8.2, the High-Risk participants in CRT1, Node 3 have a recent history of falls and a markedly reduced gait...
speed, which suggests that they may benefit from interventions which focus on gait and mobility training, walking aid prescription and promotion of engagement in appropriate physical activity (PA). The two High-Risk individuals in Node 5 clearly exhibit very high level mobility – based on their gait speed and TUG results – and thus may be better served by interventions which target awareness of fall-risk behaviours and strategies to reduce them. This small subgroup may not have been identified had regression techniques been used, since it these individuals do not reflect the “average” of the group. Finally, when comparing their classification performances in previous studies of clinical and sensor-based fall-risk assessment, CRTs were found to outperform multiple logistic regression models (Marschollek et al. 2011a).

8.4.1 Comparing Single Variables: Clinical versus Sensor-Derived

Single variables were initially compared using AUC values which indicated that a number of clinical and sensor-derived variables had moderate or excellent abilities to discriminate between Low-Risk and High-Risk participants. This was useful for initially screening the many potentially relevant variables in this study, but is of limited meaning since AUC only provides an overall summary of discriminative capacity (Zou et al. 2007). From a clinical perspective, it is more meaningful to use ROC curves to identify optimally sensitive and specific cut-off values for the most accurate variables which can be used to classify individuals as being at high or low risk of falling (Akobeng 2007b).

In this sense, sensor-derived variables outperformed clinical variables when examined singly, particularly cadence and mean step time. This emphasises how useful a 5m walk test can be to perform in practice, since it is a quick and easily performed test which allows gait speed, cadence and mean step time to be obtained, all of which were among the top-performing variables. Equally, this highlights the great potential for clinically-meaningful applications of simple sensors to analyse gait in clinical practice. The simple gait variables identified in the current study could easily be obtained using readily available equipment such as a mobile phone, thus specific and potentially costly clinical equipment would not be required to measure these variables.

Clinical variables were also useful classifiers of fall-risk, with BBS and gait speed both displaying sensitivity, specificity, PPV and NPV in the region of 85%. The optimal BBS fall-risk cut-off score for participants in the current study was 49.5, which is
higher than the originally recommended score of 45 (Berg et al. 1992). This further supports the findings of previous studies, described in Chapter 2, which also utilised higher BBS fall-risk cut-off scores among ambulant community-dwelling older adults to improve its accuracy in predicting falls. The optimal gait speed cut-off value for classifying High-Risk participants was similar to that reported in previously published literature, at 1.02m/s (Fritz and Lusardi 2009).

Our results also support previous observations that PA levels are an important component of fall-risk, since a low PASE score was a highly sensitive (92.1%) classifier of fall-risk. However, the considerably lower specificity (72.7%) indicates that high PA levels do not necessarily equate to low fall-risk levels. This illustrates the limitations of considering single variables in isolation as classifiers of fall-risk, since this method overlooks the influences of potential confounding variables. When examining the classification properties of PASE score, it is necessary to remember that the relationship between PA and fall-risk is complex (Peeters et al. 2010a), and that other factors such as the type of PA undertaken (Gill et al. 2008), the level of risk exposure (Peeters et al. 2010b) and the fit between the person, task and environment (Wert et al. 2010, Faulkner et al. 2009) must be factored in to clinical decision-making.

The best performing single variable overall was sensor-derived cadence, with excellent sensitivity and specificity in classifying High-Risk participants. Cadence also displayed positive and negative predictive values of 90.9% for our sample, which means that an individual who exhibited a cadence of greater than 109.3 steps per minute had, approximately, a 91% chance of being Low-Risk. As such, the predictive values calculated in this study are highly meaningful for clinicians, as they answer the question of how likely it is that an individual is at risk or not at risk for falls given a particular test result (Lalkhen and McCluskey 2008).

However, predictive values are dependent on the prevalence of fall-risk in the sample (Akobeng 2007a, Lalkhen and McCluskey 2008). In our sample, that prevalence was approximately 50% since participants were recruited in two groups of approximately equal size, one at High-Risk for falls and one Low-Risk. This is a higher prevalence than in the general population of community-dwelling older adults, approximately 15-30% of whom fall each year (Soriano et al. 2007, Tinetti et al. 1988, Campbell et al. 1989, Shin et al. 2009). This has practical implications for the generalisability of our findings, since in a population with a lower prevalence of fall-risk PPVs will be lower.
(Lalkhen and McCluskey 2008). For example, if the prevalence of high fall-risk in our sample was only 15%, the PPV of cadence would have dropped to 63.6% i.e. a cadence ≤109.3 steps per minute would indicate a 63.6% chance that an individual was actually at high risk of falling. Conversely, the NPV in this sample would rise, such that a higher cadence would indicate to the clinician that an individual would have a 99% chance of not being high-risk for falls. This demonstrates the importance of establishing normative values and fall-risk thresholds for specific sensor-derived markers of fall-risk in a range of populations of varying levels of risk. Such research is necessary to inform the selection of optimal fall-risk cut-off values for specific groups, which can then be used to inform clinical decision-making. For example, high-fall risk groups may be identified so that focused falls prevention and safety awareness interventions can be implemented among such individuals, whereas low fall-risk individuals may be targeted with less costly and more appropriate health promotion interventions.

8.4.2 Classification and Regression Trees

The overall classification accuracy of all three CRT models was excellent, at 95.8% for all. Notably, no single variable was more accurate than the CRT models, which indicates that fall-risk is best determined using a multi-faceted approach to assessment, as per current clinical guidelines (American Geriatrics Society and British Geriatrics Society 2011). All CRT models showed positive and negative predictive values of over 90%, which indicates that these models can determine whether an individual in our sample is at high risk of falling or not with a high degree of certainty. However, as noted in section 10.4.1, PPV and NPV will change according to the prevalence of fall-risk in the sample.

CRT1, which used only variables obtained from clinical assessment, was based on one-year fall history, gait speed, TUG time and FTSS time. This model exhibited excellent accuracy; overall it was equally as accurate as CRT2 and CRT3, but was marginally more sensitive (94.7% versus 92.1%) and less specific (97% versus 100%). A previous longitudinal study also used falls in the previous year, TUG and FTSS performances as part of a classification tree to predict three-year risk of recurrent falls in community-dwelling older adults (Stel et al. 2003a). Thus, it is likely that the components of CRT1 could be useful to clinicians as a simple fall-risk assessment battery for the wider
population from which our sample was drawn, perhaps in clinical settings in which a more in-depth assessment is not feasible.

CRT2 and CRT3 were both based on sensor-derived cadence and AP Stand SEF variables, since the same tree was obtained when both clinical and sensor variables were entered into the model (CRT3) as when sensor variables only were entered (CRT2). These results, when considered along with those of CRT1, show that sensor-derived variables could classify High-Risk individuals in our sample equally as well as clinical variables, but that adding sensor-derived variables did not improve classification accuracy compared to clinical assessments alone. This is in contrast to previous findings in a sample of geriatric clinic inpatients, where adding sensor data to clinical assessment tool data improved the ability to classify in-hospital fallers using CRT models (Marschollek et al. 2009). However, that study only included three clinical assessment tools in the clinical assessment CRT model – TUG, St. Thomas Fall Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY) and Barthel Index – so their overall clinical assessment was not as comprehensive as that adopted in the current study. Even adding basic clinical data such as age, gender and body mass index improved their clinical model such that its performance matched that of the sensor-based model, as seen when the same sample was followed up one year after discharge from hospital (Marschollek et al. 2011b).

In terms of classification properties, our sensor-based CRT model outperformed logistic regression models derived from sensor-based TUG variables described in previous studies, which reported accuracies of 88% (Weiss et al. 2011) and 76.8% (Greene et al. 2010) in classifying participants based on falls history. Our model also outperformed the sensor-based classification tree models developed by Geitzelt et al. (2009) and Marschollek et al. (2011a). These findings may be explained by the larger array of sensor-based variables available for input in our model, since the studies cited used only selected variables from TUG and 20m walk performances. Equally, our larger sample size with a higher prevalence of falls may also have influenced these results.

The performances of our CRT models appear to compare favourably to commonly-used clinical fall-risk assessment tools, such as the BBS (Berg 1989b) and the Tinetti Performance Oriented Mobility Assessment (Tinetti 1986), although further prospective research is required to determine their abilities to predict future falls. When predicting falls in community-dwelling older adults, the Tinetti assessment tool has been found to
have a sensitivity of 70% and 50% specificity (Raîche et al. 2000), while the BBS has shown 53% sensitivity and 92% specificity (Bogle Thorbahn and Newton 1996). However, given the exceptionally high levels of classification accuracy obtained for our models, comparisons with other assessment methods must be considered with caution. If our models were to be applied in prospective studies and used to predict falls incidence, it would not be reasonable to expect such accuracy. Our classification was based upon a simple binary categorisation which was determined upon recruitment – participants were either in the High-Risk group or the Low-Risk group. Predicting the incidence of falls is much more prone to variability, particularly when using a broad definition of what constitutes a fall (Lamb et al. 2005), as this encompasses a range of fall types and precipitating factors that are not possible to predict with total accuracy based on baseline characteristics alone.

Due to the size of our sample and the potential for our sampling and classification criteria to have positively biased the accuracy of our CRT models, the potential issue of over-fitting of our CRT models must be considered (Strobl et al. 2009). With only 71 participants, who were recruited as two distinct groups of older adults – one at high risk and one at low risk for falling – it is not possible to say that our sample is truly representative of the general population of community-dwelling older adults. The CRT models created using our data set may have adapted to the specific characteristics of our sample, and therefore cannot be expected to exhibit such high levels of accuracy when generalised to the total population of community-dwelling older adults. Further testing of the classification accuracy of these models among larger, randomly-selected samples of community-dwelling older adults would be required to determine their applicability to the population at large.

8.4.3 Limitations

Cadence, in steps per minute, was assessed in this study via sensor-derived measurement of step count during the 5m walk test. One may argue that cadence is not strictly a sensor-based variable, since it can be calculated by counting the number of steps taken over a fixed period of time, either by observation at the time of testing or via video recording (Whittle 2007, pp.143-145). However, measuring cadence using sensors has the advantage of reducing the chance of human error in counting steps, as
well as being one of many potentially useful variables which may be extracted from sensor-based gait data simultaneously.

The analyses conducted use purely quantifiable methods to classify participants’ level of fall-risk. Previously, a geriatric team rating of patients’ fall-risk was shown to be a more accurate predictor of falls during a one-year follow-up period than TUG performance or STRATIFY score (Marschollek et al. 2011b). Although it did not outperform prediction models containing multiple variables, this still emphasises the important role that clinical reasoning and professional judgement play in fall-risk assessment in practice. Realistically, clinicians will decide whether an individual is at risk of falling or not using a combination of assessment tools, their knowledge of evidence-based fall-risk factors and their own clinical judgement. Thus, considering our findings from a practical standpoint, the SBFRA results described must be viewed as a useful means of augmenting the clinical reasoning process, rather than as a replacement for it.

8.5 Chapter Summary and Clinical Implications

This chapter has built upon the results presented in previous chapters to produce promising outcomes in favour of the use of SBFRA and the capacity of such methods to perform clinically meaningful fall-risk assessment in a sample of community-dwelling older adults, which was our primary overall research question. Sensor-derived variables marginally outperformed clinical variables in terms of their capacity to classify individuals based on their level of fall-risk, both singly and when combined to form classification trees. However, the classification properties of both assessment methods were excellent in our sample.

In terms of the practical implications of our findings in this chapter, our results emphasise the importance of conducting multi-faceted fall-risk assessments. The excellent classification properties of the clinical and sensor-based variables derived from the 5m walk test and the PASE are of immediate clinical relevance, since they illustrate the importance of including gait and PA assessments as part of a comprehensive fall-risk assessment. The sensor-derived variables displayed promising results in our sample, and further research to determine classification accuracy among larger, random samples of older adults, and to establish optimal cut-off points and
classification properties in other specific clinical populations is required. Overall, the sensor-based variables identified in this research have the potential to provide clinically meaningful information and can be useful to augment current fall-risk assessment methods as part of the clinical reasoning process.
CHAPTER 9. GENERAL DISCUSSION
9.1 Introduction

The primary purpose of this thesis was to investigate if evaluation of task performance via body-worn wireless inertial sensors could present a clinically-meaningful method of assessing fall-risk in community-dwelling older adults. The potential value or meaning which sensor-based fall-risk assessment (SBFRA) could offer in a clinical context was specifically judged in this thesis based on the ability of the sensor-based variables obtained to classify older adults according to their level of fall-risk, since the identification of individuals who are at risk of falling is crucial to the provision of timely and effective falls prevention services.

The secondary research question involved the exploration of clinical and sensor-based fall-risk profiles among High-Risk community-dwelling older adults before and after participating in a standardised community-based falls prevention intervention. This question aimed to provide original and meaningful information to clinicians on a sample community-based falls prevention intervention in Ireland, and to explore the use of SBFRA in this novel context.

Throughout the research process described in this thesis, a range of significant and original findings in relation to these research questions were produced. The following section will summarise the key findings noted during this work, with specific reference to their bearings on the overarching research questions, as well as their practical and clinical implications.

9.2 Summary of Key Findings

In Chapter 2, a systematic review identified the TUG, FTSS and tests of gait as potentially the most informative and clinically meaningful tasks to consider for inclusion in SBFRA procedures. This also highlighted that variables which reflect postural sway and gait performance should be considered for extraction from sensor-based data, and emphasised that clear and consistent methods of extracting variables must be developed.

Chapters 3 and 4 synthesised essential background literature to further inform the main study design, implementation and data analysis methods. The feasibility study described in Chapter 3 provided invaluable results and experiences which informed the design of the main study within the current research. The lessons learned regarding the feasibility
of implementing a study of SBFRA in a community setting, the practical aspects of SBFRA data collection, the learning and development opportunities provided by this feasibility study in relation to SBFRA data analysis, and the clinical research partnerships established contributed immensely to further methodological considerations and overall study design.

Chapter 3 also described how collaborative research partnerships with clinicians providing community-based falls prevention interventions were developed in order to facilitate a further study which addressed both our primary and secondary research questions. The reciprocal nature of this collaboration was described, as displayed by the commentary on how evidence was reviewed and applied to standardise and optimise an exercise-based falls prevention intervention for community-dwelling older adults at risk of falling.

The literature review in Chapter 4 addressed the learning needs identified in Chapter 3 in relation to the SBFRA implementation procedures and data analysis – a vital preparatory exercise for the design and interpretation of the main study. The findings of this review added to those of Chapters 2 and 3 to inform the main study design and the selection of the static and dynamic tasks included in our SBFRA protocol. The review findings also informed the array of potential variables that could be extracted from the data obtained to perform meaningful fall-risk assessment e.g. the decision to include the 5m walk as a test of gait and the selection of useful gait-derived variables such as step count and step time variability. The review contained in this chapter also introduced the possibility of using classification tree analysis methods to perform clinically meaningful fall-risk classification comparisons between selected variables, as performed in Chapter 8, as such methods were found to have been used successfully used in other populations but not yet in community-dwelling older adults.

Chapter 5 provided details of the main study design and methodology used to address our research questions. As regards our primary research question, a range of clinical and sensor-based variables that differed between the High-Risk and Low-Risk groups were identified in Chapters 6 and 7. Clinically, these groups differed in terms of self-rated health, falls efficacy, physical activity, falls-related behaviours and functional balance and mobility performance.
The static SBFRA data in Chapter 7 identified selected sensor-derived variables which distinguished between High-Risk and Low-Risk groups, including AP and RSS acceleration SEF. The innovative analysis of inter-optimum acceleration variables in these standing balance tasks proved to be a useful pursuit, since ML mean inter-optima jerk and acceleration amplitude also differed between groups.

Chapter 7 also identified a further range of temporal and kinematic variables from sensor-based assessment of dynamic task performance which differed between the high and low fall-risk groups. The analysis of segmented TUG phase times provided a number of potentially useful variables which distinguished between the groups, including the novel analysis of the ratio between the stand-to-sit time in relation to the total turn-and-sit time. Equally, a large number of the sensor variables derived from the in-depth analysis of the Turn phase differed between High-Risk and Low-Risk participants. All sensor-derived gait variables differed between groups, which emphasised the importance of gait assessment in those at risk of falls. It also justified the decision to include the 5m walk test rather than the FTSS in our SBFRA procedure, which was made following the feasibility study in Chapter 3. Additionally, it highlights the great potential for simple sensor-based gait measures to be of use in clinical practice.

Chapter 8 built upon the results presented in previous chapters to demonstrate the excellent fall-risk classification properties of both the clinical and sensor-based assessments used in the current research. Sensor-derived variables marginally outperformed clinical assessments when considered singly. Clinical-only, sensor-only and combined clinical and sensor variables all created equally accurate classification regression tree models. By identifying a range of clinical and sensor-based variables which differed between high and low fall-risk older adults, and then demonstrating that both sets of variables exhibit excellent fall-risk classification properties, this thesis has shown that wireless inertial sensors can be used to perform clinically-meaningful fall-risk assessments in community-dwelling older adults, thus answering our overall primary research question. The simple gait and balance variables identified in the current research could easily be obtained using simple devices e.g. via a smartphone, thus they present feasible options for objective gait and balance assessment in clinical practice.
Our secondary research question involved the exploration of clinical and sensor-based fall-risk profiles among High-Risk community-dwelling older adults before and after participation in a standardised community-based falls prevention intervention. Both clinical and SBFRA findings confirmed that this group was at high risk of falling and thus were appropriately referred for intervention. The clinical outcomes assessed in Chapter 6 showed that this particular intervention had a beneficial impact on participants’ clinician-rated balance performance, and also resulted in increased physical activity (PA) levels combined with reduced engagement in fall-risk behaviours and unchanged falls efficacy. These results indicate that a short intervention of this type can promote positive changes in performance-related and behavioural factors linked to increased fall-risk, although further evaluation of the long-term effects is required. The sensor-based findings in Chapter 7 showed some indicators of improved performance when standing in more challenging balance conditions (i.e. with reduced base of support, with eyes closed) following intervention, but no changes were noted in dynamic balance task performance. Although SBFRA was feasible to use in this clinical context and provided some useful in-depth objective analysis of standing balance performance following intervention, the lack of clearly-defined SBFRA protocols backed by evidence of their psychometric properties remains a barrier to the translation of SBFRA to practice as an outcome measure.

From a practical perspective, the results of this thesis emphasise the importance of conducting comprehensive, multi-faceted fall-risk assessments, since a broad array of differences were noted between the high and low fall-risk groups and a number of distinct variables were found to be meaningful classifiers of fall-risk in our sample. Our findings in relation to SBFRA may not have immediate implications for clinical practice, but they make a significant contribution to current understandings of the clinical applications of SBFRA and provide useful suggestions for future research, which will be discussed in Section 9.5.

Of immediate clinical relevance is the potential need for clinicians to more closely assess behavioural and activity-related outcomes as part of their multifactorial fall-risk assessments, since the PASE and FaB tools were not used by the primary care services providing the intervention in the current research, but were found to differ significantly between the high and low fall-risk groups, and to detect significant changes following intervention. The PASE also exhibited excellent fall-risk classification properties, as did
many variables extracted from the 5m walk test, further supporting the inclusion of these tools in comprehensive clinical fall-risk assessments.

9.3 Strengths of Thesis

One of the primary strengths of this thesis is the translational nature of the work carried out to fulfil our research questions. Despite the proliferation of publications on the use of wireless inertial sensor technology in the falls domain, a dearth of research seeking to apply SBFRA in a meaningful clinical context still exists. Through the research questions selected and the manner in which answers to these questions were pursued, this thesis provides a unique clinically-oriented perspective on the field of SBFRA. Although some researchers in this field are attempting to bridge the gap between technology-focused research and clinical practice (Shany et al. 2012a), the work described in this thesis successfully marries both clinical and technical perspectives to a unique extent by focusing on the potential clinical relevance and applications of all findings, an aspect of SBFRA which has been neglected to certain extent thus far and requires considerable development and further research.

The amalgamation of clinical and technical expertise in the current research facilitated the development of clinical research partnerships, as described in Chapter 3, which allowed this thesis to explore the use of SBFRA in tandem with a community-based falls prevention intervention, another original aspect of this research. As a secondary and exploratory aim, this did not produce many findings of immediate clinical relevance, but did allow a number of potential barriers and facilitators to be identified in relation to the use of SBFRA methods to measure clinical outcomes, which will be described in Section 9.5.

The thoroughly considered and evidence-based approach adopted in the current research allowed some of the methodological drawbacks of previous SBFRA studies to be addressed and improved upon. Firstly, the current research included a specific, well-defined clinical population. The methods of classifying fall-risk in this population were also clearly defined. A broad range of clinical assessment tools were included in the main body of this research which provided a more comprehensive fall-risk assessment than in many previously published studies. Consequently, this enabled more comprehensive comparisons to be made between SBFRA variables and a range of
clinically relevant fall-risk factors related to demographic characteristics, functional balance performance, behavioural and psychosocial factors. As noted in Chapter 4, these were some of the main shortcomings noted in previous SBFRA research.

9.4 Limitations of Thesis

Some limitations to the methodology adopted in the current research exist. The use of a cross-sectional design in one arm of the main study was appropriate for determining the capacities of clinical and SBFRA to classify individuals based on their current fall-risk status. However, if additional time and resources were available, a longer-term prospective study could have been carried out to also examine and compare the abilities of both clinical SBFRA results to predict the occurrence of future falls.

The sample sizes of the high and low fall-risk groups recruited in the current research may also be considered as a limitation. Larger samples with a greater variety of individuals of varying levels of fall-risk would have strengthened the findings in relation to the classification capacities of the selected variables. However, the number of participants recruited was limited by organisational and service provision structures, since the interventions from which participants were recruited were the only such accessible interventions in operation at the time of conducting the main study, and these interventions could only run a limited number of repetitions with a limited number of participants within the timeframe for this research. However, the sample sizes obtained in this research compare favourably to many other studies in the field of SBFRA (Appendix G), thus this may not be considered a major limitation of the current research.

As noted in Chapter 7, the inclusion of more challenging standing balance tasks may have elicited more measurable differences between the High-Risk and Low-Risk groups, which may have added additional depth to the findings from our static sensor-derived data. As also mentioned in Chapter 7, selective analysis of the sensor data obtained was carried out for this thesis, with an emphasis on the clinical meaning and applications of all sensor-derived variables. These are opportunities for future work, given the great scope for further analysis of the sensor data obtained in the current research.
Finally, the exploratory nature of the field of SBFRA research means that the findings in relation to that aspect of this thesis are not all of immediate relevance to clinical practice. The following section will therefore describe the author’s observations on how future research on SBFRA may be directed in order to achieve successful translation to clinical practice.

9.5 Directions for Future Research

Based on the findings of this thesis and the experiences gained in carrying out the research described, a number of steps were identified which need to be taken in future studies in order for research on SBFRA to make the transition to use in clinical practice.

- A consensus on the optimal SBFRA protocols need to be established, including sensor locations, the functional tasks assessed, the type of sensors used e.g. accelerometer, gyroscope, magnetometer, and consistent applications of these protocols across a number studies needs to be achieved.
- A compendium of clinically meaningful sensor-derived variables needs to be established using consistent definitions for the selected sensor-derived variables. This will enable consistent methods of data processing, variable extraction and analysis to be achieved across a multiple studies.
- Once precise SBFRA protocols and variables have been established, their psychometric properties (e.g. test-retest and inter-rater reliability, sensitivity to change) also need to be established in a range of potential target clinical populations, such as community-dwelling older adults, people with Parkinson’s disease, and/or people with vestibular disorders.
- Reference data and fall-risk classification cut-points need to be established for the specified SBFRA protocols and variables in the target clinical populations.

A standard format for sensor-based falls detection data has been established (Klenk et al. 2013), and similar efforts are required for the purposes of fall-risk assessment. Current SBFRA research suffers from an excess of originality, with few studies implementing the same methodology as others. While this has stimulated a vast proliferation of novel and interesting research in this field, focusing on specific methods and establishing bodies of evidence relating to these specific methods is necessary to prove the clinical value of SBFRA and gain acceptance among clinicians, for whom
evidence-based practice is a key principle which guides their decision-making. A number of the sensor-derived variables of static and dynamic task performance selected in this thesis displayed highly promising results, thus further research using these same assessment and variable extraction methods to establish optimal cut-off points and classification properties in other specific clinical populations is recommended. An example of this type of focused research can be seen in recent publications which have established the test-retest reliability (Regterschot et al. 2014b) and sensitivity to change in community-dwelling older adults (Regterschot et al. 2014a) of a specific sensor-based method of analysing peak power during sit-to-stand tasks (Zijlstra et al. 2010).

Additionally, prospective studies of these specific SBFRA methods should be carried out to determine their capacities to predict future falls, rather than simply classifying levels of fall-risk based on retrospective or cross-sectional data. If SBFRA can be used to predict falls, it may offer a useful tool to aid clinicians in the early identification of individuals requiring intervention and assist in achieving timely referral to falls prevention interventions.

A further factor determining the ability of SBFRA to be translated for use in clinical practice is the usability of sensors for this purpose. Most clinicians would be receptive to learning and implementing simple changes to improve their balance assessments, provided they do not involve significant training and time burdens (Sibley et al. 2013). Currently, the implementation, analysis and interpretation of SBFRA require a considerable level of technical knowledge and a prohibitive amount of time from a clinician’s perspective. Research to develop automated SBFRA data analysis via user-friendly software, as well as definitive evidence-based assessment protocols, and simple, reliable equipment are vital in order to facilitate uptake by clinicians and to translate the promising findings observed in this thesis into practice. Further studies investigating the precise usability requirements of clinicians are therefore also necessary to progress SBFRA from the research domain into clinical settings.

Finally, the work described in this thesis has focused on the assessment of supervised structured functional tasks for the purpose of determining fall-risk. Recent research has explored the potential use of data obtained from unsupervised task performance in daily life to identify frailty and predictors of falls among older adults (Weiss et al. 2013, Parvaneh et al. 2014, Rispens et al. 2014, Schwenk et al. 2014). Such studies have shown promise in identifying older adults who are at risk of falling via their habitual
patterns of gait in the home and the community (Weiss et al. 2013, Rispens et al. 2014). Unsupervised assessment methods could offer numerous advantages over structured supervised assessments (Shany et al. 2012a): for example, such methods can assess fall-risk and/or falls incidence in real-life situations; continuous monitoring could facilitate early detection of changes in performance patterns and allow timely intervention; these methods may be more convenient for older adults and may reduce clinicians’ workloads, as less face-to-face contact time would be required; they may also be useful for older adults with cognitive impairments, for whom structured assessments can be problematic. However, unsupervised assessment methods present challenges in relation to participant adherence, consistency in sensor usage, reliability in sensor positioning, and particularly in relation to data analysis methods, since large volumes of highly variable data can be obtained. Despite the many challenges, continuous, unsupervised monitoring may become an acceptable, accurate, unobtrusive method of identifying fall-risk in the future.

9.6 Conclusions
This thesis describes the progress of the current research from initial exploratory work, which focused on gathering and synthesising existing evidence, establishing the current standing of SBFRA and its potential application in clinical practice, through to the development of an evidence-based SBFRA methodology which was successfully implemented in community-based clinical settings. This process culminated in the generation of clinically-meaningful original evidence demonstrating the utility of SBFRA to classify a sample of community-dwelling older adults based on their levels of fall-risk, as well as providing a meaningful exploration of a current community-based falls prevention intervention in Ireland. Therefore, this thesis can be said to have answered its research questions and confirmed that SBFRA can be used to perform clinically-meaningful assessments of fall-risk among community-dwelling older adults. With further research to develop specific user-friendly methods, SBFRA may in future be used to augment clinical fall-risk assessment methods, thereby assisting healthcare providers in their clinical reasoning and outcome measurement pertaining to falls prevention in community-dwelling older adults.
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## Appendix A. Outlines of papers included in systematic review described in Chapter 2

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>N</th>
<th>Test(s)</th>
<th>Test Type</th>
<th>Falls Reporting</th>
<th>Follow-Up Period</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alexandre et al. (2012)</td>
<td>63</td>
<td>TUG</td>
<td>Clinical</td>
<td>Falls log collected at 3, 6 and 12 months</td>
<td>12 months</td>
<td>Optimal cut-off time = 12.47s (73.7% sensitivity, 65.8% specificity) RR=3.2; 95% CI: 1.3-7.7</td>
</tr>
<tr>
<td>Aoyama et al. (2011)</td>
<td>58</td>
<td>BBS TUG Force plate measures during standing</td>
<td>Both</td>
<td>Monthly falls calendar</td>
<td>6 months</td>
<td>Fallers displayed greater mean AP sway during bipedal stance than non-fallers (OR = 1.26, 95% CI 0.98-1.63)</td>
</tr>
<tr>
<td>Beauchet et al. (2010)</td>
<td>1759</td>
<td>OLB</td>
<td>Clinical</td>
<td>Monthly telephone call</td>
<td>12 months</td>
<td>OLB time &lt;5s: 33.3% sensitivity, 58.2% specificity Change in arm position during first 5s of OLB: 55.9% sensitivity, 71.2% specificity</td>
</tr>
<tr>
<td>Boulgarides et al. (2003)</td>
<td>99</td>
<td>BBS TUG DGI Modified CTSIB</td>
<td>Both</td>
<td>Monthly falls calendar</td>
<td>12 months</td>
<td>1 aspect of modified CTSIB (standing on firm surface, eyes closed) predicted 1 in 20 multiple fallers</td>
</tr>
<tr>
<td>Brauer et al. (2000)</td>
<td>100</td>
<td>BBS FRT Lateral reach test Step-up test Standing force plate measures LL reaction time LL EMG</td>
<td>Both</td>
<td>Monthly falls calendar</td>
<td>6 months</td>
<td>Clinical balance tests did not predict fallers. A combination of variables from the laboratory tasks provided the best overall prediction rate (77%) of fallers (sensitivity 51%) and non-fallers (specificity 91%)</td>
</tr>
<tr>
<td>Buatois et al. (2010)</td>
<td>1618</td>
<td>TUG</td>
<td>Clinical</td>
<td>Recall at</td>
<td>18-36</td>
<td>Twice as many recurrent fallers among participants</td>
</tr>
<tr>
<td>Study (Year)</td>
<td>Sample Size</td>
<td>Measure(s)</td>
<td>Assessment Frequency</td>
<td>Follow-up Period</td>
<td>Findings</td>
<td></td>
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<tr>
<td>Butler et al. (2011)</td>
<td>415</td>
<td>Maximal reach</td>
<td>Clinical</td>
<td>12 months</td>
<td>Poor performers (maximal reach $78.6 \pm 0.3$ cm) had a higher rate of falls per person (approx. 1.4 95% CI 1.2-1.6) than other groups</td>
<td></td>
</tr>
<tr>
<td>Callisaya et al. (2011)</td>
<td>412</td>
<td>Gait and gait variability (computerised walkway)</td>
<td>Lab</td>
<td>12 months</td>
<td>RR of multiple falls increased with increasing step length variability ($P = 0.03$) and double-support phase variability ($P = 0.02$) Non-linear relationships between multiple falls and gait speed ($P = 0.002$), cadence ($P = 0.004$) and step time variability ($P = 0.03$)</td>
<td></td>
</tr>
<tr>
<td>Callisaya et al. (2012)</td>
<td>176</td>
<td>Gait variables (computerised walkway)</td>
<td>Lab</td>
<td>12 months</td>
<td>Risk of multiple falls greater for those with a smaller walk ratio (shorter steps, faster cadence) during fast-walking (RR 0.92, 95% CI 0.87, 0.97) and greater reduction in walk ratio (smaller increase in step length, larger increase in cadence) when changing to fast-walking (RR 0.73, 95% CI 0.63-0.85) Quadratic relationship between fast walking speed and multiple falls, with highest rate in fastest group (1.76-2.6 m/s; RR 2.75; 95% CI 0.44-17.13)</td>
<td></td>
</tr>
<tr>
<td>Chan et al. (2007)</td>
<td>5995</td>
<td>FTSS Gait speed (6-metre walk, usual and narrow stance width)</td>
<td>Clinical</td>
<td>4.5 years</td>
<td>The slowest quartile for the FTSS had a higher risk of falls than the fastest (OR 1.25, 95% CI 1.12-1.39). The fastest narrow walkers had reduced risk of falls compared to the slowest quartile (OR 0.83, 95% CI 0.73-0.94)</td>
<td></td>
</tr>
<tr>
<td>Chu et al. (2005)</td>
<td>1517</td>
<td>POMA Gait speed (5-</td>
<td>Clinical</td>
<td>12 months</td>
<td>Gait speed (RR 0.23, 95% CI 0.11-0.50, $P &lt;0.001$) and failure to complete tandem stance (RR 1.61,</td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>Sample Size</td>
<td>Outcome Measures</td>
<td>Design</td>
<td>Frequency</td>
<td>Outcomes</td>
<td></td>
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<tr>
<td>Delbaere et al. (2010b)</td>
<td>500</td>
<td>PPA Coordinated stability test, OLB 6-metre walk with turn</td>
<td>Clinical</td>
<td>Monthly falls diaries with telephone reminders</td>
<td>12 months</td>
<td>Fallers performed more poorly in terms of PPA score (OR 1.31, 95% CI 1.06–1.61), coordinated stability error score (OR 1.21 95% CI 1.00–1.46) and OLB time (OR 0.80, 95% CI 0.67–0.97)</td>
</tr>
<tr>
<td>Doi et al. (2013)</td>
<td>73</td>
<td>FTSS TUG Trunk accelerations during 10-metre walk</td>
<td>Both</td>
<td>Weekly interview</td>
<td>12 months</td>
<td>Non-fallers performed better than fallers on FTSS (fallers: 19.6 ± 9.4s; non-fallers: 13.8 ± 5.7s; P = 0.037) and TUG (fallers: 20.7 ± 10.6s; non-fallers: 14.1 ± 7.5s; P = 0.031). Harmonic ratios of upper and lower trunk accelerations were significantly lower in fallers than non-fallers</td>
</tr>
<tr>
<td>Faulkner et al. (2009)</td>
<td>8378</td>
<td>FTSS Gait speed (6m walk) Standing balance tests</td>
<td>Clinical</td>
<td>Recall postcards/telephone calls every 4 months</td>
<td>4 years</td>
<td>Faster usual gait speed associated with increased falls risk (RR = 1.18; 95% CI 1.08–1.30). Good standing balance protective (RR=0.73, 95% CI 0.6-0.81)</td>
</tr>
<tr>
<td>Graafmans et al. (1996)</td>
<td>354</td>
<td>FTSS Tandem stance (&lt;3s) Observational gait analysis (6m with turn)</td>
<td>Clinical</td>
<td>Falls diary</td>
<td>7 months</td>
<td>FTSS failure increased single falls (OR=2.5, 95% CI 1.5-4.1) and multiple falls risk (OR=4.8, 95% CI 2.5-9.3) TS failure increased single falls (OR=2.4, 1.5-3.9) and multiple falls risk (OR=3.7, 1.9-7.3). Observed gait abnormalities increased single falls (OR=2.6, 1.6-4.3) and multiple falls risk (OR 5.3, 2.8-10.0).</td>
</tr>
<tr>
<td>Hausdorff et al. (2001)</td>
<td>52</td>
<td>TUG</td>
<td>Both</td>
<td>Weekly interview</td>
<td>12 months</td>
<td>Falls predicted by stride time variability (OR=5.3, 95% CI 3.6–8.0) and stride time variability increased falls risk (OR=2.4, 1.3-4.7)</td>
</tr>
<tr>
<td>Study</td>
<td>N</td>
<td>Methodology</td>
<td>Setting</td>
<td>Outcome Measure</td>
<td>Results</td>
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<tr>
<td>Herman et al. (2010)</td>
<td>262</td>
<td>Gait variability using force-sensitive insoles (6min walk)</td>
<td>Lab</td>
<td>Monthly falls calendar</td>
<td>95% CI 1.01–27.2) and swing time variability (OR=2.2, 95% CI 1.1–4.4)</td>
<td></td>
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<tr>
<td>Herman et al. (2011)</td>
<td>265</td>
<td>Gait characteristics using force-sensitive insoles (single- and dual-task)</td>
<td>Clinical</td>
<td>Monthly falls calendar</td>
<td>Dual-task swing time variability (OR=1.26, 95% CI 1.03-1.55) predicted falls</td>
<td></td>
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<tr>
<td>Inoue et al. (2012)</td>
<td>85</td>
<td>TUG FRT Gap between actual and estimated reach distance (GAE)</td>
<td>Clinical</td>
<td>12-month recall</td>
<td>Multiple fallers took longer (p = 0.035) to complete the TUG at baseline (10.3 ± 1.9 s), compared to non-fallers (9.5 ± 1.7 s) BBS and DGI not related to faller status</td>
<td></td>
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<tr>
<td>Kelsey et al. (2010)</td>
<td>765</td>
<td>BBS SPPB FTSS 6MWT Gait speed (4m)</td>
<td>Clinical</td>
<td>Falls calendar</td>
<td>Increased falls incidence in those scoring 48-50 (IRR 1.33, 95% CI 1.04–1.69) or &lt;48 (IRR 1.44, 95% CI 1.10–1.89) on BBS relative to those who scored ≥51. Failure to complete FTSS predictive of indoor falls (IRR 1.85, 95% CI 1.20–2.86)</td>
<td></td>
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<tr>
<td>Study</td>
<td>Sample Size</td>
<td>Methodology</td>
<td>Data Collection</td>
<td>Key Findings</td>
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<tr>
<td>Lord et al. (1996)</td>
<td>96</td>
<td>Gait analysis (instrumented walkway)</td>
<td>Lab, Bi-monthly postcards/telephone interviews, 12 months</td>
<td>Decreased falls incidence in those with gait speeds of 0.68-1.33m/s (IRR 0.59, 95% CI 0.41–0.87) and &lt;0.68m/s (IRR 0.69, 95% CI 0.43–1.10) relative to those with gait speeds ≥1.33m/s</td>
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<tr>
<td>Makizako et al. (2010)</td>
<td>45</td>
<td>Reaction times under dual and triple-task conditions</td>
<td>Lab, Recall questionnaire at follow-up, 5 months</td>
<td>Multiple fallers had significantly lower cadence, greater cadence SD, greater stance time and stance percentage than non-fallers or single fallers</td>
<td></td>
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<tr>
<td>Morrison et al. (2011)</td>
<td>205 outpt., 314 dom.</td>
<td>BOOMER (Balance Outcome Measure for Elder Rehabilitation)</td>
<td>Clinical, Weekly interviews throughout length of stay, Outpatient mean days (SD) = 51.5 (38.1), Domiciliary mean days (SD) = 47.7 (39.4), 12 months</td>
<td>Fallers had significantly slower reaction times than non-fallers under both dual-task conditions (dynamic balance and cognitive), but not in triple-task condition</td>
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<tr>
<td>Olsson Muller et al. (2012)</td>
<td>85</td>
<td>TUG Romberg test (+ semi-tandem and tandem variations)</td>
<td>Clinical, 3-month falls recall via interviews at 6 and 12 months, 12 months</td>
<td>Lower BOOMER scores significantly associated with falls; Outpatient IRR 0.82 (95% CI 1.07-1.09), P &lt; 0.01 Domiciliary IRR 0.80 (95% CI 0.69-0.94), P = 0.01</td>
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<tr>
<td>Pai et al. (2010)</td>
<td>13</td>
<td>TUG Reaction to experimental slips on sit-to-stand</td>
<td>Both, 12-month recall at follow-up, 2.5 years</td>
<td>TUG time &gt;9s: 50% sensitivity (95% CI 9.2,90.8), 56% specificity (95% CI 40.2,96.1), Slip score &gt;6 (maximum 14): 75% sensitivity (95% CI 21.9,98.7), 89% specificity (95% CI 50.7,99.4)</td>
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<tr>
<td>Study (Year)</td>
<td>N</td>
<td>Measures</td>
<td>Method</td>
<td>Follow-up</td>
<td>Results</td>
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<tr>
<td>Panzer et al. (2011)</td>
<td>74</td>
<td>POMA Gait speed (8.1m)</td>
<td>Both</td>
<td>12 months</td>
<td>POMA predicted fall status with 51% sensitivity and 100% specificity. Sensory Organisation Test: 32% sensitivity, 93% specificity. Fallers were significantly slower than non-fallers in gait speed, turning and stepping tasks, had a shorter maximal lean and greater sway during quiet standing and sit-to-stand.</td>
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<tr>
<td></td>
<td></td>
<td>Sensory Organisation Test Force-plate measures: Maximal lean Romberg Test Sit-to-Stand Turn and sit Stepping into bathtub Walking down 3 steps</td>
<td>Weekly postcards</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Quach et al. (2011)</td>
<td>600</td>
<td>Gait speed (4-metre walk)</td>
<td>Clinical</td>
<td>18 months</td>
<td>Participants with faster (&gt;1.3 m/s) (IRR 2.12, 95% CI 1.48–3.04) and slower (&lt;0.6 m/s, IRR 1.60, 95% CI 1.06–2.42) gait speeds at higher risk of falls than those with normal gait speeds (1.0–&lt;1.3 m/s)</td>
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<td></td>
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<td>Monthly falls calendars</td>
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<tr>
<td>Srygley et al. (2009)</td>
<td>266</td>
<td>BBS TUG DGI Pull test Swing time &amp; variability</td>
<td>Both</td>
<td>12 months</td>
<td>Higher TUG time significantly associated with multiple falls (P=0.035)</td>
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<td></td>
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<td></td>
<td>Monthly falls calendar</td>
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<tr>
<td>Stalenhoef et al. (2002)</td>
<td>311</td>
<td>FRT GUGT Romberg test Postural sway Bending down test</td>
<td>Both</td>
<td>9 months</td>
<td>Positive Romberg test (OR=3.7, 95% CI 1.8-7.8), GUGT score ≥3 (OR=3.6, 95% CI 1.6-7.4) and FRT ≤15cm (OR=2.0, 95% CI 1.0-3.9), abnormal postural sway (OR=7.2, 95% CI 2.7-19.2), Trendelenburg test (OR=1.5, 95% CI 0.8-2.9) and performance on bending down test (OR=2.5, 95%</td>
<td></td>
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<tr>
<td>Study</td>
<td>Sample Size</td>
<td>Test(s)</td>
<td>Setting</td>
<td>Measurement</td>
<td>Outcome(s)</td>
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<td>Stel et al. (2003b)</td>
<td>439</td>
<td>Trendelenburg test</td>
<td>Both</td>
<td>Monthly falls calendar</td>
<td>Walking test (OR = 2.2; 95% CI 1.1–4.1), ML sway (OR = 2.8; 95% CI 1.1–6.9) and tandem stand (OR = 2.1; 95% CI 1.1–3.8) associated with recurrent falling</td>
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<tr>
<td>Swanenburg et al. (2010)</td>
<td>270</td>
<td>Walking test</td>
<td>Lab</td>
<td>Monthly falls calendar</td>
<td>Root mean square amplitude in the ML direction predicted multiple falls in the single-task condition (OR 21.8, 95% CI 3.2–149.3)</td>
<td></td>
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<tr>
<td>Tromp et al. (2001)</td>
<td>1285</td>
<td>FTSS Walking test</td>
<td>Clinical</td>
<td>Weekly falls calendar</td>
<td>FTSS performance predicted falls (OR=1.2 per point decrease, 95% CI 1.1–1.4) and recurrent falls (OR=1.4 per point decrease, 95% CI 1.2–1.6)</td>
<td></td>
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<tr>
<td>Viccaro et al. (2011)</td>
<td>457</td>
<td>Gait speed (4-metre walk)</td>
<td>Clinical</td>
<td>Face-to-face recall at 3-month intervals</td>
<td>Both TUG and gait speed demonstrated similarly acceptable predictive values for multiple falls</td>
<td></td>
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<tr>
<td>Wright et al. (2012)</td>
<td>35</td>
<td>Motion analysis of standing 360° turns</td>
<td>Lab</td>
<td>Monthly falls questionnaire</td>
<td>Fallers differed from non-fallers in pelvis onset ($P = 0.002$); mean angular separation in the transverse plane between the head and trunk ($P = 0.018$); peak angular separation in the transverse plane between the trunk and pelvis ($P = 0.013$); and mean angular separation between the trunk and pelvis ($P &lt; 0.001$)</td>
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</tbody>
</table>
| Wrisley and Kumar (2010)      | 35          | FGA                                          | Clinical| Monthly falls calendar               | FGA score $\leq 20$ predicted fallers with 100% sensitivity and 83% specificity  
DGI score $\leq 20$: 100% sensitivity and 76% specificity  
TUG $\geq 12.3$s: 83% sensitivity and 97% specificity                                                                                           |
| Yamada and Ichihashi (2010)  | 171         | Trail-Walking Test (TWT)                     | Clinical| Monthly telephone interview          | TWT performance could correctly classify 77.8% of fallers; 66.1% sensitivity, specificity 83.9%                                                                                           |
Inability to complete the FTSS did not significantly predict falls (OR 4.22, 95% CI 0.82-21.71, \( P = 0.09 \))

| Zhang et al. (2013) | 562 | FTSS | Clinical 12-month recall at follow-up | 3 years | Inability to complete the FTSS did not significantly predict falls (OR 4.22, 95% CI 0.82-21.71, \( P = 0.09 \)) |

*Note.* \( N \) = number of participants, TUG = Timed Up and Go Test; BBS = Berg Balance Scale; OLB = One-Legged Balance; DGI = Dynamic Gait Index; FRT = Functional Reach Test; CTSIB = Clinical Test of Sensory Organisation and Balance; LL = Lower Limb; EMG = Electromyography; FTSS = Five Times Sit-to-Stand Test; POMA = Performance-Oriented Mobility Assessment; PPA = Physiological Profile Assessment; SPPB = Short Physical Performance Battery; 6MWT = 6 Minute Walk Test; GUGT = Get Up and Go Test; FGA = Functional Gait Assessment; RR = relative risk; 95% CI = 95% confidence interval; OR = odds ratio; \( P \) = significance value; IRR = incidence rate ratio; SD = standard deviation; AP = antero-posterior; ML = medio-lateral; outpt. = outpatients; dom. = domiciliary.
An Investigation of Physical Activity Patterns and Fall-Risk Factors in Community-Dwelling Older Adults Participating in a Falls Prevention Programme

PARTICIPANT INFORMATION STATEMENT

You are invited to take part in the research project identified above which is being conducted by researchers from the Department of Physiotherapy and the Department of Electronic and Computer Engineering Department at the University of Limerick, in conjunction with the Health Service Executive.

Aims

The study is being carried out to examine the effects of participation in a falls prevention programme on people over the age of 65. The falls prevention programme will focus on exercise, with the aim of preventing falls and reducing the risk of falling.

Procedures

We are seeking people over the age of 65 years who have been referred to participate in a falls prevention programme.

If you decide to participate, you will be asked to:
• Complete the consent form attached to this information letter and contact the researcher at the telephone number listed above. The researcher will answer any questions you may have at this stage.
• If you are still willing to participate, an appointment will be made for the researcher to visit you in your own home to carry out the initial assessments. These assessments will take no longer than 60 minutes.
• Make sure you are eligible to participate and to arrange a convenient time to visit you at home and conduct an assessment lasting approximately one hour. This assessment will consist of answering some questions about your health and some simple measurements of your movement.
• Wear a small sensor on your waist (the size of a pager) for 3 days before the programme and 3 days after the programme to measure your movement and activity levels.
• Participate in a falls prevention programme coordinated by the physiotherapy department of your local day care centre. The programme will last for 8 weeks, and include assessment, structured group exercise classes, a home exercise programme, education sessions, and a home safety assessment by an occupational therapist.
• Participate in a follow-up assessment to be conducted after the falls prevention program is complete.
• You will also be asked to participate in a brief audio-taped interview (in person, or by telephone) lasting approximately 20 minutes, to find out what you thought about the project. If you agree to participate in an interview, you may stop the interview at any time. If you do not wish to continue, the audio recording will be erased and the information provided will not be included in the study.

Benefits

Benefits will include receiving services that are known to prevent falls for older people.

Risks

There are no known or potential risks to participating in this study.

Exclusion from participation

If you are unable to participate in an exercise program you will be excluded from participating in the study.

Alternative Treatment

If you cannot participate or choose not to participate in this study, you will still receive usual care from your Primary Care Team.
Confidentiality
Information obtained from your participation will be stored anonymously using an identification number and will only be accessed by the researchers involved in the study. Information will be securely stored by the researchers in a locked cupboard or in a computer file accessible only by the researchers. All information resulting from this research will be stored securely by the researchers for a period of seven years, after which it will be destroyed. Individual participants will not be identifiable in any reports or publications arising from the project.

Compensation
There are no payments offered for participation in this study.

Voluntary Participation
Participation in this research is entirely your choice. Only those people who give their informed consent will be contacted by the researcher and included in the research. If you decide not to participate, your relationship with the University or your Primary Care Team will not be affected, and you will not be disadvantaged in any way.

Stopping the Study
If you decide to participate, you may withdraw from the project at any time without giving a reason, and you have the option to withdraw any information you have provided.

Permission
Researchers have received ethical approval to conduct this study.

Further information
Please read this information statement, and be sure that you understand its contents before you decide whether or not to participate. You are invited to contact me or any of the researchers listed below to discuss any questions you may have before deciding to participate in the study. If you do decide to participate in this research study, please complete the attached consent form.
Other Investigators in the research team who may be in contact with you are:
Dr Amanda Clifford and Valerie Power, Physiotherapy, UL
Dr Alan Bourke and John James Guiry, Electronic and Computer Engineering, UL

Thank you for considering this invitation.

Yours faithfully,

Dr. Lynette Mackenzie
Contact phone number: 061 23XXXX

If you have concerns about this study and wish to contact someone independent, you may contact:
The Chairperson of the EHS Faculty Ethics Committee
University of Limerick
Limerick
061-2XXXXX

This information sheet is for you to keep.
Appendix C. Participant Consent Form for Feasibility Study

Dr Lynette Mackenzie (Principal Investigator)
Department of Occupational Therapy
University of Limerick
Limerick, Ireland
Tel: 061 23XXXX
Fax: 061 234251
Email: Lynette.Mackenzie@sydney.edu.au

A PILOT STUDY TO EVALUATE THE FEASIBILITY OF IMPLEMENTING A COMMUNITY-BASED, EVIDENCE-FOCUSED FALLS PREVENTION PROGRAM

PARTICIPANT CONSENT FORM

I, .............................................................................[PRINT NAME], give consent to my participation in the above-named research project

In giving my consent I acknowledge that:

1. The procedures required for the project and the time involved (including any inconvenience or risk, and their implications) have been explained to me, and any questions I have about the project have been answered to my satisfaction.

2. I have read the Participant Information Statement and have been given the opportunity to discuss the information and my involvement in the project with the researcher/s.

3. I understand that I can withdraw from the study at any time, without affecting my relationship with the researchers now or in the future.
4. I understand that my involvement is strictly confidential and no information about me will be used in any way that reveals my identity.

5. I understand that being in this study is completely voluntary – I am not under any obligation to consent.

6. If I agree to participate in an interview, I understand that I can stop the interview at any time if I do not wish to continue, the audio recording will be erased and the information provided will not be included in the study.

7. I will inform the researcher of any adverse effects that may arise through my participation in the study.

8. I consent to: –

   i) Audio-taping YES □ NO □

   ii) Home visits by researchers YES □ NO □

   iii) Receiving feedback about the study YES □ NO □

Address: ______________________________________________________________

_____________________________________________________________________

Telephone number:

_____________________________________________________________________

Signed: ..............................................................................................................

Date: ...............................................................................................................
Appendix D. Medical Clearance Form for Feasibility Study Participants

Community-Based Falls Prevention Program

Research Study Ethics Number (xxx)

Date: __________

Dear ________________________________

Your patient ________________________

Address __________________________________________________

has been referred to our Falls Prevention Program by
__________________________________________

I would be grateful if you would review the program outline, inclusion and exclusion criteria overleaf and tick the appropriate boxes if you are happy/unhappy for him/her to attend the class. If I do not hear from you I will assume the patient is NOT fit to attend and will inform him/her and the original referrer.

☐ Yes, the patient can participate
☐ No, the patient cannot participate

__________________________________________
CONSULTANT/G.P. SIGNATURE

Date: _________________

PLEASE PUT OFFICE STAMP HERE
Falls Prevention Program Outline

As part of a pilot study, the University of Limerick will be running a falls prevention program in collaboration with clinicians in Primary Care Team 1 in the mid-west, commencing in October 2010.

This program will be the focus of a research project. Eligible older participants will be identified by either the GP or Public Health Nurse and from current occupational therapy and physiotherapy waiting lists. Those eligible will receive an invitation to participate, and are free to accept or decline without affecting their future access to other such services.

The program will run for a 5-6 week period. It will comprise of an exercise program delivered by a physiotherapist in the participant’s home which aims to improve strength, balance, flexibility and stamina, and also assessment and appropriate modification of the participant’s home environment by an occupational therapist. Participants’ physical activity will be monitored using an accelerometer before, during and after the program. Participants will also be asked to keep a daily falls calendar for 6 months from the start of the program.

To participate, patients MUST meet the following inclusion criteria:

- Must be greater than 75 years of age on date of referral
- Must have had a fall in previous 12 months and/or a fear of falling
- Must have medical cause of falls ruled out
- Must have healed fracture or be 3 months post hip replacement (if applicable)
- Must be able to stand up and walk independently (with assistive device or without)
- Must have medical clearance from G.P. or Consultant to participate
- Must have a reasonable expectation of completing the program
MUST NOT possess any of the following exclusion criteria:

- A pacemaker or any other internal electronic device
- Unstable angina or uncontrolled heart disease/blood pressure
- Tachycardia or uncontrolled arrhythmia
- Severe breathlessness or dizziness
- Unmanaged pain or acute systemic illness (e.g. cancer)
- Severe cognitive impairment
- CVA
- Parkinson’s disease

Please note that patients who you deem unsuitable for this program can be referred for individual physiotherapy in the usual way.

We would be grateful if you would consider your patients for this new initiative. Thank you for your time and help.

Yours Sincerely,

___________________________
Dr. Lynette MacKenzie (Principal Investigator, Dept. of Occupational Therapy, UL)

Dr. Amanda Clifford (Supervisor/Researching Physiotherapist, Dept. of Physiotherapy, UL) 061 234118 / Amanda.Clifford@ul.ie

Valerie Power (Researching Physiotherapist, Dept. of Physiotherapy, UL)

Eileen O’Connor (Physiotherapy Clinical Specialist, Primary Care Team) 065 6863840 / eileen.oconnor2@hse.ie
Appendix E. Ethics Approval Letter for Feasibility Study

06th October, 2010.

Dr. Amanda Clifford
Occupational Therapy Department,
University of Limerick,
Castletroy,
Limerick.

Re: Protocol Title:
A Pilot study to evaluate the feasibility of implementing a community based, evidence focused falls prevention programme

Dear Dr. Clifford,

Thank you for attending the Research Ethics Committee meeting on the 22nd September 2010 in connection with your study.

I wish to advise that the Committee has now approved your study. However, you should note that your study cannot commence until you also receive Risk Management approval. This approval will be issued to you shortly.

You are obliged to inform us as soon as your study is completed or if it terminates early for any reason.

I wish you every success in your study.

Yours sincerely,

[Signature]

Marie Hickey Dwyer,
Consultant Ophthalmic Surgeon,
Chairperson, Ethics Research Committee.
## Appendix F. Summary of studies included in the systematic review of exercise programmes for falls prevention (Power and Clifford 2013)

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Format</th>
<th>Frequency</th>
<th>Intensity</th>
<th>Duration per Bout</th>
<th>Total Volume</th>
<th>Volume per Week</th>
<th>Effect on Falls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barnett et al.</td>
<td>Combination</td>
<td>Group: 1x/week HEP: Variable</td>
<td>Unspecified</td>
<td>Group: 1hr</td>
<td>Approx. 37hrs plus HEP over 12 months</td>
<td>0.7hrs (excluding HEP)</td>
<td>IRR = 0.60, 95% CI [0.36, 0.99]</td>
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<tr>
<td>(2003)</td>
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<tr>
<td>Buchner et al.</td>
<td>Group</td>
<td>3x/week</td>
<td>Endurance group: 75% HR reserve x30-35mins</td>
<td>1hr</td>
<td>Approx. 72-78hrs over 24-26 weeks</td>
<td>2.8-3.3hrs</td>
<td>RH of time to first fall = 0.53, 95% CI [0.30, 0.91]</td>
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<tr>
<td>(1997)</td>
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<td></td>
<td>Strength group: 2 sets x 10 reps; 1st set 50-60% 1RM, 2nd set 75% 1RM</td>
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<td>E+S group: 20mins endurance, 1 set 75% 1RM</td>
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<tr>
<td>Campbell et al.</td>
<td>Independent</td>
<td>HEP 3x/week; Walking 3x/week</td>
<td>Variable levels</td>
<td>HEP: 30mins</td>
<td>Approx. 72hrs over 12 months</td>
<td>1.4hrs</td>
<td>Lower annual falls rate in IG than CG, difference = 0.47; 95% CI [0.04, 0.90]</td>
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<tr>
<td>(1997)</td>
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<tr>
<td>Campbell et al.</td>
<td>Independent</td>
<td>HEP 3x/week; Walking 3x/week</td>
<td>Variable levels</td>
<td>HEP: 30mins</td>
<td>Approx.144hrs over 2 years</td>
<td>1.4hrs</td>
<td>RH for all falls in IG = 0.69, 95% CI [0.49, 0.97]</td>
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<td>(1999)</td>
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<tr>
<td>Carter et al.</td>
<td>Group</td>
<td>2x/week</td>
<td>Unspecified</td>
<td>40mins</td>
<td>Approx. 26.6hrs over 20 weeks</td>
<td>1.3hrs</td>
<td>During intervention, IG had 7 falls, CG had 8 falls</td>
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<tr>
<td>(2002)</td>
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<tr>
<td>Clemson et al.</td>
<td>Independent</td>
<td>Unspecified</td>
<td>Individualised</td>
<td>Unspecified</td>
<td>Unspecified over 6 months</td>
<td>Unspecified</td>
<td>RR = 0.21, 95% CI [0.06, 0.67]</td>
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<tr>
<td>(2010)</td>
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<tr>
<td>Day et al.</td>
<td>Combination</td>
<td>Group: 1hr</td>
<td>Unspecified</td>
<td>Group: 1hr</td>
<td>Approx.15hrs</td>
<td>1hr</td>
<td>IRR for exercise alone</td>
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<tr>
<td>(2002) / Fitzharris et al. (2010)</td>
<td>1x/week HEP: 7x/week</td>
<td>plus unspecified HEP over 15 weeks</td>
<td>= 0.79, 95% CI [0.67, 0.94]</td>
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<tr>
<td>Freiberger et al. (2007)</td>
<td>Combination Group: 2x/week HEP: 7x/week</td>
<td>Group: 1hr Approx. 12hrs over 6 months</td>
<td>2hrs Falls in fitness group: RR = 0.64, 95% CI [0.38, 1.06]</td>
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<tr>
<td>Haines et al. (2009)</td>
<td>Independent 2x/week Variable levels Approx. 15mins</td>
<td>Approx. 12hrs over 6 months 0.5hrs</td>
<td>IRR = 0.72, 95% CI [0.33-1.57]</td>
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<tr>
<td>Huang et al. (2010)</td>
<td>Group 3x/week Unspecified 40mins</td>
<td>Approx. 40hrs over 5 months 1.9hrs</td>
<td>At 1.5 years, OR = 0.13, 95% CI [0.06, 0.273]</td>
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<tr>
<td>Inokuchi et al. (2007)</td>
<td>Combination Group: 1x/week HEP: 7x/week Strength: Gravity-resisted Group: 2hrs HEP: 15-20mins Approx. 64hrs over 17 weeks 3.8hrs</td>
<td>Mean number of falls significantly lower in IG than CG, p =.036</td>
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<tr>
<td>Kamide et al. (2009)</td>
<td>Independent 3x/week Strength: 1-2 sets x15 reps, “moderate intensity”</td>
<td>Unspecified</td>
<td>At 12 months, 0 falls in IG, 1 fall in CG</td>
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<tr>
<td>Kemmler et al. (2010)</td>
<td>Combination IG: Group: 2x/week HEP: 2x/week CG: 1x/week IG: Aerobic: 70-80% HRmax Strength: 1-3 sets x8-15 reps HEP: 1-2 sets x6-15 reps CG: 5-10mins walking at 50-60% HRmax IG: Group: 1hr HEP: 20mins CG: 1hr IG: Approx. 203hrs over 18 months CG: Approx. 78hrs over 18 months</td>
<td>IG: 2.6hrs CG: 1hr RR of falls = 0.54, 95% CI [0.35, 0.84] RR of injurious falls = 0.33, 95% CI [0.15, 0.74]</td>
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<tr>
<td>Latham et al. (2003)</td>
<td>Independent 3x/week 3 sets x8reps, 60-80% 1RM</td>
<td>Unspecified</td>
<td>Unspecified Unspecified</td>
<td>RR = 0.96, 95% CI [0.67, 1.36]</td>
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<tr>
<td>Study</td>
<td>Group</td>
<td>Frequency</td>
<td>Intensity</td>
<td>Duration</td>
<td>Results</td>
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<tr>
<td>Lin et al. (2006)</td>
<td>Group</td>
<td>6x/week</td>
<td>Unspecified</td>
<td>1hr</td>
<td>Approx. 312hrs over 12 months 6hrs</td>
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<td></td>
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<td></td>
<td>Injurious falls reduced by 44% in CG, 75% in tai chi villagers &amp; 94% in tai chi practitioners</td>
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<tr>
<td>Lord et al. (2005)</td>
<td>Group</td>
<td>Extensive Intervention: 2x/week</td>
<td>Extensive Intervention: Progression according to RPE and ACSM guidelines</td>
<td>Extensive Intervention: 40-50mins</td>
<td>Extensive Intervention: RR = 1.03, 95% CI [0.78, 1.35] Minimal Intervention: RR = 0.90, 95% CI [0.69, 1.17]</td>
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<tr>
<td>Means et al. (2005)</td>
<td>Group</td>
<td>3x/week</td>
<td>Low-intensity for 1st week (RPE = 11), moderate thereafter (RPE = 13)</td>
<td>1.5hrs</td>
<td>Approx. 27hrs over 6 weeks 4.5hrs</td>
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<td></td>
<td>Baseline fallers reporting no falls at follow-up: IG = 87%; CG = 34.5%</td>
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<tr>
<td>Nitz and Choy (2004)</td>
<td>Group</td>
<td>1x/week</td>
<td>Balance Group: Specific, progressive balance task workstations CG: Non-specific balance exercise with increasing speed and combinations</td>
<td>1hr</td>
<td>Approx. 10hrs over 10 weeks 1hr</td>
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<td></td>
<td>Significant reductions in falls in Balance Group (p = 0.000) and CG (p = 0.024) at 3 months</td>
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<tr>
<td>Reinsch et al. (1992)</td>
<td>Group</td>
<td>Exercise Group: 3x/week</td>
<td>“Low-intensity”</td>
<td>Both Groups: 1hr</td>
<td>Exercise Group: Approx. 156hrs over 12 months Exercise Group: 3hrs Exercise &amp;</td>
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<td></td>
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<td>No significant difference in the number of fallers between all groups at</td>
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<tr>
<td>Study</td>
<td>Group Type</td>
<td>Exercise &amp; CBT Group:</td>
<td>CBT Group:</td>
<td>12 months ($p = .53$)</td>
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<tr>
<td>Robertson et al. (2001a)</td>
<td>Independent</td>
<td>Exercise &amp; CBT: 2x/week</td>
<td>Approx. 104hrs over 12 months</td>
<td>0.54, 95% CI [0.32, 0.90]</td>
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<tr>
<td>Robertson et al. (2001b)</td>
<td>Independent</td>
<td>HEP: 3x/week; Walking 2x/week</td>
<td>Variable</td>
<td>0.70, 95% CI [0.59, 0.84]</td>
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<tr>
<td>Rubenstein et al. (2000)</td>
<td>Group</td>
<td>HEP: 3x/week; Walking 2x/week</td>
<td>Variable</td>
<td>Lower activity-adjusted 3-month fall rate in IG than CG (6 falls/1000 hours activity vs. 16.2 falls/1000 hours, $p = .03$)</td>
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<tr>
<td>Shumway-Cook et al. (2007)</td>
<td>Group</td>
<td>HEP: 3x/week</td>
<td>Variable in difficulty</td>
<td>0.75, 95% CI [0.52, 1.09]</td>
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<tr>
<td>Skelton et al. (2005)</td>
<td>Combination</td>
<td>IG: Class: 1x/week HEP: 2x/week</td>
<td>CG; HEP IG: Variable levels in HEP; more challenging in class CG: Low-intensity</td>
<td>0.46, 95% CI [0.34, 0.63]</td>
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<tr>
<td>Study</td>
<td>Type</td>
<td>Frequency</td>
<td>Exercise Details</td>
<td>Fall Rate Measures</td>
<td>Notes</td>
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<tr>
<td>Steinberg et al. (2000)</td>
<td>Combination</td>
<td>x2/week</td>
<td>HEP: Class: 1x/month; Unspecified HEP</td>
<td>Unspecified</td>
<td>Approx. 17hrs group exercise over 17 months Unspecified Hazard Ratio for time to first fall in exercise group = 0.67; 95% CI [0.42-1.07]</td>
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<tr>
<td>Suzuki et al. (2004)</td>
<td>Combination</td>
<td></td>
<td>Resistance training: “Moderate” Tai Chi: Progressive duration, up to 30mins</td>
<td>Group: 1hr HEP: 30mins</td>
<td>1.9hrs After 20 months 13.6% in IG fell vs. 54.5% in CG</td>
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<tr>
<td>Weerdesteyn et al. (2006)</td>
<td>Group</td>
<td>2x/week</td>
<td>“Low-intensity”</td>
<td>1.5hrs Approx. 15hrs over 5 weeks</td>
<td>3hrs IRR at 7-months = 0.54, 95% CI [0.36, 0.79]</td>
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<tr>
<td>Wolf et al. (1996)</td>
<td>Combination</td>
<td></td>
<td>Tai Chi: Progressively more difficult forms Balance: Sway targets progressed; floor movements added</td>
<td>Tai Chi: Group: 22.5mins HEP: 30mins Balance: 45mins</td>
<td>4.3hrs RR of multiple falls for Tai Chi group = 0.53, 95% CI [0.32, 0.86]</td>
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<tr>
<td>Woo et al. (2007)</td>
<td>Group</td>
<td>3x/week</td>
<td>Tai Chi: Unspecified Resistance Group: “Medium”</td>
<td>Unspecified over 12 months</td>
<td>Numbers of falls during study period = Tai Chi Group: 15/60; Resistance Group: 24/60; CG: 31/60 (non-significant differences)</td>
<td></td>
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<tr>
<td>Wu et al. (2010)</td>
<td>Combination</td>
<td>3x/week</td>
<td>Unspecified</td>
<td>1hr Approx. 45hrs over 15 weeks</td>
<td>3hrs Mean number of falls and injurious falls reduced in</td>
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<tr>
<td>Yamada et al. (2010)</td>
<td>Group</td>
<td>1x/week</td>
<td>Aerobic: “Moderate” Strength: “Progressive resistive exercises” Balance: Progressive in difficulty</td>
<td>1.5hrs</td>
<td>Approx. 24hrs over 16 weeks</td>
<td>1.5hrs</td>
<td>At 6 months, IRR = 0.20, 95% CI [0.04, 0.91] At 12 months, IRR = 0.45, 95% CI [0.16, 1.77]</td>
</tr>
</tbody>
</table>

*Note.* HEP = home exercise programme; hr/hrs = hour(s); mins = minutes; reps = repetitions; HR = heart rate; HRmax = maximum heart rate; IRR = incidence rate ratio; RH = relative hazard; 1RM = 1-repetition maximum; IG = intervention group; CG = control group; 95% CI = 95% confidence interval; RR = relative risk; SD = standard deviation; $p$ = significance value; RPE = rate of perceived exertion; ACSM = American College of Sports Medicine; CBT = cognitive behavioural therapy;
### Appendix G. Methodological overviews of SBFRA studies reviewed in Chapter 4.

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Design</th>
<th>Sample Size</th>
<th>Participants</th>
<th>Setting(s)</th>
<th>Fall-Risk Classification Method(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Auvinet et al. 2003)</td>
<td>Cross-sectional</td>
<td>N=53 (20 fallers, 33 non-fallers)</td>
<td>Non-fallers: Mean age 77.2 ± 6.5 years, no falls history Fallers: Mean age 80.8 ± 5.0 years, average of 3.6 ± 4.0 falls in previous year</td>
<td>Hospital</td>
<td>Faller status based on fall history in previous year</td>
</tr>
<tr>
<td>(Caby et al. 2011)</td>
<td>Cross-sectional</td>
<td>N=20 (15 at risk for falling, 5 not at risk)</td>
<td>Aged &gt;70 years, geriatric inpatients</td>
<td>Hospital</td>
<td>Comprehensive clinical gait and balance assessment by a physiotherapist</td>
</tr>
<tr>
<td>(de Bruin et al. 2007)</td>
<td>Pilot reliability study</td>
<td>N=11</td>
<td>Aged ≥70 years</td>
<td>Residential Care</td>
<td>Falls Efficacy Scale</td>
</tr>
<tr>
<td>(Doheny et al. 2011)</td>
<td>Cross-sectional</td>
<td>N=39 (19 fallers, 20 non-fallers)</td>
<td>Community-dwelling, mean age 71.4 ±7.3 years</td>
<td>Home</td>
<td>Faller status defined as &gt;1 fall in the previous five years, or 1 fall which required medical attention, or a fear of falling or one of the following cardiovascular risk factors: orthostatic hypotension, carotid sinus hypersensitivity or vasovagal syncope</td>
</tr>
<tr>
<td>(Doheny et al. 2012b)</td>
<td>Cross-sectional</td>
<td>N=110</td>
<td>Aged ≥60 years</td>
<td>Not specified</td>
<td>Fallers – had a fall in the previous 5 years</td>
</tr>
<tr>
<td>(Doheny et al. 2012a)</td>
<td>Cross-sectional</td>
<td>N=40</td>
<td>Aged &gt;60 years, community-dwelling</td>
<td>Home</td>
<td>Self-reported 1-year falls history</td>
</tr>
<tr>
<td>(Gietzelt et al. 2009)</td>
<td>Cross-sectional</td>
<td>N=241 (Group 1 = 131, Group 2 = 20, Group 3 = 90)</td>
<td>Group 1: Healthy non-fallers Group 2: Geriatric patients, Group 1: Science fair Groups 2 and 3: STRATIFY score (Group 1 assumed to be not at risk – not actually assessed using</td>
<td>Home</td>
<td>Faller status based on fall history in previous year</td>
</tr>
<tr>
<td>Study</td>
<td>Design</td>
<td>Sample Description</td>
<td>Hospital</td>
<td>Notes</td>
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<tr>
<td>Giansanti et al. 2008</td>
<td>Cross-sectional</td>
<td>Training data set: n=30 in each group Validation: n=100 in each group</td>
<td>Hospital</td>
<td>Not specified 3 categories based on POMA (&lt;19 = high risk; 19-24 = medium risk; 25-28 = low risk)</td>
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<tr>
<td>Greene et al. 2010</td>
<td>Cross-sectional</td>
<td>N=349 (207 fallers, 142 non-fallers) Community-dwelling, ≥65 years</td>
<td>Clinic</td>
<td>Self-reported history of falling in the past 5 years Berg Balance Scale</td>
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<tr>
<td>Greene et al. 2012a</td>
<td>Prospective</td>
<td>N=226 Community-dwelling, mean age 71.5 ± 6.7 years</td>
<td>Geriatric research clinic</td>
<td>Self-reported falls history at 2-year follow-up</td>
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<tr>
<td>Greene et al. 2012b</td>
<td>Cross-sectional</td>
<td>N=120 (65 fallers, 55 non-fallers) Community-dwelling, aged ≥60 years, medically stable, independently ambulant</td>
<td>Geriatric research clinic</td>
<td>Self-reported 5-year falls history</td>
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</tr>
<tr>
<td>Itoh et al. 2012</td>
<td>Cross-sectional</td>
<td>N=30 Aged ≥63 years</td>
<td>Public health centre</td>
<td>FRT, hurdle walk test, Tokyo Metropolitan Institute of Gerontology index of competence, a fall-risk assessment, 1-year self-reported falls history, self-reported carelessness</td>
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<tr>
<td>Marschollek et al. 2009</td>
<td>Cross-sectional</td>
<td>N=119 Inpatients, mean age 80 years</td>
<td>Geriatric Clinic</td>
<td>TUG, STRATIFY, Barthel Index, in-patient falls records</td>
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<tr>
<td>Marschollek et al. 2011a</td>
<td>Prospective</td>
<td>N=119 (n=46 at follow-up) Follow-up group: Inpatients at baseline, mean age 81.3 years</td>
<td>Geriatric Clinic</td>
<td>Self-reported falls at 1-year follow-up</td>
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<tr>
<td>Menz et al. 2003a</td>
<td>Cross-sectional</td>
<td>N=100 Community-dwelling, aged 75-93 years</td>
<td>Laboratory</td>
<td>PPA</td>
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<tr>
<td>Study</td>
<td>Design</td>
<td>N</td>
<td>Population</td>
<td>Setting</td>
<td>Risk Assessment Measures</td>
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<tr>
<td>Najafi et al. 2002</td>
<td>Cross-sectional</td>
<td>N=11</td>
<td>Community-dwelling, mean age 79±6 years</td>
<td>Laboratory</td>
<td>Combined fall-risk score derived from POMA, 1-year falls history, vision, cognition and depression</td>
</tr>
<tr>
<td>Narayanan et al. 2010</td>
<td>Cross-sectional</td>
<td>N=68</td>
<td>Aged 72-91 years, falls clinic attendees</td>
<td>Falls clinic</td>
<td>PPA</td>
</tr>
<tr>
<td>O'Sullivan et al. 2009</td>
<td>Cross-sectional</td>
<td>N=21</td>
<td>Day hospital physiotherapy patients, mean age 78±7.6 years</td>
<td>Day hospital</td>
<td>Berg Balance Scale, TUG, 1-year falls history</td>
</tr>
<tr>
<td>Riva et al. 2013</td>
<td>Cross-sectional</td>
<td>N=131</td>
<td>Aged 50-75 years</td>
<td>National fair</td>
<td>Self-reported 1-year falls history</td>
</tr>
<tr>
<td>Schwesig et al. 2013</td>
<td>Prospective cohort</td>
<td>N=146</td>
<td>Aged 62-101 years, nursing home residents</td>
<td>Nursing home</td>
<td>Falls documented by caregivers prospectively for 12 months</td>
</tr>
<tr>
<td>Toebes et al. 2012</td>
<td>Cross-sectional</td>
<td>N=134</td>
<td>Aged 50-75 years</td>
<td>National fair</td>
<td>Self-reported 1-year falls history</td>
</tr>
<tr>
<td>Weiss et al. 2011</td>
<td>Cross-sectional</td>
<td>N=41</td>
<td>Community-dwelling, mean age 76±3.9 years</td>
<td>Laboratory</td>
<td>Fallers – 2 or more falls in previous year</td>
</tr>
</tbody>
</table>

*Note. STRATIFY = St. Thomas Fall Risk Assessment Tool in Falling Elderly; POMA = Performance Oriented Mobility Assessment; FRT = Functional Reach test; TUG = Timed Up and Go test; PPA = Physiological Profile Assessment.*
**Appendix H. Details of sensor-based fall-risk assessment methods, variables and main results**

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Sensor Type(s)</th>
<th>Sensor Location(s)</th>
<th>Sampling Frequency</th>
<th>Sensor Wear Time</th>
<th>Data filtering</th>
<th>Task(s) Performed</th>
<th>Variable(s) Extracted</th>
<th>Association with Fall-Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Auvinet et al. 2003)</td>
<td>2 accelerometers: 1 aligned with vertical axis, 1 with ML axis</td>
<td>Lower back at L3-L4 level</td>
<td>50Hz</td>
<td>Duration of testing</td>
<td>Not specified</td>
<td>• 40m walk</td>
<td>• Walking speed • Stride length • Stride frequency • Stride symmetry • Stride regularity</td>
<td>All features differed significantly between fallers and controls</td>
</tr>
<tr>
<td>(Caby et al. 2011)</td>
<td>10 tri-axial accelerometers</td>
<td>1 accelerometer on each ankle, knee, wrist, elbow and shoulder</td>
<td>50Hz</td>
<td>Duration of testing</td>
<td>Not specified</td>
<td>• 25m walk</td>
<td>• 67 time and frequency-related features extracted</td>
<td>Correlation between arms and features related to step frequency best discriminated between those at risk and not at risk</td>
</tr>
<tr>
<td>(de Bruin et al. 2007)</td>
<td>Sagittal plane gyroscope Biaxial accelerometer (vertical and frontal)</td>
<td>Chest</td>
<td>40Hz</td>
<td>Worn continuously for 2 days, then 1 day a week later</td>
<td>Analogue low pass filter with 17Hz cut-off frequency</td>
<td>• STS transitions • Walking • Sitting, standing, lying</td>
<td>• STS and STS durations • Time spent in activity states</td>
<td>FES scores correlated with mean STS duration ($r=0.84, p&lt;0.01$) i.e. more confidence = quicker performance</td>
</tr>
<tr>
<td>(Doheny et al. 2011)</td>
<td>2 tri-axial accelerometers</td>
<td>Sternum and anterior thigh</td>
<td>102.4Hz</td>
<td>Duration of testing</td>
<td>Band pass filtered at 0.1 to 5Hz</td>
<td>• FTSS</td>
<td>• Total FTSS time • Mean &amp; coefficient of variation of times for individual sit-stand-sit, sit-stand &amp; stand-</td>
<td>• Mean STS time • Total ML jerk • Total and all phases SEF</td>
</tr>
<tr>
<td>(Doheny et al. 2012a)</td>
<td>Tri-axial accelerometer and gyroscope</td>
<td>For gait, 1 sensor on anterior of each shin For quiet standing, on lower back at L3</td>
<td>102.4Hz</td>
<td>Duration of testing</td>
<td>Band pass filtered at 0.1 to 10Hz</td>
<td>3m walk</td>
<td>Standing 30s in 4 conditions: eyes open, eyes closed, eyes open standing</td>
<td>Gait: stride time, step time, stance time, swing time, double support, single support, stride length and stride velocity</td>
</tr>
<tr>
<td>Study</td>
<td>Type of Accelerometer/Device</td>
<td>Location</td>
<td>Frequency</td>
<td>Duration of Testing</td>
<td>Band Pass Filter</td>
<td>Parameters</td>
<td>Findings</td>
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<tr>
<td>Doheny et al. 2012b</td>
<td>Tri-axial accelerometer</td>
<td>Lower back at level of L4</td>
<td>102.4Hz</td>
<td>Duration of testing</td>
<td>Band pass filtered at 0.1 to 10 Hz</td>
<td>• Standing 35s&lt;br&gt;• Semi-tandem 40s&lt;br&gt;• Displacement - Acceleration integrated twice, then corrected for drift&lt;br&gt;• Displacement range&lt;br&gt;• Horizontal sway length&lt;br&gt;• Sway velocity&lt;br&gt;• RMS acceleration in AP, ML and horizontal axes</td>
<td>ML sway for EC and ECF; greater AP sway for EC, EOF and ECF; higher SEFAP for EOF and ECF; lower SEFML for EC</td>
<td></td>
</tr>
<tr>
<td>Giansanti et al. 2008</td>
<td>3 uniaxial accelerometers and gyroscopes</td>
<td>Lower back at level of L5</td>
<td>Unspecified</td>
<td>Duration of testing</td>
<td>2&lt;sup&gt;nd&lt;/sup&gt; order Sallen-Key filters with 11.5Hz cut-off frequency and gain of 10</td>
<td>• Standing 60s: eyes open on a solid surface; eyes open on a foam cushion;&lt;br&gt;• Gyro signals - squared modulus of angular velocity, rotational kinematic energy&lt;br&gt;• Neural network constructed based</td>
<td>Participants with higher levels of fall-risk exhibited higher values on both gyroscope-derived parameters</td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>Type of Accelerometer</td>
<td>Placement</td>
<td>Sampling Rate</td>
<td>Duration of Testing</td>
<td>Analysis Parameters</td>
<td>Decision Model</td>
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<tr>
<td>(Gietzelt et al. 2009)</td>
<td>Tri-axial accelerometer</td>
<td>Waist – attached to belt buckle</td>
<td>100Hz</td>
<td>Duration of testing</td>
<td>0.25 to 4Hz band analysed</td>
<td>• TUG • Gait variability • Step duration • Energy expenditure estimate • Pelvic sway – mean transverse acceleration deviation</td>
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<td>Decision model based on pelvic sway and energy expenditure classified those at risk with 90.5% accuracy</td>
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<tr>
<td>(Greene et al. 2010)</td>
<td>2 Tri-axial accelerometers and gyroscopes</td>
<td>Mid-shank level on each leg</td>
<td>102.4Hz</td>
<td>Duration of testing</td>
<td>2nd order Sallen-Key filters with 11.5Hz cut-off frequency and gain of 10</td>
<td>• TUG • Temporal: Gait analysis (stride, swing etc.), time for phases, steps (mean and CV) • Angular velocity: Mean, min, max during phases and mid-swing in gait in each axis</td>
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<td>29 out of 44 parameters discriminated fallers from non-fallers</td>
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<td>3 logistic regression models incorporating sensor and demographic variables discriminated between fallers and non-fallers with a mean accuracy of 76.8%</td>
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</tr>
</tbody>
</table>

(Greene et al. 2010) 2 Tri-axial Mid-shank 102.4Hz Duration of 2nd order • TUG 44 features in the 3 classifier models
<table>
<thead>
<tr>
<th>Study</th>
<th>Sensors and Locations</th>
<th>Parameters</th>
<th>Filters/Bandpass</th>
<th>Follow-up Categories</th>
<th>Identification Accuracy</th>
</tr>
</thead>
</table>
| Greene et al. 2012a           | accelerometers and gyroscopes level on each leg                                        | butterworth filter with 10Hz cut-off frequency                           |                  | following categories:  
  - Temporal gait parameters  
  - Spatial gait parameters  
  - Tri-axial angular velocity parameters  
  - Turn parameters                         | prospectively identified fallers with a mean accuracy of 79.69%            |
| Greene et al. 2012b           | Tri-axial accelerometer and gyroscope Lower back at L3 level                            | Semi-tandem stance, eyes open, 40s  
  Narrow stance, eyes closed, 30s  
  Sway – RMS amplitude of ML and AP accelerations  
  SEF and median frequency for acceleration and angular velocity  
  Spectral entropy of all signals | Band pass filtered at 0.1 to 5Hz |                                                                                           |                       |
| Itoh et al. 2012              | 4 tri-axial accelerometers 1 sensor at the lumbar spine, lateral aspect of the knee and ankle and the dorsum of the | 10m walk  
  10m hurdle walk (6 hurdles)  
  Average accelerations from each sensor position | Duration of testing Not specified Not specified | Average ML lumbar accelerations significantly differed between high and low risk groups based on FRT, falls history and |                       |
Vertical lumbar accelerations also differed based on falls history. Average AP ankle accelerations differed based on hurdle walk time.

<table>
<thead>
<tr>
<th>Study (Marschollek et al. 2009)</th>
<th>Sensor Type</th>
<th>Measurement Location</th>
<th>Frequency</th>
<th>Duration</th>
<th>Analysis</th>
<th>Predictive Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tri-axial accelerometer</td>
<td>Lower back close to body’s centre of gravity</td>
<td>100Hz</td>
<td>Duration of testing</td>
<td>0.25 to 4Hz band analysed</td>
<td>TUG</td>
<td>Pelvic sway while walking, Step length, Energy expenditure, Periodicity of gait (standard deviation), Seconds per step, Step length, Number of steps taken in TUG, Number &amp; width of peaks in the frequency band 0.25 - 4.0 Hz (based on spectral density analysis of accelerometer signals)</td>
</tr>
<tr>
<td>Waist –</td>
<td>100Hz</td>
<td>Duration of</td>
<td>0.25 to</td>
<td>TUG</td>
<td>As above</td>
<td>The most accurate</td>
</tr>
<tr>
<td>Study</td>
<td>Measurement</td>
<td>Location</td>
<td>Sampling Rate</td>
<td>Duration of Testing</td>
<td>Filtering Method</td>
<td>Variables Used</td>
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<tr>
<td>et al. 2011a</td>
<td>Accelerometer</td>
<td>Mounted on belt</td>
<td>Testing</td>
<td>4Hz band</td>
<td>Analysed</td>
<td>Classifier based on accelerometer data (variables listed above) which predicted fallers with 80% accuracy</td>
</tr>
<tr>
<td>(Menz et al. 2003a)</td>
<td>2 tri-axial</td>
<td>Head and sacrum</td>
<td>200Hz</td>
<td>Not specified</td>
<td>Analogue low pass filtering with a cut-off filter</td>
<td>• Walking 20m on level and irregular surfaces</td>
</tr>
<tr>
<td></td>
<td>accelerometers</td>
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<td></td>
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<td></td>
<td>• Walking velocity (m/s)</td>
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<td>• Cadence (steps/min)</td>
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<td>• Mean step length (cm)</td>
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<td>• Step timing variability</td>
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<td></td>
<td>• Harmonic ratio of acceleration signals (rhythm of gait)</td>
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<td>High-risk fallers walked more slowly and took shorter steps than low-risk fallers on level surface, and both low- and moderate-risk fallers on irregular surface. High-risk fallers walked with a slower cadence and greater step-timing variability than both moderate- and low-risk fallers on irregular surface.</td>
</tr>
<tr>
<td>(Najafi et al. 2002)</td>
<td>Gyroscope</td>
<td>Anterior sternum</td>
<td>40Hz</td>
<td>Duration of testing</td>
<td>Analogue low pass filtering with a cut-off filter</td>
<td>• STS &amp; stand-to-sit transitions</td>
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<td></td>
<td>• Trunk tilt angle - integrated gyro signal (discrete wavelet transform)</td>
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<td>Significantly greater mean and SD of transition duration for the high fall-risk</td>
</tr>
<tr>
<td>Study (Year)</td>
<td>Accelerometer Type</td>
<td>Measurement Site</td>
<td>Frequency</td>
<td>Testing Duration</td>
<td>Feature(s)</td>
<td>Cited Study</td>
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</tr>
<tr>
<td>Narayanan et al. 2010</td>
<td>Tri-axial accelerometer</td>
<td>Waist at level of ischial spine</td>
<td>40Hz</td>
<td>Duration of testing</td>
<td>Walking, Mean transition duration, SD of same, number of attempts for a successful transition</td>
<td>Model comprising of AST variables and 1 FTSS variable – root-mean-squared signal vector magnitude – highly correlated with fall risk score ($\rho = 0.81$)</td>
</tr>
<tr>
<td>O'Sullivan et al. 2009</td>
<td>Tri-axial accelerometer</td>
<td>Lower back at L3</td>
<td>100Hz</td>
<td>Duration of testing</td>
<td>Calibrated and pre-processed using a second order polynomial fit, RMS amplitude of resultant acceleration vector (all axes combined) for each condition</td>
<td>Fallers: greater RMS values for EO on foam mat. RMS EO on foam mat strongly correlated with TUG time and negatively correlated with BBS score</td>
</tr>
<tr>
<td>Riva et al.</td>
<td>Tri-axial accelerometer</td>
<td>On trunk, just</td>
<td>Not</td>
<td>Duration of</td>
<td>Not, 3mins</td>
<td>For trunk</td>
</tr>
<tr>
<td>Year</td>
<td>Sensors</td>
<td>Attached Location</td>
<td>Testing Duration</td>
<td>Testing Parameters</td>
<td>Accelerations</td>
<td>Associations with Fall History</td>
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<tr>
<td>2013</td>
<td>Accelerometer and gyroscope below shoulder blades</td>
<td>Specified</td>
<td>Specified</td>
<td>Treadmill walking at 4km/h (extracted from 12-17mins walking)</td>
<td>Harmonic ratio, Index of harmonicity, Multiscale entropy (MSE), Recurrence quantification analysis (RQA)</td>
<td>Positive association with fall history found for: AP MSE, AP RQA</td>
</tr>
<tr>
<td>(Schwesig et al. 2013)</td>
<td>2 sensors each with tri-axial accelerometer, gyroscope and magnetometer Attached to lateral aspect of each shoe</td>
<td>Not specified</td>
<td>Duration of testing</td>
<td>20m walk</td>
<td>Temporal and kinematic gait parameters, including symmetry indices</td>
<td>Stride time &gt;1.19s (63%, 61%) Standard deviation of landing phase &gt;15.3% (100%, 42%)</td>
</tr>
<tr>
<td>(Toebes et al. 2012)</td>
<td>Tri-axial accelerometer and gyroscope On trunk, just below shoulder blades</td>
<td>Not specified</td>
<td>Duration of testing</td>
<td>20Hz 4th order Butterworth low pass filter</td>
<td>Using each axis for acceleration, angular velocity and combined angular velocities the following were calculated: 7 gait variability parameters, 7 short-term local dynamic stability parameters, 7 long-term local dynamic stability</td>
<td>Positive association with falls history found for: ML gait variability, Short-term gait instability</td>
</tr>
<tr>
<td>(Weiss et al. 2011)</td>
<td>Tri-axial accelerometer</td>
<td>Lower back at L3-L5 region</td>
<td>256Hz</td>
<td>Duration of testing</td>
<td>low pass filter at 2.5Hz</td>
<td>TUG parameters</td>
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<td>Acceleration-derived TUG duration (s)</td>
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<td>Sit-to-Stand and Stand-to-Sit durations (s)</td>
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<td>Sit-to-Stand and Stand-to-Sit Range (g)</td>
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<td>Sit-to-Stand and Stand-to-Sit Jerk (g/s), defined as the acceleration amplitude range and slope during phases of TUG</td>
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<td>The median accel and SD of the overall TUG trial and subtasks</td>
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<td>Mean step duration and no. of steps during TUG</td>
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</tbody>
</table>

**Note.** ML = Medio-lateral; AP = Antero-posterior; STS = Sit-to-stand; FES = Falls Efficacy Scale; FTSS = Five times sit-to-stand test; RMS = Root-mean-square; Accel = Acceleration; SEF = Spectral edge frequency; EC = Eyes closed; EO = Eyes open; ECF = Eyes closed on foam; EOF = Eyes open on foam; CV = Coefficient of variation; FRT = Functional reach test; STRATIFY = St. Thomas Fall Risk Assessment Tool in Falling Elderly Inpatients; SD = Standard deviation; TUG = Timed Up and Go test; BBS = Berg Balance Scale.
Appendix I. Ethics Approval Letter for the Cork Centres of the High-Risk Group

10th August 2011

Dr Amanda Clifford
Lecturer
Department of Physiotherapy
Faculty of Education and Health Sciences
University of Limerick
Limerick

Re: An investigation of physical activity patterns and fall-risk factors in community-dwelling older adults participating in a falls prevention programme.

Dear Dr Clifford

Expedited approval is granted to carry out the above study in:

- Ard Na Ri Day Care Centre, Farranree, Cork
- Turner’s Cross Day Care Centre

The following documents were approved:

- Application Form
- Insurance Certificate
- Study Protocol
- Referral Programme
- Health Checklist
- Invitation Letters
- Information Leaflet
- Consent Form
- Exercise and Falls Prevention Calendar
- Questionnaires.

We note that the co-investigators involved in this study will be:

- Valerie Power, Eileen Moriarty, Jamie Sheehy, Teresa O’Donovan and Emer O’Donovan.

Yours sincerely

Dr Michael Hylan
Chairman
Clinical Research Ethics Committee
of the Cork Teaching Hospitals
Appendix J. Ethics Approval Letter for the Ennis Centre of the High-Risk Group

20th September, 2011.

Ms. Valerie Power,
PhD Candidate,
Department of Physiotherapy,
Faculty of Education and Health Sciences,
University of Limerick,
Ireland.

Re: An investigation of physical activity patterns and fall-risk factors in community-dwelling older adults participating in a falls prevention

Dear Ms. Power,

I am in receipt of your study as above submitted for review by our Research Ethics Committee. I have reviewed the contents of same.

I wish to advise that I have given your study Chairperson ethical approval.

You should note that your study cannot commence until you also receive approval from the Risk Management Department. You are obliged to inform us as soon as your study is completed or if it terminates early for any reason. This approval will be issued to you shortly.

I wish you every success with your study

Yours sincerely,

Marie Hickey Dwyer,
Consultant Ophthalmic Surgeon,
Chairperson, Research Ethics Committee.
### Appendix K. Record sheet detailing falls prevention programme exercise class content and progressions

<table>
<thead>
<tr>
<th>Station 1</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Comments:</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Sit to stand</td>
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<td>Tick if exercise done, record weight used/upper limb support/mobility aid used</td>
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<td>b. Knee extension</td>
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<td>c. Hip flexion</td>
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<td>Station 2</td>
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<tr>
<td>a. Semi squats</td>
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<td>b. Knee Flexion</td>
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<td>c. Hip Abduction</td>
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<td>Station 3</td>
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<tr>
<td>a. Figure of 8</td>
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<tr>
<td>b. Up and Down stairs</td>
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<td>Station 4</td>
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<tr>
<td>a. Tandem stand</td>
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<td>b. Up on toes</td>
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<tr>
<td>c. Up on heels</td>
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<td>Station 5</td>
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<tr>
<td>a. Tandem walk</td>
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<tr>
<td>Option Tandem walk airtex</td>
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<td>b. Walk backwards</td>
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<td>Station 6</td>
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<tr>
<td>a. Single leg stance</td>
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<td>Option Single leg stance airtex</td>
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<td>b. Walk sideways</td>
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<tr>
<td>a. Walk on toes</td>
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<tr>
<td>b. Walk on heels</td>
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<td>Station 8</td>
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<tr>
<td>a. stand, turn to chair and back</td>
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<td>b. plus kneel down, back up again</td>
<td></td>
<td></td>
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<tr>
<td>c. plus crawl backwards, lie on side</td>
<td></td>
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<tr>
<td>d. plus roll onto all 4’s , crawl to chair</td>
<td></td>
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<tr>
<td>e. all elements together</td>
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</tbody>
</table>
Appendix L. Letter of Invitation to Participate in the High-Risk Group

Dear Sir/Madam,

You are invited to take part in a research study entitled ‘An investigation of physical activity patterns and fall-risk factors in community-dwelling older adults participating in a falls prevention programme’. This study is being carried out by researchers at the University of Limerick and colleagues in the PCCC North/South Lee Physiotherapy services.

All individuals referred to the ‘Steady Up’ falls prevention programme are invited to take part. Participation in this study is voluntary. If you choose not to participate, you may still take part fully in the ‘Steady Up’ programme. Please find enclosed an Information Sheet which provides details of what is involved in this research study. Please read this carefully.

If you are interested in taking part, please complete and sign the enclosed Consent Form and return it to the address below.

Please contact me using the details below if you have any questions.

Yours faithfully,

________________________
Valerie Power, MISCP
PhD Candidate
Department of Clinical Therapies,
Faculty of Education and Health Sciences,
University of Limerick,
Limerick, Ireland

Phone: 08x xxxxxxx
Email: Valerie.Power@ul.ie
An Investigation of Physical Activity Patterns and Fall-Risk Factors in Community-Dwelling Older Adults Participating in a Falls Prevention Programme

PARTICIPANT INFORMATION STATEMENT

You are invited to take part in the research project named above which is being carried out by researchers from the University of Limerick, in conjunction with Health Service Executive PCCC North/South Lee staff.

Aims
The study aims to examine the effects of participating in a falls prevention programme on people aged 65 years and over. The falls prevention programme will focus on exercise and education, with the aim of preventing falls and reducing the risk of falling.

Procedures
We are seeking approximately 40 people over the age of 65 years who have been referred to participate in a falls prevention programme.

If you decide to participate, you will be asked to:

- Complete the consent form attached to this information letter and contact the researcher at the telephone number listed below. The researcher will answer any questions you may have at this stage.
- Choose a convenient appointment time for a researcher to visit you in your own home for an assessment. This assessment will involve answering some questions about your health and some simple measurements of your movement, and will take roughly 60 minutes.
- Participate in the ‘Steady Up’ programme in your local day care centre. The programme will last for 6 weeks and will include group exercise classes, a home exercise programme, education and home safety advice.
- Participate in follow-up assessments of your health, movement and activity immediately after the programme is completed.

**Benefits**
You will receive the usual falls prevention service to which you have been referred, plus free additional assessments of your risk factors for falling and physical activity levels. You will also be contributing to research which aims to improve understanding and delivery of future falls prevention services.

**Risks**
There are no known or potential risks to participating in this study.

**Alternatives**
Participation in this study is entirely voluntary. If you cannot participate or choose not to participate in this study, you will still receive the usual falls prevention programme to which you have been referred.

**Voluntary Participation**
Participation in this research study is entirely your choice. Only those people who give their informed consent will be included. If you decide not to participate, your relationship with the University or your local healthcare providers will not be affected, and you will not be disadvantaged in any way.

**Stopping the Study**
If you decide to participate, you may withdraw from the study at any time without giving a reason, and you have the option to withdraw any information you have provided.

**Confidentiality**
Information obtained from your participation will be stored anonymously using an identification number and will only be accessed by the researchers involved in the study. Information will be securely stored by the researchers in a locked cupboard or in a computer file accessible only by the researchers. All information resulting from this research will be stored securely by the researchers for a period of seven years, after which it will be destroyed. Individual participants will not be identifiable in any reports or publications arising from the project.
Permission
This study has received ethics committee approval.

Further information
Please read this information statement, and be sure that you understand its contents before you decide whether or not to participate. You are invited to contact me to discuss any questions you may have before deciding to take part.

If you do decide to participate in this research study, please complete the attached consent form and bring it with you to your first ‘Steady Up’ appointment.

Thank you for considering this invitation.

Yours faithfully,

________________________________________

Valerie Power, MISCP
PhD Candidate,
Department of Clinical Therapies,
Faculty of Education and Health Sciences,
University of Limerick
Contact telephone number: 08x xxxxxxx

If you have concerns about this study and wish to contact someone independent, you may contact:

Dr. Michael Hyland,
Chairman,
Clinical Research Ethics Committee of the Cork Teaching Hospitals,
Lancaster Hall,
6 Little Hanover Street,
Cork
021-4901901

This information sheet is for you to keep.
Appendix N. Consent Form for High-Risk Group Participants

An Investigation of Physical Activity Patterns and Fall-Risk Factors in Community-Dwelling Older Adults Participating in a Falls Prevention Programme

PARTICIPANT CONSENT FORM

I, ..........................................................................

[PRINT NAME], give consent to my participation in the above-named research project.

In giving my consent I acknowledge that:

1. The procedures required for the project and the time involved have been explained to me, and any questions I have about the project have been answered to my satisfaction.

2. I have read the Participant Information Statement and have been given the opportunity to discuss the information and my involvement in the project with the researcher/s.

3. I understand that being in this study is completely voluntary – I am not under any obligation to consent.

4. I understand that I can withdraw from the study at any time, without affecting my relationship with the researchers or restricting my access to health care services normally available to me.
5. I understand that the sponsors and investigators have such insurance as is required by law in the event of injury resulting from this research.

6. I understand that my involvement is strictly confidential and no information about me will be used in any way that reveals my identity.

I, the undersigned, hereby consent to participate as a subject in the above described project. I have received a copy of this consent form for my records. I understand that if I have any questions concerning this research, I can contact the researchers as per the information sheet provided. If I have further queries concerning my rights in connection with the research, I can contact the Clinical Research Ethics Committee of the Cork Teaching Hospitals, Lancaster Hall, 6 Little Hanover Street, Cork.

Signed: __________________________________________________________________________

Address: __________________________________________________________________________

____________________________________________________________________________________

____________________________________________________________________________________

____________________________________________________________________________________

Telephone: __________________________________________________________________________

Date: ________________________________________________________________________________

Signature of witness: __________________________________________________________________

Signature of researcher: __________________________________________________________________
Appendix O. Sample Report of Low-Risk Group Participant Results

Dear Participant,

Thank you once again for taking part in our study entitled ‘An Investigation of Physical Activity Patterns and Fall-Risk Factors in Community-Dwelling Older Adults’. Your time and efforts are vital to the continued progress of research in the field of active ageing and are greatly appreciated.

Please find enclosed a summary of your individual results from the measures undertaken as part of this study. I hope you find these results informative and would encourage you to contact me if you require further details or clarification.

You will also find enclosed a leaflet containing general information and tips on community falls prevention and healthy ageing. I hope you find this information useful.

Please do not hesitate to contact me if you have any queries regarding your results or the information leaflet.

With Thanks,

__________________________________________
Valerie Power MISCP
PhD Candidate,
Department of Clinical Therapies,
Faculty of Education and Health Sciences,
University of Limerick,
Ireland.
Telephone: +353 8x xxxxxxx
1. **Berg Balance Scale**

The Berg Balance Scale was developed to measure balance among older people by assessing the performance of functional tasks. Each of the 14 tasks is scored from 0–4, for a maximum of 56 points. The test indicates that a score of 41–56 is associated with a low fall risk, 21–40 with a medium fall risk, and 0–20 with a high fall risk. It has been evaluated in several studies and is widely used in clinical practice and in research.

**Your Score: 54 out of 56**

This score indicates a high level of functional balance performance and places you comfortably in the ‘low fall risk’ category.

2. **Timed Up and Go Test**

**Your Score: 9.9 seconds**

This test measures functional mobility by timing the acts of rising from a chair, walking 3m, turning and returning to the chair. Individuals who take longer than 13.5 seconds to complete this test have been found to be at risk of falling. Your time is considerably faster and is well within the normal range for healthy active older adults.

3. **Five Times Sit-to-Stand Test**

**Your Score: 14.1 seconds**

This test is an indicator of leg muscle power. Individuals who take longer than 15 seconds to complete this test have been found to have poor leg power and to be at risk of falling. Your time is slightly faster and is within the normal range for healthy active older adults.

4. **5-Metre Walk Test**

**Your Score: 1.06 metres per second**

Walking speed is calculated from the time it takes to walk 5 metres. Walking speed can be used as an indicator of fall-risk – those with walking speeds slower than 0.7 metres per second have been found to be at higher risk of falling. Your walking speed is faster and is well within the normal range for healthy active older adults.
5. **Modified Falls Efficacy Scale**

Your Average Score: 9.6 out of 10

This scale measures your confidence to undertake day-to-day activities without having a fall. Your score indicates that you are highly confident to do basic daily activities safely. This confidence is justified, as you have scored well on all physical performance measures.

6. **Falls Behavioural Scale for the Older Person**

Your Score: 2.89 out of 4.0

This scale represents the extent to which your behaviours in day-to-day life place you at risk of having a fall – the higher the score, the more cautious the behaviour. Your score indicates that you are moderately aware of situations and behaviours that may increase your risk, but are not overly concerned or cautious. This is appropriate given your good performance on measures of balance and mobility. I would encourage you to remain vigilant and avoid unnecessary risks.

7. **Geriatric Depression Scale**

Your Score: 2 out of 15

A score of 4 or more suggests the possible presence of depression. Your score is below that cut-off point and suggests a low number of depression-related symptoms.

8. **Physical Activity Scale for the Elderly**

Your Score: 127.1

The normal score for your gender and age group is 89.1 (± 55.5). Your score places you within this average range, indicating that your lifestyle is equally as active your peers. I would encourage you to maintain or increase your physical activity levels. To meet current physical activity guidelines, you should also add more moderate to vigorous activities (exercise that gets you breathing harder than normal) and exercises specifically aimed at strengthening your muscles to your routine, perhaps through an appropriate exercise class.

Always consult your General Practitioner prior to beginning a new physical activity regime.
Falls Prevention in the Community

Falls are common, but can often be prevented!

Factors that Increase Your Risk of Falling:
- Age
- Female gender
- History of previous falls
- Fear of falling
- Deterioration in health, mobility, and strength
- Impaired gait or balance
- Cognitive impairment
- Depression
- Multiple medications
- Poor eyesight
- Poor hearing
- Vertigo
- Poor nutrition and diet
- Badly fitting footwear
- Alcohol misuse
- Continence
- Medical conditions

Osteoporosis
It is a disease which results in porous and fragile bones. This increases the risk of fracturing (breaking) a bone. It is both preventable and treatable.

1. **Eat a Bone Friendly-Diet**
   - Calcium is necessary for building and maintaining strong bones. Foods rich in calcium include milk, cheese, yoghurts and other dairy products
   - Vitamin D is essential for the absorption of calcium, and can be found in oily fish (salmon, sardines mackerel), margarine, and sunlight.

2. **Stop Smoking**
   - Smoking decreases the body’s ability to absorb calcium
   - Smoking affects the cells that build new bone, making bones weaker

3. **Ensure a Sensible Alcohol Intake**
   - Excessive alcohol decreases the body’s ability to absorb calcium
   - Alcohol can interact with medication, and increase the risk of falls

4. **Exercise**
   - Weight bearing exercises can help to stimulate new bone growth
   - Simple exercise like walking or climbing the stairs can be helpful
   - Exercise can improve balance and co-ordination
Exercise for Falls Prevention

What Type Of Exercise Is Best?
It is important to exercise all the parts of the body. A combination of balance, co-ordination, strength, and endurance training offers benefits for people at risk of falls. To be beneficial exercise must be maintained and progressive.

Balance and co-ordination activities
- Dancing
- Yoga
- Pilates
- Tai Chi

Strength Activities
- Climbing upstairs
- Standing up from a chair
- Walking uphill
- Carrying shopping
- Housework and gardening

Endurance Activities
- Walking
- Cycling
- Dancing
- Swimming

✓ It is a good idea to check with your GP if starting a new exercise programme
✓ Wear comfortable clothing and shoes that do not restrict movement
✓ Do not exercise if you are feeling unwell

If any of the following symptoms occur when exercising, STOP! And seek medical advice from your GP.
- Heart palpitations
- Severe breathlessness, nausea or dizziness
- Chest pain
- Fainting during or just after exercise
Home Safety Tips

In General
Is your home free from clutter?
Are floors uneven or slippery?
Are all areas of your home well lit, especially at night?
Are all rugs secure, with no corners turned up?
Are flexes and cables secured and not trailing across walkways?
Is the furniture arranged to allow ease of movement with walking aids?
Keep your telephone within easy reach
Watch out for pets in the home!

Hallway/Stairs
Are there banisters/handrails on both sides of the stairs? Do you use them?
Are the light switches located at both the top and bottom of the stairs?
Avoid heavy pattern carpets or floor coverings
If using a walking aid, is one available upstairs and downstairs?

Kitchen/ Living Room
Are regularly used items stored within easy reach?
Do you wipe up all spills immediately?
Are your chairs easy to get up from?

Bedroom
Do you have a bedside lamp?
Is the bed a suitable height?
Are bedclothes trailing on the floor? If so, remove due to trip hazard
Do you sit down when dressing?
Store frequently worn clothing within easy reach

Bathroom
Ensure soap and toiletries are within easy reach
Do you have difficulty using the toilet, bath or shower? Specialist equipment may be beneficial. Talk to your GP about Community Occupational Therapy
Make sure bath mats are non-slip and secure
What Should I Do if I Fall?

- Don’t panic – try to stay calm
- Assess the situation – if you are hurt or feel unable to get up, follow THE REST AND WAIT PLAN.
- If you are unhurt and know you are able to get up, follow THE UP AND ABOUT PLAN.

THE REST AND WAIT PLAN

- Try to summon help
  - Use a pendant alarm if you have one
  - Bang on the wall
  - Call out for help
  - Crawl towards your phone and dial 999
- Keep Warm
  - Move to a soft surface such as carpet
  - Try to reach for something to cover yourself
  - Try to move out of draughts
  - Do not lie in one position for too long, as you may get cold or could develop a pressure sore
  - Roll from side to side and move your arms and legs if possible – this will help to keep you warm
- If you need to empty your bladder while on the floor, use something such as tissue or an item of clothing to soak up the wet. If it is not too painful for you, move away from the wet area.

THE UP AND ABOUT PLAN

- Roll onto your hands and knees and crawl to a stable piece of furniture such as a bed stool or chair
- With your hands on the support, place one foot flat on the floor, bending your knee in front of your tummy
- Lean forward, push on your hands and feet, and bring your feet together
- Turn and sit on the seat. Rest for a while before getting up
- Tell your GP at your next visit – you may be able to access falls prevention services in your area
Appendix Q. Copy of Recruitment Advertisement for Low-Risk Group

Are You Interested in Healthy Ageing?

At the University of Limerick we are researching physical activity and how it relates to the occurrence of falls in adults aged 65 and over.

If you are

- aged 65 or over
- have NOT had a fall in the past 12 months
- are mobile and in good health

then you may be eligible to take part in our study.

Participants will receive free physical activity and fall-risk assessments by a Chartered Physiotherapist, assisted by physiotherapy students. Once the study is complete, you will be offered information on falls prevention tips and exercise for healthy ageing.

For further information, please contact us using the details below.
Appendix R. MATLAB code used to calculate sway angle variables in standing

```matlab
function [mean_ML] = PlotDataSwayAngle(file, Ts)
%Plots and gives descriptive stats for low-pass filtered accelerometer %data. Calculates "sway angle" and related variables.
%Ts = Sampling time point increments e.g. 0.01 for 100Hz; Fs = Sampling %frequency in Hz

a = importdata(file);
Fs = 1/Ts;

% getting the time vector starting from zero
% a(:,1) contains time in milliseconds
if isstruct(a)
    a = a.data;
end

time = a(:,1) - a(1,1) * ones(size(a(:,1)));
% convert milliseconds to seconds
time = time / 1000;

acc_x = a(:,2);
acc_y = a(:,3);
acc_z = a(:,4);
%button1 = a(:,16);
%button2 = a(:,17);

%Convert uncalibrated accelerometer files to m/sec2, and exception for %already calibrated files

if (strcmpi(file, 'H01_stand_cal.dat') ||
    strcmpi(file, 'H01_EC_cal.dat') ||
    strcmpi(file, 'H01_FT_cal.dat') ||
    strcmpi(file, 'H02_stand_cal.dat') ||
    strcmpi(file, 'H02_EC_cal.dat') ||
    strcmpi(file, 'H02_FT_cal.dat') ||
    strcmpi(file, 'H03_stand_cal.dat') ||
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    strcmpi(file, 'H17_FT_cal.dat') ||
    strcmpi(file, 'H18_stand_cal.dat') ||
    strcmpi(file, 'H18_EC_cal.dat') ||
    strcmpi(file, 'H18_FT_cal.dat') ||
    strcmpi(file, 'H19_stand_cal.dat') ||
```

259
if strcmpi(file,'E09Stand_F.dat') || strcmpi(file,'E09FT_F.dat') || strcmpi(file,'E09EC_F.dat') || strcmpi(file,'E09Stand_B.dat') || strcmpi(file,'E09FT_B.dat') || strcmpi(file,'E09EC_B.dat')
\n\n  acc_x=a(:,2);
  acc_y=a(:,3);
  acc_z=a(:,4);
else
  acc_x=acc_x/100;
  acc_y=acc_y/100;
  acc_z=acc_z/100;
end

%Invert axes for selected files

if (strcmpi(file,'E06Stand_F.dat')|strcmpi(file,'E06FT_F.dat')|strcmpi(file,'E06EC_F.dat'))|strcmpi(file,'E06Stand_B.dat')|strcmpi(file,'E06FT_B.dat')|strcmpi(file,'E06EC_B.dat')
\n\n  acc_z=a(:,4);
  acc_y=a(:,3);
  acc_x=a(:,2);
\n\nelse
  acc_x=acc_x/100;
  acc_y=acc_y/100;
  acc_z=acc_z/100;
end

gain = -1;
end

% 8th order low-pass Butterworth filter (2Hz)
Fn = 2;
Wn = 2*Fn*Ts;
[c, d] = butter(8, Wn, 'low');
acc_x_LP = gain * filtfilt(c, d, acc_x);
acc_y_LP = filtfilt(c, d, acc_y);
acc_z_LP = gain * filtfilt(c, d, acc_z);

% Code added to obtain sway angle (medio-lateral)
% gravity vector:
G = [acc_x_LP'; acc_y_LP'; acc_z_LP'];
% normalise gravity vector to g
[R, C] = size(G);
G = G ./ repmat(sqrt(acc_x_LP .* acc_x_LP + acc_y_LP .* acc_y_LP + acc_z_LP .* acc_z_LP), 1, C);

% plot to verify normalisation:
% plot(G(:,1).*G(:,1)+G(:,2).*G(:,2)+G(:,3).*G(:,3));

% calculate angle (in degrees) of medio-lateral sway (as deviation from 0 (g) of y-axis)
angle_ML = (asin(G(:,2)) * 180 / pi);

% ML sway stats
mean_ML = mean(angle_ML);
SD_ML = std(angle_ML);
min_ML = min(angle_ML);
max_ML = max(angle_ML);
range_ML = range(angle_ML);
IQR_ML = iqr(angle_ML);

% calculate angle of anterior-posterior sway (as deviation from 0 (g) of z-axis)
angle_AP = asin(G(:,3)) * 180 / pi;

% AP sway stats
mean_AP = mean(angle_AP);
SD_AP = std(angle_AP);
min_AP = min(angle_AP);
max_AP = max(angle_AP);
range_AP = range(angle_AP);
IQR_AP = iqr(angle_AP);
%Sway angle-related variables
SwayArray = cell(12,1);

SwayArray{1,1}='Mean ML';
SwayArray{1,2}='SD ML';
SwayArray{1,3}='Min ML';
SwayArray{1,4}='Max ML';
SwayArray{1,5}='Range ML';
SwayArray{1,6}='IQR ML';
SwayArray{1,7}='Mean AP';
SwayArray{1,8}='SD AP';
SwayArray{1,9}='Min AP';
SwayArray{1,10}='Max AP';
SwayArray{1,11}='Range AP';
SwayArray{1,12}='IQR AP';

SwayArray{2,1}=mean(angle_ML);
SwayArray{2,2}=std(angle_ML);
SwayArray{2,3}=min(angle_ML);
SwayArray{2,4}=max(angle_ML);
SwayArray{2,5}=range(angle_ML);
SwayArray{2,6}=iqr(angle_ML);
SwayArray{2,7}=mean(angle_AP);
SwayArray{2,8}=std(angle_AP);
SwayArray{2,9}=min(angle_AP);
SwayArray{2,10}=max(angle_AP);
SwayArray{2,11}=range(angle_AP);
SwayArray{2,12}=iqr(angle_AP);

filename = strcat('./SwayAngleJun14/', strrep(file,'.dat','.xls'));
xlswrite(filename, SwayArray);

figure;
plot(time, angle_AP, 'b');
hold;
plot(time, angle_ML,'r');
title(file);
xlabel('Time (s)');
ylabel('Sway angle (degrees)');
legend('AP', 'ML');
Appendix S. MATLAB code used to calculate acceleration-related variables (whole signal averages) in standing

function [sef_RSS]=SwayBandpass(file, Ts)
%Calculates bandpass filtered acceleration data (0.1-5Hz) for
%comparison with RMS/RSS data in other studies.
%Ts = Sampling time point increments e.g. 0.01 for 100Hz; Fs =
%frequency in Hz

a=importdata(file);
Fs = 1/Ts;

% getting the time vector starting from zero
% a(:,1) contains time in milliseconds
if isstruct(a)
    a = a.data;
end
time=a(:,1)-a(1,1)*ones(size(a(:,1)));
% convert milliseconds to seconds
time=time/1000;

acc_x=a(:,2);
acc_y=a(:,3);
acc_z=a(:,4);
%button1=a(:,16);
%button2=a(:,17);

%Convert uncalibrated accelerometer files to m/sec2, and exception for
already calibrated files
if (strcmpi(file,'H01_stand_cal.dat') ||
strcmpi(file,'H01_EC_cal.dat') ||
strcmpi(file,'H01_FT_cal.dat') ||
strcmpi(file,'H02_stand_cal.dat') ||
strcmpi(file,'H02_EC_cal.dat') ||
strcmpi(file,'H02_FT_cal.dat') ||
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strcmpi(file,'H06_stand_cal.dat') ||
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strcmpi(file,'H10_stand_cal.dat') ||
strcmpi(file,'H10_EC_cal.dat') ||
strcmpi(file,'H10_FT_cal.dat') ||
strcmpi(file,'H11_stand_cal.dat') ||
strcmpi(file,'H11_EC_cal.dat') ||
strcmpi(file,'H11_FT_cal.dat') ||
strcmpi(file,'H12_stand_cal.dat') ||
strcmpi(file,'H12_EC_cal.dat') ||
strcmpi(file,'H12_FT_cal.dat') ||
strcmpi(file,'H13_stand_cal.dat') ||
strcmpi(file,'H13_EC_cal.dat') ||
strcmpi(file,'H13_FT_cal.dat') ||
strcmpi(file,'H14_stand_cal.dat') ||
strcmpi(file,'H14_EC_cal.dat') ||
strcmpi(file,'H14_FT_cal.dat') ||
strcmpi(file,'H15_stand_cal.dat') ||
strcmpi(file,'H15_EC_cal.dat') ||
strcmpi(file,'H15_FT_cal.dat') ||
strcmpi(file,'H16_stand_cal.dat') ||
strcmpi(file,'H16_EC_cal.dat') ||
strcmpi(file,'H16_FT_cal.dat') ||
strcmpi(file,'H17_stand_cal.dat') ||
strcmpi(file,'H17_EC_cal.dat') ||
strcmpi(file,'H17_FT_cal.dat') ||
strcmpi(file,'H18_stand_cal.dat') ||
strcmpi(file,'H18_EC_cal.dat') ||
strcmpi(file,'H18_FT_cal.dat') ||
strcmpi(file,'H19_stand_cal.dat') ||
strcmpi(file,'H19_EC_cal.dat') ||
strcmpi(file,'H19_FT_cal.dat') ||
strcmpi(file,'H20_stand_cal.dat') ||
strcmpi(file,'H20_EC_cal.dat') ||
strcmpi(file,'H20_FT_cal.dat') ||
strcmpi(file,'H21_stand_cal.dat') ||
strcmpi(file,'H21_EC_cal.dat') ||
strcmpi(file,'H21_FT_cal.dat') ||
strcmpi(file,'H22_stand_cal.dat') ||
strcmpi(file,'H22_EC_cal.dat') ||
strcmpi(file,'H22_FT_cal.dat') ||
strcmpi(file,'H23_stand_cal.dat') ||
strcmpi(file,'H23_EC_cal.dat') ||
strcmpi(file,'H23_FT_cal.dat') ||
strcmpi(file,'H24_stand_cal.dat') ||
strcmpi(file,'H24_EC_cal.dat') ||
strcmpi(file,'H24_FT_cal.dat') ||
strcmpi(file,'H25_stand_cal.dat') ||
strcmpi(file,'H25_EC_cal.dat') ||
strcmpi(file,'H25_FT_cal.dat')||
strcmpi(file,'H26_stand_cal.dat') ||
strcmpi(file,'H26_EC_cal.dat') ||
strcmpi(file,'H26_FT_cal.dat') ||
strcmpi(file,'H27_stand_cal.dat') ||
strcmpi(file,'H27_EC_cal.dat') ||
strcmpi(file,'H27_FT_cal.dat') ||
strcmpi(file,'H28_stand_cal.dat') ||
strcmpi(file,'H28_EC_cal.dat') ||
strcmpi(file,'H28_FT_cal.dat') ||
strcmpi(file,'H29_stand_cal.dat') ||
strcmpi(file,'H29_EC_cal.dat') ||
strcmpi(file,'H29_FT_cal.dat') ||
strcmpi(file,'H30_stand_cal.dat') ||
strcmpi(file,'H30_EC_cal.dat') ||
strcmpi(file,'H30_FT_cal.dat') ||
strcmpi(file,'H31_stand_cal.dat') ||
strcmpi(file,'H31_EC_cal.dat') ||
strcmpi(file,'H31_FT_cal.dat') ||
strcmpi(file,'H32_stand_cal.dat') ||
strcmpi(file,'H32_EC_cal.dat') ||
strcmpi(file,'H32_FT_cal.dat') ||
strcmpi(file,'H33_stand_cal.dat') ||
strcmpi(file,'H33_EC_cal.dat') ||
strcmpi(file,'H33_FT_cal.dat') ||
strcmpi(file,'H34_stand_cal.dat') ||
strcmpi(file,'H34_EC_cal.dat') ||
strcmpi(file,'H34_FT_cal.dat') ||
strcmpi(file,'H35_stand_cal.dat') ||
strcmpi(file,'H35_EC_cal.dat') ||
strcmpi(file,'H35_FT_cal.dat') ||
strcmpi(file,'H36_stand_cal.dat') ||
strcmpi(file,'H36_EC_cal.dat') ||
strcmpi(file,'H36_FT_cal.dat') ||
strcmpi(file,'H37_stand_cal.dat') ||
strcmpi(file,'H37_EC_cal.dat') ||
strcmpi(file,'H37_FT_cal.dat') ||
strcmpi(file,'H38_stand_cal.dat') ||
strcmpi(file,'H38_EC_cal.dat') ||
strcmpi(file,'H38_FT_cal.dat') ||
strcmpi(file,'H39_stand_cal.dat') ||
strcmpi(file,'H39_EC_cal.dat') ||
strcmpi(file,'H39_FT_cal.dat') ||
strcmpi(file,'H40_stand_cal.dat') ||
strcmpi(file,'H40_EC_cal.dat') ||
strcmpi(file,'H40_FT_cal.dat') ||
strcmpi(file,'H41_stand_cal.dat') ||
strcmpi(file,'H41_EC_cal.dat') ||
strcmpi(file,'H41_FT_cal.dat') ||
strcmpi(file,'H42_stand_cal.dat') ||
strcmpi(file,'H42_EC_cal.dat') ||
strcmpi(file,'H42_FT_cal.dat') ||
strcmpi(file,'H43_stand_cal.dat') ||
strcmpi(file,'H43_EC_cal.dat') ||
strcmpi(file,'H43_FT_cal.dat') ||
strcmpi(file,'H44_stand_cal.dat') ||
strcmpi(file,'H44_EC_cal.dat') ||
strcmpi(file,'H44_FT_cal.dat') ||
strcmpi(file,'H45_stand_cal.dat') ||
strcmpi(file,'H45_EC_cal.dat') ||
strcmpi(file,'H45_FT_cal.dat') ||
strcmpi(file,'H46_stand_cal.dat') ||
strcmpi(file,'H46_EC_cal.dat') ||
strcmpi(file,'H46_FT_cal.dat') ||
strcmpi(file,'H47_stand_cal.dat') ||
strcmpi(file,'H47_EC_cal.dat') ||
strcmpi(file,'H47_FT_cal.dat') ||
strcmpi(file,'H48_stand_cal.dat') ||
strcmpi(file,'H48_EC_cal.dat') ||
strcmpi(file,'H48_FT_cal.dat') ||
function acc_z=acc_z/100;
acc_y=acc_y/100
acc_x=acc_x/100;

acc_z=a(:,4);
acc_y=a(:,3);
acc_x=a(:,2);

%Invert axes for selected files

if strcmpi(file,'H18_FT_cal.dat') || strcmpi(file,'H19_stand_cal.dat') ||
  strcmpi(file,'H19_EC_cal.dat') || strcmpi(file,'H19_FT_cal.dat') ||
  strcmpi(file,'H20_stand_cal.dat') || strcmpi(file,'H20_FT_cal.dat') ||
  strcmpi(file,'H21_stand_cal.dat') || strcmpi(file,'H21_FT_cal.dat')
  acc_x=a(:,2);
  acc_y=a(:,3);
  acc_z=a(:,4);
else
  acc_x=acc_x/100;
  acc_y=acc_y/100;
  acc_z=acc_z/100;
end
(file,'H24_FT.dat')|| strcmpi(file,'H24_EC.dat')||
strcmpi(file,'H25_Stand.dat')||strcmpi(file,'H25_FT.dat')||strcmpi(file,'H25_EC.dat')||
strcmpi(file,'H26_Stand.dat')||strcmpi(file,'H26_FT.dat')||
strcmpi(file,'H26_EC.dat')||strcmpi(file,'H27_Stand.dat')||strcmpi(file,'H27_FT.dat')||
strcmpi(file,'H27_EC.dat')||strcmpi(file,'H28_Stand.dat')||strcmpi(file,'H28_FT.dat')||
strcmpi(file,'H28_EC.dat')||strcmpi(file,'H29_Stand.dat')||strcmpi(file,'H29_FT.dat')||
strcmpi(file,'H29_EC.dat')||strcmpi(file,'H30_Stand.dat')||strcmpi(file,'H30_FT.dat')||
strcmpi(file,'H30_EC.dat')||strcmpi(file,'H31_Stand.dat')||strcmpi(file,'H31_FT.dat')||
strcmpi(file,'H31_EC.dat')||strcmpi(file,'H32_Stand.dat')||strcmpi(file,'H32_FT.dat')||
strcmpi(file,'H32_EC.dat')||strcmpi(file,'H33_Stand.dat')||strcmpi(file,'H33_FT.dat')||
strcmpi(file,'H33_EC.dat')||strcmpi(file,'H34_Stand.dat')||strcmpi(file,'H34_FT.dat')||
strcmpi(file,'H34_EC.dat')||strcmpi(file,'H35_Stand.dat')||strcmpi(file,'H35_FT.dat')||
strcmpi(file,'H35_EC.dat')||strcmpi(file,'H36_Stand.dat')||strcmpi(file,'H36_FT.dat')||
strcmpi(file,'H36_EC.dat'))

gain = -1;
end

%convert accel to G from m/sec^2
acc_x = acc_x./9.81;
acc_y = acc_y./9.81;
acc_z = acc_z./9.81;

%Bandpass filter with normalised cut-off frequencies 0.1-5Hz
w1=(0.1*2*pi)/(Fs*pi);
w2=(5*2*pi)/(Fs*pi);
Wn=[w1, w2];
[c,d]=butter(4,Wn,'bandpass');
acc_x_BP=gain*filtfilt(c,d,acc_x);
acc_y_BP=filtfilt(c,d,acc_y);
acc_z_BP=gain*filtfilt(c,d,acc_z);

%Mean measured accelerations
mean_acc_y = mean(acc_y_BP);
[R,C] = size(acc_y_BP);
mean_acc_y = repmat(mean_acc_y, R, C);

mean_acc_z = mean(acc_z_BP);
[R,C] = size(acc_z_BP);
mean_acc_z = repmat(mean_acc_z, R, C);

%True ML acceleration
Acc_ML = (acc_y_BP - mean_acc_y)./cos(asin(mean_acc_y));

%True AP acceleration
Acc_AP = (acc_z_BP - mean_acc_z)./cos(asin(mean_acc_z));

%RMS of filtered acc amplitudes: x=Vert, y=ML, z=AP (approx.) and corrected AP and ML acceleration
RMS_x = sqrt(mean(acc_x_BP.^2));
RMS_y = sqrt(mean(acc_y_BP.^2));
RMS_z = sqrt(mean(acc_z_BP.^2));
RMS_ML = sqrt(mean(Acc_ML.^2));
RMS_AP = sqrt(mean(Acc_AP.^2));

figure;
plot(time, acc_y_BP, 'y');
hold;
plot(time,acc_z_BP, 'g');
plot(time,Acc_ML, 'r');
plot(time,Acc_AP, 'b')
title(file);
xlabel('Time (s)');
ylabel('Acceleration (g)');
legend('Y', 'Z', 'ML', 'AP');
hold;

%Band-pass filtered RSS acceleration data and related variables
ax=acc_x_BP.*acc_x_BP;
ay=acc_y_BP.*acc_y_BP;
az=acc_z_BP.*acc_z_BP;
RSS_acc_BP=sqrt(ax+ay+az);
RSS_RMS_BP=sqrt(mean(RSS_acc_BP.^2));
SD_RSS=std(RSS_acc_BP);
Median_RSS=median(RSS_acc_BP);
IQR_RSS=iqr(RSS_acc_BP);
Range_RSS=range(RSS_acc_BP);
Min_RSS=min(RSS_acc_BP);
Max_RSS=max(RSS_acc_BP);

figure;
plot(time, RSS_acc_BP, 'b');
hold;

% Frequency Analysis

% Frequency for "true" ML acceleration
L=length(Acc_ML);
NFFT = 2^nextpow2(L);
Y=fft(Acc_ML,NFFT)/L;
freq_ML= Fs/2*linspace(0,1,NFFT/2+1);
Power_ML = 2*abs(Y(1:NFFT/2+1));

% Frequency for "true" AP accelerations
L=length(Acc_AP);
NFFT = 2^nextpow2(L);
Y=fft(Acc_AP,NFFT)/L;
freq_AP = Fs/2*linspace(0,1,NFFT/2+1);
Power_AP = 2*abs(Y(1:NFFT/2+1));

% Frequency for resultant acceleration vector
L=length(RSS_acc_BP);
NFFT = 2^nextpow2(L);
Y=fft(RSS_acc_BP,NFFT)/L;
freq_RSS = Fs/2*linspace(0,1,NFFT/2+1);
Power_RSS = 2*abs(Y(1:NFFT/2+1));

%Spectral edge frequency for corrected AP, ML and resultant acceleration vector (RSS)
max_index = find(freq_AP > 5, 1, 'first');
Power_AP_norm = Power_AP(1:max_index)./sum(Power_AP(1:max_index));
Power_AP_cum = cumsum(Power_AP_norm);
idx = find(Power_AP_cum > 0.95,1,'first');
sef_AP = freq_AP(idx);

max_index = find(freq_ML > 5, 1, 'first');
Power_ML_norm = Power_ML(1:max_index)./sum(Power_ML(1:max_index));
Power_ML_cum = cumsum(Power_ML_norm);
idx = find(Power_ML_cum > 0.95,1,'first');
sef_ML = freq_ML(idx);

max_index = find(freq_RSS > 5, 1, 'first');
Power_RSS_norm = Power_RSS(1:max_index)./sum(Power_RSS(1:max_index));
Power_RSS_cum = cumsum(Power_RSS_norm);
idx = find(Power_RSS_cum > 0.95,1,'first');
sef_RSS = freq_RSS(idx);

figure;
plot(freq_RSS,Power_RSS);
hold;
yL = get(gca, 'YLim');
line([sef_RSS sef_RSS],yL,'Color','r');
title('Spectral Edge Frequency - RSS');
xlabel('Frequency (Hz)');
ylabel('Power (m/s^2/Hz)');

%Acceleration variables output
AccelArray = cell(13,1);
AccelArray{1,1}='RMS X';
AccelArray{1,2}='RMS Y';
AccelArray{1,3}='RMS Z';
AccelArray{1,4}='RMS ML';
AccelArray{1,5}='RMS AP';
AccelArray{1,6}='RMS RSS';
AccelArray{1,7}='SD RSS';
AccelArray{1,8}='Median RSS';
AccelArray{1,9}='Min RSS';
AccelArray{1,10}='Max RSS';
AccelArray{1,11}='SEF ML';
AccelArray{1,12}='SEF AP';
AccelArray{1,13}='SEF RSS';

AccelArray{2,1}=RMS_x;
AccelArray{2,2}=RMS_y;
AccelArray{2,3}=RMS_z;
AccelArray{2,4}=RMS_ML;
AccelArray{2,5}=RMS_AP;
AccelArray{2,6}=RSS_RMS_BP;
AccelArray{2,7}=SD_RSS;
AccelArray{2,8}=Median_RSS;
AccelArray{2,9}=Min_RSS;
AccelArray{2,10}=Max_RSS;
AccelArray{2,11}=sef_ML;
AccelArray{2,12}=sef_AP;
AccelArray{2,13}=sef_RSS;

filename = strcat('./AccelJun14/', strrep(file, '.dat', '.xls'));
xlswrite(filename, AccelArray);
Appendix T. MATLAB code used to perform acceleration signal optima analysis

```matlab
function [Fs]=DetermineSwayOptima(file, Ts)
%Plotting and analysing standing data optima

a=importdata(file);
Fs = 1/Ts;
% getting the time vector starting from zero
% a(:,1) contains time in milliseconds
if isstruct(a)
    a = a.data;
end

time=a(:,1)-a(1,1)*ones(size(a(:,1)));
% convert milliseconds to seconds

time=time/1000;

acc_x=a(:,2);
acc_y=a(:,3);
acc_z=a(:,4);

%Convert uncalibrated accelerometer files to m/sec^2, and exception for already calibrated files

    acc_x=a(:,2);
    acc_y=a(:,3);
```
acc_z = a(:,4);
else
    acc_x = acc_x / 100;
    acc_y = acc_y / 100;
    acc_z = acc_z / 100;
end

% Invert axes for selected files

if strcmpi(file, 'E06Stand_F.dat') || strcmpi(file, 'F06FT_F.dat') || strcmpi(file, 'E06EC_F.dat') || strcmpi(file, 'F07FT_F.dat') || strcmpi(file, 'E07EC_F.dat') || strcmpi(file, 'E08Stand_B.dat') || strcmpi(file, 'E08FT_B.dat') || strcmpi(file, 'E08EC_B.dat') || strcmpi(file, 'E08FT_F.dat') || strcmpi(file, 'E08EC_F.dat') || strcmpi(file, 'E09Stand_B.dat') || strcmpi(file, 'E09FT_B.dat') || strcmpi(file, 'E09EC_F.dat') || strcmpi(file, 'F04Stand_F.dat') || strcmpi(file, 'F04FT_F.dat') || strcmpi(file, 'F04EC_F.dat') || strcmpi(file, 'F08Stand_B.dat') || strcmpi(file, 'F08EC_B.dat') || strcmpi(file, 'F10Stand_B.dat') || strcmpi(file, 'F07FT_B.dat') || strcmpi(file, 'F10FT_B.dat') || strcmpi(file, 'F10EC_F.dat') || strcmpi(file, 'F11Stand_B.dat') || strcmpi(file, 'F11FT_B.dat') || strcmpi(file, 'F11EC_F.dat') || strcmpi(file, 'F12Stand_B.dat') || strcmpi(file, 'F12FT_B.dat') || strcmpi(file, 'F12EC_B.dat') || strcmpi(file, 'F13Stand_B.dat') || strcmpi(file, 'F13FT_B.dat') || strcmpi(file, 'F13EC_B.dat') || strcmpi(file, 'F14Stand_B.dat') || strcmpi(file, 'F14FT_B.dat') || strcmpi(file, 'F14EC_F.dat') || strcmpi(file, 'T09Stand_F.dat') || strcmpi(file, 'T09FT_F.dat') || strcmpi(file, 'T10Stand_B.dat') || strcmpi(file, 'T10FT_B.dat') || strcmpi(file, 'T10EC_F.dat') || strcmpi(file, 'T11Stand_B.dat') || strcmpi(file, 'T11FT_B.dat') || strcmpi(file, 'T11EC_F.dat') || strcmpi(file, 'T12Stand_B.dat') || strcmpi(file, 'T12FT_B.dat') || strcmpi(file, 'T12EC_B.dat') || strcmpi(file, 'T12FT_F.dat') || strcmpi(file, 'T12EC_F.dat') || strcmpi(file, 'T13Stand_B.dat') || strcmpi(file, 'T13FT_B.dat') || strcmpi(file, 'T13EC_B.dat') || strcmpi(file, 'T13FT_F.dat') || strcmpi(file, 'T14Stand_B.dat') || strcmpi(file, 'T14FT_B.dat') || strcmpi(file, 'T14EC_F.dat') || strcmpi(file, 'T15Stand_B.dat') || strcmpi(file, 'T15FT_B.dat') || strcmpi(file, 'T15EC_B.dat') || strcmpi(file, 'T16Stand_B.dat') || strcmpi(file, 'T16FT_B.dat') || strcmpi(file, 'T16EC_B.dat') || strcmpi(file, 'T16FT_F.dat') || strcmpi(file, 'T16EC_F.dat') || strcmpi(file, 'H20_Stand_cal.dat') || strcmpi(file, 'H21_Stand_cal.dat') || strcmpi(file, 'H22_Stand_cal.dat') || strcmpi(file, 'H23_Stand_cal.dat') || strcmpi(file, 'H24_Stand_cal.dat') || strcmpi(file, 'H25_Stand_cal.dat') || strcmpi(file, 'H26_Stand_cal.dat') || strcmpi(file, 'H27_Stand_cal.dat') || strcmpi(file, 'H28_Stand_cal.dat') || strcmpi(file, 'H29_Stand_cal.dat');

    gain = -1;

end

% convert accel to G from m/sec^2
acc_x = acc_x/9.81;
acc_y = acc_y/9.81;
acc_z = acc_z/9.81;

% 8th order low-pass Butterworth filter (2Hz)
Fn=2;
Wn=2*Fn*Ts;
[c,d]=butter(8,Wn, 'low');
acc_x_LP=gain*filtfilt(c,d,acc_x);
acc_y_LP=filtfilt(c,d,acc_y);
acc_z_LP=gain*filtfilt(c,d,acc_z);

% RMS of acc amplitudes: x=Vert, y=ML, z=AP (approx.)
RMS_x = sqrt(mean(acc_x_LP.^2));
RMS_y = sqrt(mean(acc_y_LP.^2));
RMS_z = sqrt(mean(acc_z_LP.^2));
RMS_values = [RMS_x, RMS_y, RMS_z]

% RSS acceleration data
ax=acc_x.*acc_x;
ay=acc_y.*acc_y;
az=acc_z.*acc_z;
RSS_acc=sqrt(ax+ay+az);

% RSS acceleration data
ax=acc_x_LP.*acc_x_LP;
ay=acc_y_LP.*acc_y_LP;
az=acc_z_LP.*acc_z_LP;
RSS_acc_LP=sqrt(ax+ay+az);

% Correcting for sensor tilt angle
% Mean measured accelerations
mean_acc_y = mean(acc_y_LP);
[R,C] = size(acc_y_LP);
mean_acc_y = repmat(mean_acc_y, R, C);
mean_acc_z = mean(acc_z_LP);
[R,C] = size(acc_z_LP);
mean_acc_z = repmat(mean_acc_z, R, C);

% True ML accel
Acc_ML = (acc_y_LP - mean_acc_y)./cos(asin(mean_acc_y));

% True AP accel
Acc_AP = (acc_z_LP - mean_acc_z)./cos(asin(mean_acc_z));

figure;
plot(time, Acc_ML,'r', time, Acc_AP,'b');
hold;
title(file)
xlabel('Time (s)');
ylabel('Acceleration (g)');
legend ('Accel ML', 'Accel AP');

%Added by Pepijn to find optima of the function (ML signal):
V = AXIS;
Z_diff = diff(Acc_ML)/Ts;

% drag window through Z_diff and compare endpoints: if the sign of the
% derivative is different for the two end points there is a optimum in
% between. Register the point at which the derivative changes as the
% mid-point of the window
window_size = 11; %window size in samples
window_halfwidth = floor(window_size);
peak_detected = false;

zero_area_indices = zeros(1,length(Z_diff));
current_zero_area_indices = zeros(1,length(Z_diff));
i=window_halfwidth+1;
j=1;
k=1;
while (i<length(Z_diff)-window_halfwidth)
    start_point = Z_diff(i-window_halfwidth);
    end_point = Z_diff(i+window_halfwidth);

    % change of sign: optimum in between
    if (peak_detected == true)& (start_point*end_point > 0)
        current_zero_area_indices =
        current_zero_area_indices(1,1:find(current_zero_area_indices==0,1)-1);
        zero_area_indices(k:k+length(current_zero_area_indices)-1) =
        current_zero_area_indices;
        peak_detected = false;
        j=1;
        k=k+length(current_zero_area_indices);
        current_zero_area_indices = zeros(1,length(Z_diff));
    end
    if (start_point*end_point < 0)
        peak_detected = true;
        current_zero_area_indices(j) = i;
        j=j+1;
    end
    i=i+1;
end
%zero_area_indices = find(abs(Z_diff)<max(abs(Z_diff)/50))
zero_area_indices=zero_area_indices(1,1:find(zero_area_indices==0,1)-1);

% with mid-point of intervals with change in sign found, find exact optimum
% location, its value and the type:

i=1;
length(zero_area_indices)
optimum_index = zeros(1,length(Z_diff));
optimum_time = optimum_index;
optimum_type = zeros(1,length(Z_diff));
optimum_value = zeros(1,length(Z_diff));
optimum_ctr=1;
while (i<length(zero_area_indices)-1)
    i_start = i;
    disp('Next optimum: ')
    while ((zero_area_indices(i+1)-zero_area_indices(i)==1) & i<length(zero_area_indices)-1)
        i=i+1;
    end
    if (i_start == i)
        optimum_index(1,optimum_ctr) = zero_area_indices(i);
        optimum_type(1,optimum_ctr) = sign((Acc_ML(zero_area_indices(i)+1)-2*Acc_ML(optimum_index(1,optimum_ctr))+Acc_ML(zero_area_indices(i)-1))/((2*Ts)^2));
        optimum_ctr=optimum_ctr+1
    end
    if (i_start < i)
        optimum_index(1,optimum_ctr) = round((zero_area_indices(i)+zero_area_indices(i_start))/2);
        optimum_type(1,optimum_ctr) = sign((Acc_ML(zero_area_indices(i))-
2*Acc_ML(optimum_index(1,optimum_ctr))+Acc_ML(zero_area_indices(i_start)))/((zero_area_indices(i)-zero_area_indices(i_start))^2));
% now we know what type it is, find exact optimum location:
        if (optimum_type(1,optimum_ctr) == -1)
            optimum_index(1,optimum_ctr) = find(Acc_ML(zero_area_indices(i_start):zero_area_indices(i))==max(Acc_ML(zero_area_indices(i_start):zero_area_indices(i)))+zero_area_indices(i_start)-1;
        else
            optimum_index(1,optimum_ctr) = find(Acc_ML(zero_area_indices(i_start):zero_area_indices(i))==min(Acc_ML(zero_area_indices(i_start):zero_area_indices(i)))+zero_area_indices(i_start)-1;
        end
        optimum_value(1,optimum_ctr)=Acc_ML(optimum_index(1,optimum_ctr));
        optimum_time(1,optimum_ctr)=time(optimum_index(1,optimum_ctr));
        optimum_ctr=optimum_ctr+1
    end
    i=i+1;
end

optimum_index = optimum_index(1:optimum_ctr-1);
optimum_time = optimum_time(1:optimum_ctr-1);
optimum_type = optimum_type(1:optimum_ctr-1);
optimum_value = optimum_value(1:optimum_ctr-1);
% -1 in optimum_type indicates a maximum in the plot. Look for the first minimum and take the preceding maximum as the start of the experiment.

ind = find(optimum_type==1,1);
begin_ind = max(ind-1,1);

optimum_index = optimum_index(1,begin_ind:end);
optimum_type = optimum_type(1,begin_ind:end);

i=1;
numberOfOptima = length(optimum_index);
while (i<numberOfOptima-1)
    if ((optimum_type(i)*optimum_type(i+1) == 1) & (i<length(optimum_index)-2))
        optimum_index = [optimum_index(1,1:i)
                        optimum_index(1,i+2:end)];
        optimum_time = [optimum_time(1,1:i)
                        optimum_time(1,i+2:end)];
        optimum_type = [optimum_type(1,1:i)
                        optimum_type(1,i+2:end)];
        optimum_value = [optimum_value(1,1:i)
                         optimum_value(1,i+2:end)];
        numberOfOptima = length(optimum_index)-1;
    end
    i=i+1;
end

optimum_index
optimum_type
optimum_value

plot(optimum_time, optimum_value, '^black', 'MarkerFaceColor', 'red');

% determine time from max to next min as falling_time
% determine time from min to next max as rising_time
% determine change (in g) from max to next min as falling_amplitude
% determine change (in g) from min to next max as rising_amplitude
% determine jerk (g/s) as rising(rising) amplitude/rising(falling) time

rising_times = zeros(1,length(optimum_index)-1);
falling_times = zeros(1,length(optimum_index)-1);
rising_amplitude = zeros(1,length(optimum_index)-1);
falling_amplitude = zeros(1,length(optimum_index)-1);
sway_jerk = zeros(1,length(optimum_index));

falling_ctr=1;
rising_ctr=1;
for (i=1:length(optimum_index)-1)
    if (optimum_type(i,-1)==-1)
        falling_times(falling_ctr)=(optimum_index(1,i+1)-
                        optimum_index(1,i))*Ts;
        falling_amplitude(falling_ctr) = abs(optimum_value(1,i)-
                        optimum_value(1,i+1));
        falling_ctr=falling_ctr+1;
    end
    if (optimum_type(i+1,1)==-1)
        rising_times(rising_ctr)=(optimum_index(1,i+1)-
                        optimum_index(1,i))*Ts;
        rising_amplitude(rising_ctr) = abs(optimum_value(1,i+1)-
                        optimum_value(1,i));
        rising_ctr=rising_ctr+1;
    end
end
sway_jerk(i)=falling_amplitude(falling_ctr)/falling_times(falling_ctr);
    falling_ctr=falling_ctr+1;
else
    rising_times(rising_ctr)=(optimum_index(1,i+1)-
    optimum_index(1,i))*Ts;
    rising_amplitude(rising_ctr) = abs(optimum_value(1,i)-
    optimum_value(1,i+1));
sway_jerk(i)=rising_amplitude(rising_ctr)/rising_times(rising_ctr);
    rising_ctr=rising_ctr+1;
end
end

falling_times = falling_times(1,1:falling_ctr)
rising_times = rising_times(1,1:rising_ctr)
falling_amplitude = falling_amplitude(1,1:falling_ctr)
rising_amplitude = rising_amplitude(1,1:risingCtr)
sway_jerk

%Excel summary file of optima (added by Valerie 26-11-2013)
outcomeArray = cell(11,length(optimum_value));

outcomeArray{1,1}='Number of Optima';
outcomeArray{2,1}='Peak Angle Values';
outcomeArray{3,1}='Falling Times';
outcomeArray{4,1}='Rising Times';
outcomeArray{5,1}='Falling Amplitudes';
outcomeArray{6,1}='Rising Amplitudes';
outcomeArray{7,1}='Rising/Falling Jerk';
outcomeArray{8,1}='Mean Rising/Falling Jerk';
outcomeArray{9,1}='Mean Peak-to-Peak Amplitude';
outcomeArray{10,1}='Min Peak-to-Peak Amplitude';
outcomeArray{11,1}='Max Peak-to-Peak Amplitude';

outcomeArray{1,2}=numberOfOptima;
for (i=1:length(optimum_value))
    outcomeArray{2,i+1}=optimum_value(1,i);
end
for (i=1:length(falling_times))
    outcomeArray{3,i+1}=falling_times(1,i);
end
for (i=1:length(rising_times))
    outcomeArray{4,i+1}=rising_times(1,i);
end
for (i=1:length(falling_amplitude))
    outcomeArray{5,i+1}=falling_amplitude(1,i);
end
for (i=1:length(rising_amplitude))
    outcomeArray{6,i+1}=rising_amplitude(1,i);
end
for (i=1:length(sway_jerk))
    outcomeArray{7,i+1}=sway_jerk(i);
end
outcomeArray{8,2}=mean(sway_jerk);
MeanRising=mean(rising_amplitude);
MeanFalling=mean(falling_amplitude);
outcomeArray{9,2}=mean(MeanRising+MeanFalling);
MinRising=min(rising_amplitude);
MinFalling=min(falling_amplitude);
outcomeArray{10,2} = min(MinRising, MinFalling);
MaxRising = max(rising_amplitude);
MaxFalling = max(falling_amplitude);
outcomeArray{11,2} = max(MaxRising, MaxFalling);

filename = strcat('./excelswayoptimaML/', strrep(file, '.dat', '.xls'));
xlswrite(filename, outcomeArray);

% Added by Pepijn to find optima of the function (AP signal):
V = AXIS;

Z_diff = diff(Acc_AP)/Ts;

% drag window through Z_diff and compare endpoints: if the sign of the % derivative is different for the two end points there is a optimum in % between. Register the point at which the derivative changes as the % mid-point of the window
window_size = 11; % window size in samples
window_halfwidth = floor(window_size);
peak_detected = false;
zero_area_indices = zeros(1, length(Z_diff));
current_zero_area_indices = zeros(1, length(Z_diff));
i = window_halfwidth + 1;
j = 1;
k = 1;
while i < length(Z_diff) - window_halfwidth
    start_point = Z_diff(i - window_halfwidth);
    end_point = Z_diff(i + window_halfwidth);
    if (peak_detected == true) & (start_point * end_point > 0)
        current_zero_area_indices(1, 1:find(current_zero_area_indices == 0, 1) - 1) =
        current_zero_area_indices(k: k + length(current_zero_area_indices) - 1) =
        current_zero_area_indices;
        peak_detected = false;
        j = 1;
        k = k + length(current_zero_area_indices);
        current_zero_area_indices = zeros(1, length(Z_diff));
    end
    if (start_point * end_point < 0)
        peak_detected = true;
        current_zero_area_indices(j) = i;
        j = j + 1;
    end
    i = i + 1;
end
zero_area_indices = find(abs(Z_diff) < max(abs(Z_diff) / 50))

zero_area_indices = zero_area_indices(1, 1:find(zero_area_indices == 0, 1) - 1);
% with mid-point of intervals with change in sign found, find exact optimum
% location, its value and the type:

i=1;
length(zero_area_indices)
optimum_index = zeros(1,length(Z_diff));
optimum_time = optimum_index;
optimum_type = zeros(1,length(Z_diff));
optimum_value = zeros(1,length(Z_diff));
optimumCtr=1;
while (i<length(zero_area_indices)-1)
    i_start = i;
    disp('Next optimum: ')
    while (((zero_area_indices(i+1)-zero_area_indices(i))==1) & i<length(zero_area_indices)-1)
        i=i+1;
    end
    if (i_start == i)
        optimum_index(1,optimumCtr) = zero_area_indices(i);
        optimum_type(1,optimumCtr) = sign((Acc_AP(zero_area_indices(i)+1)-
            2*Acc_AP(optimum_index(1,optimumCtr))+Acc_ML(zero_area_indices(i)-
            1))/((2*Ts)^2));
        optimumCtr=optimumCtr+1
    end
    if (i_start < i)
        optimum_index(1,optimumCtr) = round(((zero_area_indices(i)+zero_area_indices(i_start))/2);
        optimum_type(1,optimumCtr) =
            sign((Acc_AP(zero_area_indices(i))-2*Acc_AP(optimum_index(1,optimumCtr))+Acc_AP(zero_area_indices(i_start)))/((zero_area_indices(i)-zero_area_indices(i_start))^2));
        if (optimum_type(1,optimumCtr) == -1)
            optimum_index(1,optimumCtr) = find(Acc_AP(zero_area_indices(i_start):zero_area_indices(i))==max(Acc_AP(zero_area_indices(i_start):zero_area_indices(i))))+zero_area_indices(i_start)-1;
        else
            optimum_index(1,optimumCtr) = find(Acc_AP(zero_area_indices(i_start):zero_area_indices(i))==min(Acc_AP(zero_area_indices(i_start):zero_area_indices(i))))+zero_area_indices(i_start)-1;
        end
    end
    optimum_value(1,optimumCtr)=Acc_AP(optimum_index(1,optimumCtr));
    optimum_time(1,optimumCtr)=time(optimum_index(1,optimumCtr));
    optimumCtr=optimumCtr+1
end
i=i+1;
end

optimum_index = optimum_index(1:optimumCtr-1);
optimum_time = optimum_time(1:optimumCtr-1);
optimum_type = optimum_type(1:optimumCtr-1);
optimum_value = optimum_value(1:optimumCtr-1);
% -1 in optimum_type indicates a maximum in the plot. Look for the first minimum and take the preceding maximum as the start of the experiment.

ind = find(optimum_type==1,1);
begin_ind = max(ind-1,1);

optimum_index = optimum_index(1,begin_ind:end);
optimum_type = optimum_type(1,begin_ind:end);

i=1;
numberOfOptima = length(optimum_index);
while (i<numberOfOptima-1)
    if (i<length(optimum_index)-2)
        optimum_index = [optimum_index(1,1:i) optimum_index(1,i+2:end)];
optimum_time = [optimum_time(1,1:i) optimum_time(1,i+2:end)];
optimum_type = [optimum_type(1,1:i) optimum_type(1,i+2:end)];
optimum_value = [optimum_value(1,1:i) optimum_value(1,i+2:end)];
        end
        i=i+1;
    end

optimum_index
optimum_type
optimum_value

plot(optimum_time, optimum_value, 'black', 'MarkerFaceColor', 'blue')

% determine time from max to next min as falling_time
% determine time from min to next max as rising_time
% determine change (in g) from max to next min as falling_amplitude
% determine change (in g) from min to next max as rising_amplitude
% determine jerk (g/s) as rising(falling)_amplitude/rising(falling)_time

rising_times = zeros(1,length(optimum_index)-1);
falling_times = zeros(1,length(optimum_index)-1);
rising_amplitude = zeros(1,length(optimum_index)-1);
falling_amplitude = zeros(1,length(optimum_index)-1);
sway_jerk = zeros(1,length(optimum_index));

falling_ctr=1;
rising_ctr=1;
for (i=1:length(optimum_index)-1)
    if (optimum_type(1,i)==-1)
        falling_times(falling_ctr)=(optimum_index(1,i+1)-
        optimum_index(1,i))*Ts;
        falling_amplitude(falling_ctr) = abs(optimum_value(1,i)-
        optimum_value(1,i+1));
        sway_jerk(i)=falling_amplitude(falling_ctr)/falling_times(falling_ctr) ;
    end
falling_ctr=falling_ctr+1;
else
  rising_times(rising_ctr)=(optimum_index(1,i+1) - optimum_index(1,i))*Ts;
  rising_amplitude(rising_ctr) = abs(optimum_value(1,i) - optimum_value(1,i+1));
end

sway_jerk(i)=rising_amplitude(rising_ctr)/rising_times(rising_ctr);
  rising_ctr=rising_ctr+1;
end

falling_times = falling_times(1,1:falling_ctr)
rising_times = rising_times(1,1:rising_ctr)
falling_amplitude = falling_amplitude(1,1:falling_ctr)
rising_amplitude = rising_amplitude(1,1:rising_ctr)
sway_jerk

%Excel summary file of sway optima (added by Valerie 26-11-2013)
outcomeArray = cell(11,length(optimum_value));

outcomeArray{1,1}='Number of Optima';
outcomeArray{2,1}='Peak Angle Values';
outcomeArray{3,1}='Falling Times';
outcomeArray{4,1}='Rising Times';
outcomeArray{5,1}='Falling Amplitudes';
outcomeArray{6,1}='Rising Amplitudes';
outcomeArray{7,1}='Rising/Falling Jerk';
outcomeArray{8,1}='Mean Rising/Falling Jerk';
outcomeArray{9,1}='Mean Peak-to-Peak Amplitude';
outcomeArray{10,1}='Min Peak-to-Peak Amplitude';
outcomeArray{11,1}='Max Peak-to-Peak Amplitude';

outcomeArray{1,2}=numberOfOptima;
for (i=1:length(optimum_value))
  outcomeArray{2,i+1}=optimum_value(1,i);
end
for (i=1:length(falling_times))
  outcomeArray{3,i+1}=falling_times(1,i);
end
for (i=1:length(rising_times))
  outcomeArray{4,i+1}=rising_times(1,i);
end
for (i=1:length(falling_amplitude))
  outcomeArray{5,i+1}=falling_amplitude(1,i);
end
for (i=1:length(rising_amplitude))
  outcomeArray{6,i+1}=rising_amplitude(1,i);
end
for (i=1:length(sway_jerk))
  outcomeArray{7,i+1}=sway_jerk(1,i);
end
outcomeArray{8,2}=mean(sway_jerk);
MeanRising=mean(rising_amplitude);
MeanFalling=mean(falling_amplitude);
outcomeArray{9,2}=mean(MeanRising+MeanFalling);
MinRising=min(rising_amplitude);
MinFalling=min(falling_amplitude);
outcomeArray{10,2}=min(MinRising,MinFalling);
MaxRising=max(rising_amplitude);
MaxFalling=max(falling_amplitude);
outcomeArray{11,2}=max(MaxRising,MaxFalling);

filename = strcat('./excelswayoptimaAP/', strrep(file,'.dat', '.xls'));
xlswrite(filename, outcomeArray);
Appendix U. MATLAB code used to perform 5m walk data processing and gait variable extraction

```matlab
function [RMS_values]=PlotData5mWalk(file, Ts)
%Plots accelerometer data (all 3 axes) for 5m and extracts selected gait variables
%Ts = Sampling time point increments e.g. 0.01 for 100Hz; Fs = Sampling frequency in Hz

a=importdata(file);

% getting the time vector starting from zero % a(:,1) contains time in milliseconds
if isstruct(a)
    a = a.data;
end

time=a(:,1)-a(1,1)*ones(size(a(:,1))); % convert milliseconds to seconds
time=time/1000;

acc_x=a(:,2);
acc_y=a(:,3);
acc_z=a(:,4);
%button1=a(:,16);
%button2=a(:,17);

%Convert uncalibrated accelerometer files to m/sec2, and exception for already calibrated files

if (strcmpi(file,'H01_5mwalk1_cal.dat')||strcmpi(file,'H01_5mwalk2_cal.dat') ||strcmpi(file,'H02_5mwalk1_cal.dat')||strcmpi(file,'H02_5mwalk2_cal.dat')||strcmpi(file,'H03_5mwalk1_cal.dat')||strcmpi(file,'H03_5mwalk2_cal.dat')||strcmpi(file,'H04_5mwalk1_cal.dat')||strcmpi(file,'H04_5mwalk2_cal.dat')||strcmpi(file,'H05_5mwalk1_cal.dat')||strcmpi(file,'H05_5mwalk2_cal.dat')||strcmpi(file,'H06_5mwalk1_cal.dat')||strcmpi(file,'H06_5mwalk2_cal.dat')||strcmpi(file,'H07_5mwalk1_cal.dat')||strcmpi(file,'H07_5mwalk2_cal.dat')||strcmpi(file,'H08_5mwalk1_cal.dat')||strcmpi(file,'H08_5mwalk2_cal.dat')||strcmpi(file,'H09_5mwalk1_cal.dat')||strcmpi(file,'H09_5mwalk2_cal.dat')||strcmpi(file,'H10_5mwalk1_cal.dat')||strcmpi(file,'H10_5mwalk2_cal.dat')||strcmpi(file,'H11_5mwalk1_cal.dat')||strcmpi(file,'H11_5mwalk2_cal.dat')||strcmpi(file,'H12_5mwalk1_cal.dat')||strcmpi(file,'H12_5mwalk2_cal.dat')||strcmpi(file,'H13_5mwalk1_cal.dat')||strcmpi(file,'H13_5mwalk2_cal.dat')||strcmpi(file,'H14_5mwalk1_cal.dat')||strcmpi(file,'H14_5mwalk2_cal.dat')||strcmpi(file,'H15_5mwalk1_cal.dat')||strcmpi(file,'H15_5mwalk2_cal.dat')||strcmpi(file,'H16_5mwalk1_cal.dat')||strcmpi(file,'H16_5mwalk2_cal.dat')||strcmpi(file,'H17_5mwalk1_cal.dat')||strcmpi(file,'H17_5mwalk2_cal.dat')||strcmpi(file,'H18_5mwalk1_cal.dat'))
```

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%Invert axes for selected files

gain = 1;
if
 (strcmpi(file,'H05_5mwalk1_cal.dat')) || strcmpi(file,'H05_5mwalk2_cal.dat')
|| strcmpi(file,'E065m1_F.dat') || strcmpi(file,'E065m2_F.dat') || strcmpi(file,'E075m1_F.dat') || strcmpi(file,'E075m2_F.dat') || strcmpi(file,'E085m1_B.dat') || strcmpi(file,'E085m2_B.dat') || strcmpi(file,'E095m1_B.dat') || strcmpi(file,'E095m2_B.dat') || strcmpi(file,'F045m1_F.dat') || strcmpi(file,'F045m2_F.dat') || strcmpi(file,'T095m1_F.dat') || strcmpi(file,'T095m2_F.dat') || strcmpi(file,'T105m1_F.dat') || strcmpi(file,'T105m2_F.dat') || strcmpi(file,'T115m1_F.dat') || strcmpi(file,'T115m2_F.dat') || strcmpi(file,'T125m1_F.dat') || strcmpi(file,'T125m2_F.dat') || strcmpi(file,'T155m1_F.dat') || strcmpi(file,'T155m2_F.dat') || strcmpi(file,'T205m1_F.dat') || strcmpi(file,'T205m2_F.dat') || strcmpi(file,'T255m1_F.dat') || strcmpi(file,'T255m2_F.dat')
else
 acc_x=acc_x/100;
 acc_y=acc_y/100;
 acc_z=acc_z/100;
end

acc_x=a(:,2);
acc_y=a(:,3);
acc_z=a(:,4);

acc_x=acc_x/100;
acc_y=acc_y/100;
acc_z=acc_z/100;
gain = -1;
end

%convert accel to G from m/sec^2
acc_x = acc_x./9.81;
acc_y = acc_y./9.81;
acc_z = acc_z./9.81;

Fn=3;
Wn=2*Fn*Ts;
[c,d]=butter(2,Wn,'low');
acc_x_LP=gain*filtfilt(c,d,acc_x);
acc_y_LP=filtfilt(c,d,acc_y);
acc_z_LP=gain*filtfilt(c,d,acc_z);

%Mean measured accelerations
mean_acc_y = mean(acc_y_LP);
[R,C] = size(acc_y_LP);
mean_acc_y = repmat(mean_acc_y, R, C);

mean_acc_z = mean(acc_z_LP);
[R,C] = size(acc_z_LP);
mean_acc_z = repmat(mean_acc_z, R, C);

%True ML accel
Acc_ML = (acc_y_LP - mean_acc_y)./cos(asin(mean_acc_y));

%True AP accel
Acc_AP = (acc_z_LP - mean_acc_z)./cos(asin(mean_acc_z));

%RMS of acc amplitudes: x=Vert, y=ML, z=AP (uncorrected)
RMS_x = sqrt(mean(acc_x_LP.^2));
RMS_y = sqrt(mean(acc_y_LP.^2));
RMS_z = sqrt(mean(acc_z_LP.^2));
RMS_ML = sqrt(mean(Acc_ML.^2));
RMS_AP = sqrt(mean(Acc_AP.^2));

%RSS acceleration data
ax=acc_x_LP.*acc_x_LP;
ay=acc_y_LP.*acc_y_LP;
az=acc_z_LP.*acc_z_LP;
RSS_acc_LP=sqrt(ax+ay+az);
RSS_RMS_LP=sqrt(mean(RSS_acc_LP.^2));

RMS_values = [RMS_ML, RMS_AP, RSS_RMS_LP]

figure;
plot(time, acc_x_LP, 'r');
hold;
plot(time, acc_y_LP, 'g');
plot(time, acc_z_LP, 'magenta');
plot(time, Acc_ML, 'b');
plot(time, Acc_AP, 'r');
legend('Y (ML uncorrected)', 'Z (AP uncorrected)', '"True" ML', '"True" AP');
title(file);
xlabel('Time (s)');
ylabel('Acceleration (g)');

figure;
plot(time, RSS_acc, 'r');
```matlab
% hold;
plot(time, RSS_acc_LP, 'b');
hold;
title(file);
xlabel('Time (s)');
ylabel('Acceleration (g)');
legend ('RSS');

% Added to find optima of the function:
V = AXIS;
Z_diff = diff(RSS_acc_LP)/Ts;

% drag window through Z_diff and compare endpoints: if the sign of the % derivative is different for the two end points there is a optimum in % between. Register the point at which the derivative changes as the % mid-point of the window
window_size = 3; %window size in samples
window_halfwidth = floor(window_size);
peak_detected = false;

zero_area_indices = zeros(1,length(Z_diff));
current_zero_area_indices = zeros(1,length(Z_diff));
i=window_halfwidth+1;
j=1;
k=1;
while (i<length(Z_diff)-window_halfwidth)
    start_point = Z_diff(i-window_halfwidth);
    end_point = Z_diff(i+window_halfwidth);
    % change of sign: optimum in between
    if (peak_detected == true) && (start_point*end_point > 0)
        current_zero_area_indices(1,1:find(current_zero_area_indices==0,1)-1) = current_zero_area_indices(k:k+length(current_zero_area_indices)-1);
        peak_detected = false;
        j=1;
        k=k+length(current_zero_area_indices);
        current_zero_area_indices = zeros(1,length(Z_diff));
    end
    if (start_point*end_point < 0)
        peak_detected = true;
        current_zero_area_indices(j) = i;
        j=j+1;
    end
    i=i+1;
end
%zero_area_indices = find(abs(Z_diff)<max(abs(Z_diff)/50))

zero_area_indices = zero_area_indices(1,1:find(zero_area_indices==0,1)-1);

% with mid-point of intervals with change in sign found, find exact optimum
% location, its value and the type:
i=1;
length(zero_area_indices);
```
optimum_index = zeros(1,length(Z_diff));
optimum_time = optimum_index;
optimum_type = zeros(1,length(Z_diff));
optimum_value = zeros(1,length(Z_diff));
optim_ctr=1;
while (i<length(zero_area_indices)-1);
    i_start = i;
disp('Next optimum:');
    while ((zero_area_indices(i+1)-zero_area_indices(i)==1) &
    i<length(zero_area_indices)-1);
        i=i+1;
    end
    if (i_start == i);
        optimum_index(1,optimCtr) = zero_area_indices(i);
        optimum_type(1,optimCtr) =
        sign((RSS_acc_LP(zero_area_indices(i)+1)-
        2*RSS_acc_LP(optimum_index(1,optimCtr))+RSS_acc_LP(zero_area_indices(i)
        -1))/((2*Ts)^2));
        optimCtr=optimCtr+1;
    end
    if (i_start < i);
        optimum_index(1,optimCtr) =
        round(((zero_area_indices(i)+zero_area_indices(i_start))/2);
        optimum_type(1,optimCtr) =
        sign((RSS_acc_LP(zero_area_indices(i))-
        2*RSS_acc_LP(optimum_index(1,optimCtr))+RSS_acc_LP(zero_area_indices(i_start)))
        /((zero_area_indices(i)-zero_area_indices(i_start))^2));
        % now we know what type it is, find exact optimum location:
        if (optim_type(1,optimCtr) == -1);
            optimum_index(1,optimCtr) =
            find(RSS_acc_LP(zero_area_indices(i_start):zero_area_indices(i))]==max(;
            RSS_acc_LP(zero_area_indices(i_start):zero_area_indices(i))))+zero_are
            a_indices(i_start)
        else
            optimum_index(1,optimCtr) =
            find(RSS_acc_LP(zero_area_indices(i_start):zero_area_indices(i))]==min(;
            RSS_acc_LP(zero_area_indices(i_start):zero_area_indices(i))))+zero_are
            a_indices(i_start)
        end
        optimum_value(1,optimCtr)=RSS_acc_LP(optimum_index(1,optimCtr));
        optimum_time(1,optimCtr)=time(optimum_index(1,optimCtr));
        optimCtr=optimCtr+1;
    end
    i=i+1;
end

optimum_index = optimum_index(1:optimCtr-1);
optimum_time = optimum_time(1:optimCtr-1);
optimum_type = optimum_type(1:optimCtr-1);
optimum_value = optimum_value(1:optimCtr-1);

StepCount = length(optimum_index(optimum_value>=10));
StepTimePoints = optimum_time(optimum_value>=10);

plot (optimum_time(optimum_value>=10),
optimum_value(optimum_value>=10), 'xr');

StepTimes = zeros(1, length(StepTimePoints)-1);

for i=1:length(StepTimePoints)-1
StepTimes(i) = (StepTimePoints(1,i+1) - StepTimePoints(1,i));
end

StepTimes = StepTimes(1,1:i);

%Excel summary file of 5m walk variables
outcomeArray = cell(7,length(optimum_value));

outcomeArray{1,1} = 'Step Count';
outcomeArray{2,1} = 'Step Times';
outcomeArray{3,1} = 'Mean Step Time';
outcomeArray{4,1} = 'SD Step Time';
outcomeArray{5,1} = 'Median Step Time';
outcomeArray{6,1} = '25th Percentile Step Time';
outcomeArray{7,1} = '75th Percentile Step Time';

outcomeArray{1,2} = StepCount;
for (i=1:length(StepTimes))
  outcomeArray{2,i+1} = StepTimes(1,i);
end
outcomeArray{3,2} = mean(StepTimes);
outcomeArray{4,2} = std(StepTimes);
outcomeArray{5,2} = median(StepTimes);
outcomeArray{6,2} = prctile(StepTimes,25);
outcomeArray{7,2} = prctile(StepTimes,75);

filename = strcat('./excel5mwalk/', strrep(file, '.dat', '.xls'));
xlswrite(filename, outcomeArray);