Classification of Frailty among Community Dwelling Older Adults Using Parameters of Physical Activity Obtained Independently and Unsupervised

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A Thesis submitted to Dundalk Institute of Technology in fulfilment of the requirements for the degree of Doctor of Philosophy

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We, the undersigned declare that this thesis entitled

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is entirely the author's own work and has not been taken from the work of others, except as cited and acknowledged within the text.

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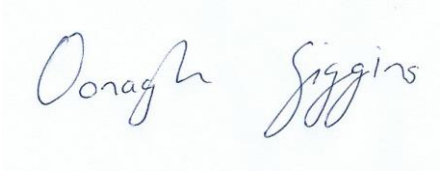
Supervisor Signature: 

Date: 20th April 2023

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Statement of Original Authorship

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work, and that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Role of Candidate

The candidate prepared and was responsible for every element of the study design, the ethics submission, participant recruitment, data collection, data management and the majority of the data analysis presented in this thesis, under the guidance of the supervisory panel.

Collaborations

Dr. Matthew W. Flood of the Luxembourg Institute of Health performed the extraction, processing and gait analysis presented in chapter Four.

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Publications Arising From This Thesis

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Peer Reviewed Conference Poster

Vavasour, G., Giggins, O.M., Doyle, J. and Kelly, D., (2022). Can Older Adults Capture an objective Frailty Risk Score Unsupervised, in Their Own Home? in: *Proceedings of the 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC).*

List of Abbreviations and Acronyms

ADLs	Activities of daily living
AXIS	Appraisal Tool for Cross-sectional Studies
BMI	Body mass index
COVID-19	Corona virus December 2019
CRF	Case report form
CHS	United States Cardiovascular health study
CSHA	Canadian study of health and ageing
CCI	Correctly classified instances
CPM	Counts per minute
CINAHL	Cumulative Index to Nursing and Allied Health Literature
DoF	Degrees of freedom
DPIA	Data protection impact assessment
DPO	Data protection officer
DAI	Deficit accumulation index
F	Frail
FFP	Fried's Frailty Phenotype
FEFAQ	Frail Elderly Functional Assessment Questionnaire
FM	Female
M	Male
GP	General Practitioner
GDPR	General Data Protection Regulations
g	G-Force
HSE	Health Service Executive
Hz	Hertz
ID	Identification
ISAR-HPQ	Identification of Seniors At Risk-Hospitalized Patients' Questionnaire
JA	Joint Action
L3	Third Lumbar Spine Vertebra
LOA	Limits Of Agreement
MVPA	Moderate to Vigorous Physical Activity
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAX_ST	Maximum Sedentary Time
MStrT	Mean Stride Time
NF	Non-Frail
n	Number
n-Bouts	Number of Bouts of Activity
PIL	Participant Information Leaflet
PF	Pre-Frail
PA	Physical Activity
PC	Personal Computer
PICO	Person, Intervention, Comparator, Outcome
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO	An International Database of Prospectively Registered Systematic Reviews In Health And Social Care
QTUG	Quantified Timed Up and Go Test
r^s	Spearman's correlation coefficient
STS	Sit To Stand
SC	Step-Count
ST	Sedentary Time
s	Seconds
SF-36	Short Form-36 Health Survey Questionnaire
SPPB	Short Physical Performance Battery of Tests
SD	Standard Deviation

SUS	System Usability Score
TILDA	The Irish Longitudinal Study on Ageing
TUG	Timed Up and Go Test
TUG-COG	Timed Up and Go Test with Cognitive Component
TUG-MAN	Timed Up and Go Test with Manual Component
TM	Treadmill
TAM	Technology Acceptance Model
TK_{GED}	Teager-Kaiser Gait Event Detection Algorithm
USB-C	Universal Serial Bus Type-C Connector
WHO	World Health Organisation

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Abstract

Classification of Frailty among Community Dwelling Older Adults Using Parameters of Physical Activity Obtained Independently and Unsupervised.

Grainne Vavasour

The global population is ageing at an unprecedented rate, with the percentage of those aged over 65 years expected to double and those aged over 80 years expected to treble by the year 2050. With ageing comes biological and physiological changes that affect functional capacity. Frailty is a potentially avoidable, reversible biopsychosocial condition associated with biological but not chronological age, affecting a quarter of all community-dwelling older adults. Frailty results in disability, increased dependency and institutionalisation.

Screening for frailty could help reduce its prevalence and mitigate the adverse outcomes however, traditional screening tools are time-consuming to perform, require clinician input and by their subjective nature are flawed. The use of wearable sensors has been proposed as a means of screening for frailty and parameters of mobility and physical activity have been identified as being associated with frailty.

The goal of this thesis was to examine if community-dwelling older adults could capture parameters of mobility and physical activity independently in their own home and if these parameters could discriminate between frail and non-frail status.

This work provides evidence that a single parameter of mobility and physical activity obtained from a single body-worn sensor correlates with frailty. It also provides evidence that community-dwelling older adults can independently capture parameters of mobility and physical activity, unsupervised in their own home using a consumer-grade wearable device, and that these data can predict pre-frailty and frailty with acceptable accuracy. Thresholds for parameters of physical activity predictive of frailty have been identified.

The results of this thesis will guide future work to focus community-dwelling older adults on the importance of frailty screening and guide the development of a user-friendly device or sensor system suitable for use by older adults for continuous data collection relevant to frailty.

Chapter One – Thesis Overview

1.0 Motivation

According to the National Census of Ireland 2016, the population of adults aged over 65 years has increased by 19.1% since 2011 (CSO 2019) and continues to grow steadily in Ireland and worldwide. Between 2015 and 2050 the proportion of the world's population over 60 years will nearly double from 12% to 22%. (World Health Organization 2018). Biologically, ageing is associated with a gradual accumulation of molecular and cellular damage, which over time leads to a decline in physiological reserves, functional capacity and an increased susceptibility to disease. These changes are not consistent among older adults however and are influenced by extrinsic factors including an individuals' behaviours and the environment (WHO 2015; Singer et al. 2019). Therefore, shifting the focus from the changes in population distribution to the functional capacity and health status of an ageing population is perhaps a more constructive and pro-active approach that can alter the impact of an ageing population on society (Chang et al. 2019).

Frailty is a complex phenomenon threatening 24% of community-dwelling adults over 65 years of age in Ireland, while the figure for pre-frailty, those at higher risk of progressing to frailty and its negative sequelae is 45% (O'Halloran and O'Shea 2018; Roe et al. 2017). Due to the heterogeneity of studies, global figures are difficult to establish, however, a systematic review of research in Europe, USA, UK, Ireland, and Asia indicates that the prevalence of frailty and pre-frailty is as high as 27% and 50% respectively (Choi and Kim 2015). The global incidence of frailty and pre-frailty is reported as 43.4 and 62.7 per 1000 respectively (Ofori-Asenso et al. 2019).

In recognition of this, several global, European and national strategies have emerged to address the challenges of an ageing population, aiming to reduce disability, hospital admission and the exponential rise in the cost of health care delivery. The European Commission and many of its member states have funded a joint action on the prevention of frailty – ADVANTAGE JA (ADVANTAGE JA 2019). This joint action aims to prepare common guidelines or frameworks on the prevention and management of frailty. Its objectives include empowering older people to lead the

necessary changes, promoting healthy ageing and frailty prevention, early diagnosis and appropriate clinical management of frailty. There is evidence that preventing frailty can mitigate many of the major negative health-related outcomes associated with ageing (WHO 2015).

Traditionally a frailty assessment is carried out in a clinical setting using a variety of assessment tools. Frailty assessment tools can be divided into those that rely totally on subjective reports, those that are objective, and those that involve a combination of the two. The various frailty assessment tools are described in more detail in chapter two. Frailty assessments have been criticised as being time-consuming, cumbersome, and costly to implement (Lee et al. 2018; Straiton et al. 2018).

There is a large body of evidence on the relationship between physical activity (PA), sedentary behaviours, and health, with inactivity being one of the main risk factors for declining health (WHO 2020). The association between PA and the risk of frailty is also well documented in the literature (Blodgett et al. 2015b; Lewis et al. 2018) with most frailty assessment tools including a measure of mobility and / or PA. Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure (Casperson et al. 1985) and traditional measures of PA rely on either self-report in the form of questionnaires or diaries, direct observation, or objective measures of energy expenditure. Each of these options present their own difficulties including costs, researcher/therapist/clinician and participant/patient burden, and potential for bias (Strath et al. 2013). Facilitating adults to objectively monitor and quantify their own mobility and PA promotes self-care and can enable early detection of declining activity, thus indicating to the individual their risk of developing frailty.

The use of smartphones and wearable sensors has become a pervasive means of monitoring mobility and PA (Bai et al. 2016; Burton et al. 2018; Hsieh et al. 2019). It has been suggested that their use could more significantly assist in the objective collection of meaningful data regarding mobility and PA and detection of risk factors of declining activity in community-dwelling settings (Tsipouras et al. 2018). Capturing data of mobility and PA in a community-dwelling setting will potentially be a more accurate reflection of everyday performance as opposed to measurements of capacity that laboratory-based assessments arguably provide (Jansen et al. 2019).

1.1 Aims and Objectives

The overarching aim of this thesis is to determine if quantitative measures of mobility and PA captured independently by older adults can be used to discriminate between frail (F) and non-frail (NF) community-dwelling older adults.

To achieve this the following objectives were identified;

1. To carry out a systematic review of the literature to examine how wearable sensors have been utilised to evaluate frailty in older adults.
2. To compare parameters of mobility and PA obtained from body-worn inertial sensors on different body-locations to those obtained from a criterion measure and with a validated inertial sensor and software system.
3. To investigate whether community-dwelling older adults can capture objective mobility and PA data using body-worn sensors unsupervised, in their own home.
4. To determine whether body-worn sensor data captured by community-dwelling older adults unsupervised can discriminate between non-frail, pre-frail and frail community-dwelling older adults.
5. To examine the usability and acceptance of performing mobility measurements using a wearable sensor system among community-dwelling older adults.

1.2 Contribution

The main contributions of this thesis are:

- A Systematic Literature Review

A systematic review of the literature presented in chapter 3 provides a comprehensive appraisal and critique of how wearable technology has been previously used to evaluate frailty in older adults. Specifically, the review identifies which parameters of mobility and PA obtained from wearable sensors have been used to assess and quantify frailty, which type of body-worn sensors and specific body-locations have been used, and how different parameters are associated with the discrimination of

the various stages of frailty. This review is the first to comprehensively synthesise data from the last decade of research in this field.

- Evidence to support a convenient body-location for a single wearable sensor to record a single parameter of mobility in older adults that could be used to identify functional decline.

Results from the laboratory-based study presented in chapter 4 confirms the waist as a suitable body-location for a body-worn sensor to accurately obtain parameters of gait. It is a first step in identifying the potential for a single wearable sensor to record a single parameter of mobility in older adults that could be used to identify a risk of frailty.

- Evidence that community-dwelling older adults can capture an objective frailty score and objective measures of PA associated with frailty using a sensor system or a smartwatch, independently, unsupervised in their own home.

The findings of a home-based study presented in chapter 5 demonstrate the ability of community-dwelling older adults to independently capture a frailty risk score and continuous data correlated with frailty, unsupervised in their own home. Measures of step-count (SC) and sedentary time (ST) obtained from a consumer grade wearable device are found to correlate significantly with frailty, confirming the literature and suggesting that breaks in ST can reduce the risk of frailty. Thresholds for parameters of PA predictive of frailty are identified with varying degrees of accuracy for each variable captured, further assisting with the independent identification of frailty risk by older adults using a wrist-worn smartwatch.

1.3 Thesis Outline

This chapter has provided the background, the motivation for the research and the valuable contribution the thesis makes. The remaining chapters in this thesis are organised as follows:

Chapter Two:

This chapter outlines the relevant literature on frailty, its definition and assessment tools, PA, and its correlation with frailty, and the potential of wearable sensors to capture the parameters of PA relevant to frailty.

Chapter Three:

This chapter presents a systematic review examining how wearable sensors have been used to assess frailty. It presents the findings of 29 studies that demonstrate how wearable sensors have been successfully used to evaluate frailty in older adults. The review demonstrates the need for further research to identify a feasible, user-friendly device and body-location that can be used to identify signs of pre-frailty in community-dwelling older adults.

Chapter Four:

This chapter presents a laboratory-based study that compared the accuracy of measurements of mobility, gait and PA obtained from body-worn sensors placed at different locations on the body to those obtained from clinical observation and from a validated inertial sensor and software system. This study was a first step in identifying the potential for a single wearable sensor to record a simple parameter of mobility and PA in older adults that could identify a risk of frailty.

Chapter Five:

This chapter presents an observational study, which sought to investigate whether community-dwelling older adults could capture objective data of mobility and PA using a body-worn sensor and software system unsupervised, in their own home. It compares data captured from a body-worn sensor and software system and from a wrist-worn smartwatch with traditional mobility and PA assessment tools and a validated frailty assessment tool. This chapter also presents the usability and acceptance of the technology among community-dwelling older adults.

Chapter Six:

This chapter outlines the contribution this work has made, provides a conclusion and recommendations for further research.

Chapter Two - Literature Review

2.0 Introduction

The syndrome of frailty is perhaps the greatest challenge facing an ageing population. While there is no universally accepted definition, there is a consensus that frailty is a medical syndrome with multiple causes and contributors, characterised by reduced gait speed, weakness, low levels of activity, and exhaustion (Rodríguez-Mañas et al. 2013). The World Health Organisation (WHO) has adopted the definition that frailty is a progressive age-related decline in physiological systems that results in decreased reserves of intrinsic capacity, which confers extreme vulnerability to stressors and increases the risk of a range of adverse health outcomes (WHO 2015). The consequence of this syndrome is an increased risk of falls, delirium, disability, institutionalisation and death resulting in a cascade of increased dependency, hospital admissions, length of hospital stay and utilisation of health care resources (Chang et al. 2018; Fried et al. 2001; Liu et al. 2019; Rockwood K 2005; Zhang et al. 2018). Its impact is far-reaching, affecting the individual physically, psychologically, and socially (WHO 2015). A systematic review examining the global economic burden of frailty demonstrates that frailty care provision accounts for 40 – 76% of overall health care provision costs (Alkhodary et al. 2020). Frailty impacts on society, drains health care resources and as such is an emerging public health priority (Buckinx et al. 2015; Cesari et al. 2016).

This chapter will examine frailty, its definition and assessment tools, PA, and its correlation with frailty and the parameters of PA that correlate with frailty phenotypes. Finally, the chapter will discuss the potential of wearable sensors to capture data to detect frailty.

2.1 Literature Search Strategy

Using the framework PICO (person, intervention, comparison, and outcome), the databases CINAHL Ovid, PubMed and MEDLINE were searched for literature. The search engine Google Scholar was included to access full text articles where necessary. Keywords included (P) elderly, community-dwelling older adults, (I) wearables, sensors, (C) measurements of PA and (O) frailty, frailty syndrome, frailty index. Boolean operators were used with keyword searches to optimise pertinent

results. The search was limited to journal articles with full text available in the English language, published in the previous ten years. Articles were included if they were primary studies, systematic or scoping literature reviews. Grey literature was also examined from national and international health and social care organisations. Papers were excluded if they did not directly relate to the screening question 'does this paper examine frailty and/or parameters of PA related to frailty'. Titles and abstracts were scanned for appropriateness. Where there was broad commonality, the more recent publications were prioritised. Older, seminal papers as referenced in the selected literature were also included.

2.2 Frailty

Frailty is associated with but is not an inevitable part of ageing. It is reflective of biological as opposed to chronological age and is influenced by physical, psychological, and social factors (WHO 2015). Despite the abundance of literature relating to frailty in the last three decades, there is no consensus on its operational definition. As far back as 1992, frailty was purported to be a reduction in total physiological reserve with increased susceptibility to disability (Buchner and Wagner 1992). It has been described as the poor resolution of homeostasis and vulnerability to adverse outcomes (Clegg et al. 2015; Fried et al. 2001), a multi-dimensional syndrome of loss of energy, physical ability, cognition, and health that gives rise to vulnerability (Rockwood K 2005) and the consequence of accumulated age-related defects in different physiological systems (Xue 2011). The WHO has adopted the definition that frailty is a progressive age-related decline in physiological systems that results in decreased reserves of intrinsic capacity, which confers extreme vulnerability to stressors and increases the risk of a range of adverse health outcomes (WHO 2015).

Two approaches to defining frailty have dominated the literature; one suggesting that frailty is a distinct clinical syndrome with a biological basis (Fried et al. 2001), the other suggesting that frailty is the result of an accumulation of impairments and conditions (Rockwood K 2005). A Delphi process while achieving a majority agreement on a conceptual framework to include domains of physical function, nutritional status, mental health, and cognition; failed to achieve its aim of reaching consensus on an operational definition (Rodríguez-Mañas et al. 2013). There is strong agreement that

frailty can be defined as a multi-dimensional clinical syndrome characterised by decreased reserves and increased vulnerability to extrinsic stressors whereby minimal stress can result in functional impairment (Morley et al. 2013). Another conceptual model of frailty has been proposed, emphasising the importance of including psychological and societal factors contributing to frailty, as well as the physical aspects commonly referred to (Gobbens et al. 2010). The physical factors that are recognised as contributing to the syndrome of frailty include advancing age, female gender, disease burden of multi-morbidities, obesity, and polypharmacy (Rockwood K 2005; Sanders et al. 2011; Blodgett et al. 2015a) while psychosocial factors contributing to frailty include lower levels of education, isolation, lack of social support, loneliness, and depression (Buttery et al. 2015; Gobbens et al. 2010; Santos-Eggimann and Sirven 2016).

The syndrome of frailty is dynamic in nature and transition can occur in either direction between robust or non-frail, pre-frail and frail. A meta-analysis of 16 studies indicates that of those older adults identified as pre-frail at baseline, over a period of 4 years 23.1% transitioned to non-frail, 18.2% transitioned to frail while 58.2% remained unchanged (Kojima et al. 2019). This concurs with findings of The Irish Longitudinal Study on Ageing (TILDA), which demonstrated that 1 in 10 older adults had what the authors refer to as a positive transition i.e., transition from frail to pre-frail to non-frail (O'Halloran and O'Shea 2018). In contrast, of those older adults identified in (Kojima et al. 2019) as frail at baseline, only 3.3% reverted to non-frail, 40.3% reverted to pre-frail, while 54.5% remained frail. This supports earlier findings that suggest positive transition between frailty levels depends on the baseline frailty level and that negative transitions are more likely (Gill et al. 2006). Reversibility of frailty has been further demonstrated in more recent studies (Zanforlini et al. 2019). Factors found to influence the transition from pre-frail to non-frail include younger age, aerobic exercise and resistance training (Liu and Fielding 2011; Zanforlini et al. 2019) and early intervention (O'Halloran and O'Shea 2018).

The prevalence of frailty and pre-frailty in Europe, USA, UK, Ireland and Asia is estimated at 27% and 50% respectively, based on Fried's frailty phenotype (Choi and Kim 2015). In Ireland in 2015, overall, an estimated total of 3.9 million bed days were used in public and private hospitals, 10.6

million bed days in long-term and intermediate facilities and over 25 million visits to general practitioners (GPs), practice and public health nurses and allied health professionals (Wren et al. 2017). Frailty significantly impacted on this utilisation of health care resources accounting for more than double the number of GP visits, unplanned hospital admissions and length of hospital-stay compared with non-frail older adults (Roe et al. 2017).

Increasing demands on our health service and the evidenced negative transitions between stages of frailty compels us to find ways to mitigate the impact of declining function associated with an ageing population. Identifying those with pre-frailty or at risk of developing frailty could help target interventions that may reduce the negative sequelae of frailty syndrome and its incumbent costs; financial, physical, and psychological.

2.3 Frailty Assessment Tools

Although the prevalence of frailty and its adverse health outcomes are widely documented (Pritchard et al. 2017; Roe et al. 2017) there is little consensus or consistency in the approach used by researchers and clinicians in its assessment. It is suggested that the results of frailty prevalence studies depend very much on the assessment tool used in the screening (Sutton et al. 2016; Xue et al. 2020). While there is general acceptance and agreement on the concept of frailty, there remains the lack of an internationally accepted definition resulting perhaps in the lack of consistency in the approach to assessment and screening. This lack of consensus is suggested as the reason for such a variety of assessment tools and the reason many studies apply adaptations or modifications of validated tools, resulting in substantial variation in outcomes (Theou et al. 2015). Frailty assessment tools can be divided into those that rely totally on subjective reports, those that are objective, and those that involve a combination of the two. Tools are validated for use in different settings including community, primary care, and acute care, require varying lengths of time and level of expertise to administer (Health Improvement Scotland 2019).

A systematic review of the literature examining instruments for the detection of frailty (Faller et al. 2019) identified 51 tools for use in community, hospital, emergency medicine and out-patient clinic

settings. An earlier review identified 67 tools (Buta et al. 2016). This is indicative of the extent of the debate around the best measure of frailty and the lack of consensus regarding its definition. The various purposes for use of assessment tools observed in the literature include identifying frailty as a risk factor for adverse health outcomes; identifying risk factors for frailty; identifying frailty for inclusion criteria or in methodology of studies involving frailty; assessing biomarkers of frailty; estimation of frailty prevalence; and to a lesser extent which is a matter of concern, guiding clinical decision-making and for targeting interventions (Buta et al. 2016; Varadhan and Buta 2015). This may illustrate a common perception that assessment tools are time-consuming, cumbersome, and costly to use (Lee et al. 2018; Straiton et al. 2018). For these reasons it is suggested that they are not feasible for use in large populations (Cesari et al. 2014).

In their systematic review of 132 articles, (Buta et al. 2016) report that nine tools were highly cited. The authors suggest that wide adoption of a tool is insufficient to recommend its use, rather an instrument should be chosen based on the identified purpose, the construct validity of the instrument for the intended purpose, and its feasibility. This is recognised by (Cesari et al. 2014) and supported by (Rockwood et al. 2015) who insist that in the absence of a 'gold standard', the purpose or context must determine the appropriate instrument. According to (Buta et al. 2016) the three most cited assessment tools are the Physical Frailty Phenotype (Fried et al. 2001) more commonly and hereafter referred to as Fried's Frailty Phenotype (FFP), the Deficit Accumulation Index (DAI) (Rockwood K 2005), and the Gill Frailty Measure (Gill et al. 1995). In an earlier review (Cesari et al. 2014) it is suggested that while many other instruments to assess frailty have been proposed, the FFP and the DAI have dominated the literature. This is supported by findings in a later systematic review (Clegg et al. 2015).

The FFP and DAI have been developed and validated in large epidemiological studies; the United States Cardiovascular Health Study (CHS) (Fried et al. 2001) and the Canadian Study of Health and Ageing (CSHA) (Rockwood K 2005) respectively. The FFP considers frailty to be a decline in physical function and is based on five pre-defined physical criteria of; unintentional weight loss, sarcopaenia, fatigue, slow gait speed and reduced level of PA, with the presence of three or more

criteria indicating the presence of frailty. It is a combination of self-report and objective measurement, validated for clinic and population screening with the ability to predict adverse outcomes (Dent et al. 2016).

Also suitable for clinic and population screening is the DAI (commonly referred to in the literature as the Frailty Index), which looks at frailty as an accumulation of deficits across various domains such as physical function, cognition, self-rated health, and biomarkers (Mitnitski et al. 2001). It is expressed as a ratio of the deficits present to the total number of deficits considered. It is more time-consuming than other scales but requires no special equipment. The DAI, like most scales that include objective measurements requires specialist training to administer (Dent et al. 2016).

The Edmonton Frail Scale is a nine-item questionnaire including physical, psychological, and social components of frailty, validated for adverse outcome prediction in a clinic setting (Rolfson et al. 2006). The Tilburg Frailty Scale is a 15-item self-administered questionnaire validated for community-dwelling screening. It requires no special equipment or specialist training and has recently been shown to have excellent predictive validity for disability (Gobbens et al. 2020). Questionnaires have the added advantage of being less time-consuming but may over-screen, especially in hospital settings (Dent et al. 2016).

Other options for frailty screening include individual physical factors associated with frailty. Gait-speed and grip-strength are domains of many frailty measures but have been explored as separate potentially efficient, easy-to-use assessment tools in their own right (Dent et al. 2016). Gait-speed measured over a short distance has been shown to be a strong independent indicator of frailty and disability (Gill et al. 2006; Abellan Van Kan et al. 2009; Hoogendijk et al. 2015; Pamoukdjian et al. 2015), and grip-strength as a stand-alone entity has been validated for the prediction of functional decline and disability in male hospitalised older adults (García-Peñ et al. 2013; Roberts et al. 2012).

2.4 Physical Activity and Frailty

According to the WHO, health is central to our functional capacity, independence, and experience of older age (WHO 2020). Physical performance measures of gait, mobility, and PA are central to health.

The risk of functional decline, a precursor to frailty and disability, has been shown to be influenced by changes in these measures (McPhee et al. 2016). For maintenance of health, minimum recommendations for PA have been endorsed. For adults aged 18 – 64 years, minimum requirements are at least 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity or an equivalent combination per week, in bouts of no less than ten minutes (World Health Organisation 2011). The minimum recommendations for older adults >65 years is the same (WHO 2020). It is important to note however that the resting metabolic rate in older adults may be less than in younger adults and so the required intensity of PA may not necessarily be the same. The energy cost of walking for example is higher in older adults(Hall et al. 2014). Results of a meta-analysis supports this suggestion with reports of health benefits among older adults with lower intensity levels of PA (McMurray et al. 2014; Hupin et al. 2015).

Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure (Casperson et al. 1985). Everyone performs PA to sustain life; however, the extent depends usually on personal choice and differs from person to person. It can be subdivided into light, moderate, or vigorous intensity (Casperson et al. 1985; Hupin et al. 2015). Walking is considered the main contributor to PA in adults and as a choice of exercise it increases with age (Eyler et al. 2003). Simply put, exercise is defined as any activity requiring physical effort, carried out to sustain or improve health and fitness and has been described as a subcategory of PA (Casperson et al. 1985). Measuring PA and identifying those who do not meet the minimum requirements can increase awareness and help target interventions to lessen the adverse effect that reduced activity has on functional capacity (Evenson et al. 2015). Most assessment tools for identifying frailty or functional dependence incorporate a measurement of mobility (Fried et al. 2001; Rockwood K 2005; Gill et al. 1995).

There are changes in physical characteristics that are associated with frailty (Bortone et al. 2021; Hwang et al. 2021; Minici et al. 2022). They include gait, defined as a person's manner of walking (Kharb et al. 2011), mobility, the ability to move or be moved freely in space (Casperson et al. 1985) and PA, any bodily movement produced by skeletal muscles that results in energy expenditure. They

can each be measured in different settings with measurement tools ranging from costly, laboratory-based observations of gait, to structured, performance-based instruments for mobility assessment, and questionnaires or self-reported estimates for PA. The choice of assessment tool depends on the setting and should meet important considerations including the appropriateness for the target population, practical aspects of administration and because of the contribution of physical, psychological, and social components to overall health, would ideally include psychometric properties (Soubra et al. 2019).

Laboratory-based instruments such as force plates and motion analysis capture systems are considered gold-standard for the evaluation of gait-analysis and have the advantage of objectively measuring a wide range of gait parameters including gait-speed, step-time, stride-length and gait-variability, changes in which are related to health and frailty (Ciprandi et al. 2017; Schwenk et al. 2015a; Hafer and Zernicke 2020). However, self-selected gait-speed alone has been shown to be a sensitive indicator of health and a reliable predictor of frailty and disability (Abellan Van Kan et al. 2009; Gill et al. 2006; Hoogendijk et al. 2015; Studenski et al. 2011). Walking ability is purported to be a sensitive indicator of overall health (Pirker and Katzenschlager 2017) and it is suggested that it may be the best predictor of overall performance (Alexander et al. 2000).

Performance-based measures of mobility of which there are a multitude, are proposed as significant predictors of disability in both mobility and activities of daily living. Measures of mobility include: timed chair rise (Csuka and McCarty 1985), six-minute walk test (Enright et al. 2003), Timed Up and Go test (Podsiadlo and Richardson 1991), Short Physical Performance Battery (Guralnik et al. 1995), Physical Performance Test (VanSwearingen and Brach 2001), Barthel Index (Mahoney and Barthel 1965), SF-36 (Lins and Carvalho 2016), Late Life Function and Disability Instrument (Haley et al. 2002), each validated for use in specific settings and requiring some degree of specialist or trained analyst to administer and compute the relevant score. Self or proxy-reported estimates of mobility by their nature are subjective with a risk of reporter bias (Razjouyan et al. 2018) and have poor validity (Phillips et al. 2018). They may not match the magnitude of changes of performance-based measures that have been shown to be responsive to change (VanSwearingen and Brach 2001). Objective

performance-based measures in combination with self-reported estimates are thought to be more predictive of declining health and function and hospitalisation than self-report alone (Studenski et al. 2011).

2.5 Physical Activity Associated with Frailty Phenotypes

Measurements of gait speed (Apsega et al. 2020; Galán-Mercant and Cuesta-Vargas 2013; Pamoukdjian et al. 2015; Schwenk et al. 2015; Zhou et al. 2019;), step-count (Chen et al. 2020; Jansen et al. 2019; Razjouyan et al. 2018; Theou et al. 2012; Yuki et al. 2019;), postural transitions (Greene et al. 2014; Millor et al. 2017; Parvaneh et al. 2017;) and sedentary time (Huisingh-Scheetz et al. 2018; Kikuchi et al. 2020; Ziller et al. 2020;) are believed to best indicate frailty and its levels. A cross-sectional study by (Schwenk et al. 2015a) observed measurements of gait, balance, and PA in community-dwelling older adults to investigate if these metrics could be used to discriminate between frailty levels. Temporal-spatial parameters of gait were obtained from sensors positioned on the thigh and shank during a 4.57m over ground walk in the participant's home, under single and dual-task conditions. The dual task condition involved walking while counting backwards by 1 from 100. Balance parameters of postural sway of ankle, hip and centre of mass were obtained from sensors positioned on the shank and lower back during a 15-second stand with feet together and eyes closed. Measures of PA including duration of walking, standing, sitting and lying, step-count and duration of sit to stand transitions were collected over a period of 24-hours by a sensor system positioned in a tee shirt pocket positioned at the sternum. The results indicated that walking speed, stride length and double support during gait significantly have the capacity to discriminate between levels of frailty. Gait, balance, and PA parameters most sensitive for pre-frailty screening were gait speed, hip sway, and total number of steps, respectively. Gait speed best discriminated between non-frail and pre-frail while stride length best discriminated between pre-frail and frail. While gait speed had the highest validity in pre-frail screening, total number of steps was found to be the most sensitive metric (Schwenk et al. 2015a). A similar study by (Thiede et al. 2016) examined measures of gait and balance obtained from inertial sensors positioned on the shank, thigh and lower back. Gait was assessed during a minimum 25-step over ground walk at self-selected speed, fast speed and dual task

of counting backward from 100 by 1 at self-selected speed. Balance was assessed during 30-s Romberg tests with arms crossed and feet positioned as close together as possible without touching under two different conditions of eyes open and eyes closed. Findings concur with those of (Schwenk et al. 2015a) whereby gait parameters, specifically speed, cycle time and double support correlated with frailty levels. However, none of the balance variables showed significant associations. This is surprising considering both studies used the same technology with comparable sensor positioning. However, the study by (Thiede et al. 2016) was clinic-based and included a younger age group (>50 years of age compared with >65 years) which may have influenced outcomes.

Further studies examining parameters of PA obtained from a wearable sensor suggest that bouts of activity are best capable of discriminating between levels of frailty. The total number of steps and the longest unbroken bout of stepping were a significant independent predictor for pre-frail status (Chen et al. 2020; Razjouyan et al. 2018). These findings concur with those of cross-sectional observational studies (Blodgett et al. 2015b; Del Pozo-Cruz et al. 2017) which identify a significant correlation between sedentary time and frailty. Results of these studies suggest that sedentary behaviour, i.e., time spent in sedentary activity per day and percentage of the day spent sedentary in bouts of more than ten minutes are associated with frailty. These findings are supported in later studies, but further research is recommended to establish the relevant cut-off points for the intensity of PA that constitutes sedentary time, and for the length of time spent in sedentary activity that influences frailty (Chen et al. 2020; Kikuchi et al. 2020).

These studies demonstrate that parameters of gait, mobility and PA can be used to discriminate between and therefore identify levels of frailty. The parameters that have been purported as best for discriminating between levels of frailty include gait speed, number of steps, stride length, bouts of activity and/or sedentary time and postural transitions. The benefits of these findings will be in establishing if these measurements can be made on a continuous basis, independently, if the data can be captured by the individual and used to monitor activity levels and behaviours. The importance of community-based monitoring, during everyday activities has been proposed to establish activity

behaviours that reflect performance as opposed to the measure of capacity established in laboratory or clinic-based monitoring (Jansen et al. 2019).

While there is consensus in the literature regarding the potential for parameters of gait, mobility, and PA to contribute to the identification of frailty and discriminate between levels of frailty, there is dispute regarding the optimal parameters. It has been suggested that a combination of parameters is more accurate than individual variables (Greene et al. 2014). A possible explanation for the lack of clarity is the heterogeneity in study methodologies throughout the literature with gait analysis for example being conducted over distances varying from 3-meters to 20-meters, balance examined under different conditions and time periods, and different cut-off points for PA, intensity, and bouts of sedentary time. Identifying specific metrics that correlate best with frailty phenotypes could advance the goal of early recognition and frailty prevention.

2.6 Wearable Technology

Facilitating adults to monitor their own activity levels and physical function promotes self-care, can enable early detection of inactivity and prevent its progression, thus potentially altering the transition from robust or pre-frail to frail. Wearable sensors are devices that incorporate various technologies capable of physiological, biomechanical and motion sensing. Wireless inertial units are the most used sensors in wearable systems (Zampogna et al. 2020). In the form of accelerometers, gyroscopes, pedometers or heart-rate monitors, wearable sensors have the capacity to measure activity frequency, duration, and intensity. Accelerometers measure linear acceleration in real time and can detect movement in up to three planes, i.e., vertical, antero-posterior and medio-lateral. Pedometers measure the number of steps taken and correlate well with uni-axial accelerometers (O'Neill et al. 2017). Gyroscopes measure changes in orientation such as rotational or angular velocity, acceleration or displacement. Heart rate monitors are one type of sensor among others capable of capturing indications of physical activities that do not require trunk displacement and can be used to indicate energy expenditure and PA behaviours e.g., sedentary time (Theou et al. 2012). Wearable technology can be incorporated in sensors fitted into shoes and clothing, worn as pendants, attached to the wrist, ankle, or trunk, or carried in a pocket.

The literature supports the validity and reliability of using wearable sensors to detect objective measurements that correlate with frailty phenotypes (McCullagh et al. 2016; Straiton et al. 2018; Zacharaki et al. 2020; Minici et al. 2022). Research grade devices capture granular data which is stored on board the device for later extraction, processing and analysis with specially developed algorithms. However, there has been a remarkable growth in the availability of consumer grade activity trackers in recent years which purport to measure parameters of gait, mobility and PA, those same parameters that have been identified as being predictive of levels of frailty. Data from consumer grade devices are retrieved, processed and analysed either on board the device or by a remote computer or cloud-based application, and presented in a way that can be interpreted by the user. Similarly, medical wearable devices which are used by medical staff and/or patients to diagnose, monitor or treat illness, capture large amounts of data which are processed on board and presented to users in an understandable way in real time. Studies to date investigating the accuracy and reliability of various consumer-level devices in measuring parameters of physical function are contradictory (Kooiman et al. 2015; Peake et al. 2018; Sears et al. 2017; Tedesco et al. 2019a).

A laboratory and free-living-based study examining ten consumer-grade activity trackers to measure step-count in young healthy adults found high reliability and validity in most at speeds of 4.8km/h in activity trackers worn on the lower back, waist, wrist and carried in a front trouser-pocket (Kooiman et al. 2015). This is in contrast with a small sample-size study measuring step-count of young adults on a treadmill using consumer-grade wrist-worn devices, which found all devices tended to underestimate steps. Accuracy decreased with both increasing and decreasing speeds (Sears et al. 2017). A study involving older adults had comparable results, with decreasing accuracy with slower speeds and with greater percentage errors than earlier studies (Tedesco et al. 2019a). A study of older adults examining step-count from three different pedometers and an accelerometer found no significant difference between devices during walking at a self-selected-speed but significant differences during treadmill walking (Johnson 2015).

Conclusion

Despite the inaccuracies, there is a growing interest in the public domain for wearable sensors (Sears et al. 2017), and it has been suggested that there is an increasing acceptance among older adults of their use (Preusse et al. 2017; Lee et al. 2020). To facilitate older adults to independently monitor parameters of gait, mobility and PA, further research is needed to identify a suitable device, location, and parameter to identify frailty and discriminate between non-frail, pre-frail and frail older adults.

This chapter has examined the aetiology of frailty, its prevalence, and the implications for both the individual and the health service. The review has introduced the concept of the use of wearable sensors in community-dwelling older adults to facilitate the identification of frailty and suggests the feasibility and utility of such a model. Chapter 3 will examine how wearable technology has been used to evaluate frailty in older adults.

Chapter Three - Systematic Review

3.0 Background

Traditionally, measurement of mobility and PA has relied on the use of self-reported questionnaires, surveys or diaries, or direct observation of physical performance tests, each with inherent difficulties and limitations. While these methods can be cost-effective and simple to administer, they carry a risk of bias from recall, desire to perform better and participant reactivity, a well-recognised phenomenon of behaviour change due to the awareness of being observed (Sylvia et al. 2014).

Recent advances in technology provide the opportunity for objective measurement of mobility and PA using wearable sensors. This allows for unbiased examination of PA patterns and behaviours which can inform guidelines and promote more widespread participation (Doherty et al. 2017; Jansen et al. 2015; Straiton et al. 2018).

Considering the increasing population of older adults, 95% of who in Ireland are community-dwelling (CSO 2019), identifying a way for individuals to independently and objectively monitor their risk of developing frailty is vital. Earlier reviews have reported on the use of wearable sensors in relation to gait analysis (Schwenk et al. 2013), falls risk (Pang et al. 2019), rehabilitation (Patel et al. 2012) and levels of PA in hospitalised frail older adults (McCullagh et al. 2016) and community-dwelling older adults (Straiton et al. 2018).

This chapter presents a systematic review, which was conducted to explore how wearable sensors have been used to identify frailty and pre-frailty in older adults and how results compare with a traditional frailty classification tool. The objective of undertaking this review was to inform the research and determine if quantitative measures of PA and mobility obtained from a body-worn sensor can be used to discriminate between frail and non-frail community-dwelling older adults. This review has been published (Vavasour et al. 2021) and the paper is included as an appendix to this thesis (Appendix 3.1).

3.1 Methods

3.1.1 Search Strategy

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al. 2009) and is registered with the International prospective register of systematic reviews (PROSPERO) (registration number CRD42020163082). Using the PICO framework (Population, Intervention, Comparator and Outcome) to develop search terms, the electronic databases MEDLINE, Science Direct, Scopus, and CINAHL were searched as per previous reviews (Straiton et al. 2018; Binotto et al. 2018; Kojima et al. 2019). The search was carried out in March 2020 and updated November 24th, 2020 to ensure all recently published articles meeting the criteria were included. For the purpose of this thesis, a further search was performed on 21 July 2022 to retrieve any further articles published since the review was published (Vavasour et al. 2021). The search strategy was developed in consultation with a librarian. The complete search strategy used in MEDLINE and adapted to the other electronic sources is shown in Appendix 3.2. Reference lists of eligible papers were manually searched for additional studies.

3.1.2 Study selection

Papers were selected if they were available in English and met the following criteria: primary observational studies, performed in a laboratory, clinical or free-living (home/community) environment; recruited older adults > 60 years of age; involved the use of any consumer, research, or medical-grade wearable sensor providing quantitative measurements of mobility and/or PA, and included a standardised frailty classification tool. Studies were excluded if they used non-wearable sensors (e.g., ambient sensor) for outcome measurement, or outlined mobility/PA algorithm or application development exclusively.

Titles and abstracts were screened by one investigator. Full texts of studies identified by this review were screened for eligibility by three investigators independently. Consensus was reached through discussion.

3.1.3 Data Extraction

Data extracted from each study included first author, year of publication, number of participants and age profile, study setting, wearable sensor used (make, model and manufacturer), study objectives and methods, parameters of PA/ mobility measured, frailty measure, reported findings and their statistical analysis. Studies selected for review need to be critically appraised for quality, strengths and limitations and relevance. There are a multitude of appraisal tools available, the selection of which should be guided by the nature of the study being reviewed (CASP 2022). For example, a quality appraisal tool for systematic reviews which must examine the quality of the conduct of each study included in the review (Shea et al. 2017) will differ from that for randomised control trials which must include an appraisal of the risk of bias associated with participant recruitment (Higgins et al. 2011). The selected studies were assessed using the Appraisal Tool for Cross-sectional Studies (AXIS) (Downes et al. 2016a) selected because of its development through the rigorous Delphi process and the inclusion of components to evaluate the quality of both the methodology and the reporting of each study.

3.2 Analysis

Due to the heterogeneity of the study methodology, methods of analysis and outcomes reported, a meta-analysis was not possible in this review and therefore a narrative synthesis is presented.

3.3 Results

3.3.1 Literature Search

The initial search identified 376 papers published since 2010. Following screening of titles and abstracts and removal of duplicates, 35 articles were deemed appropriate for full text screening. Five further articles were identified from manual search of references of eligible studies. One paper (Apsega et al. 2020) was published after the updated search in November 2020 but was included when discovered incidentally. No further articles were identified in the updated search performed in July 2022. Of the 40 articles reviewed, 11 were excluded (See Appendix 3.3). The remaining 29 were included in the review (Appendix 3.4). Fig. 1 outlines the selection process.

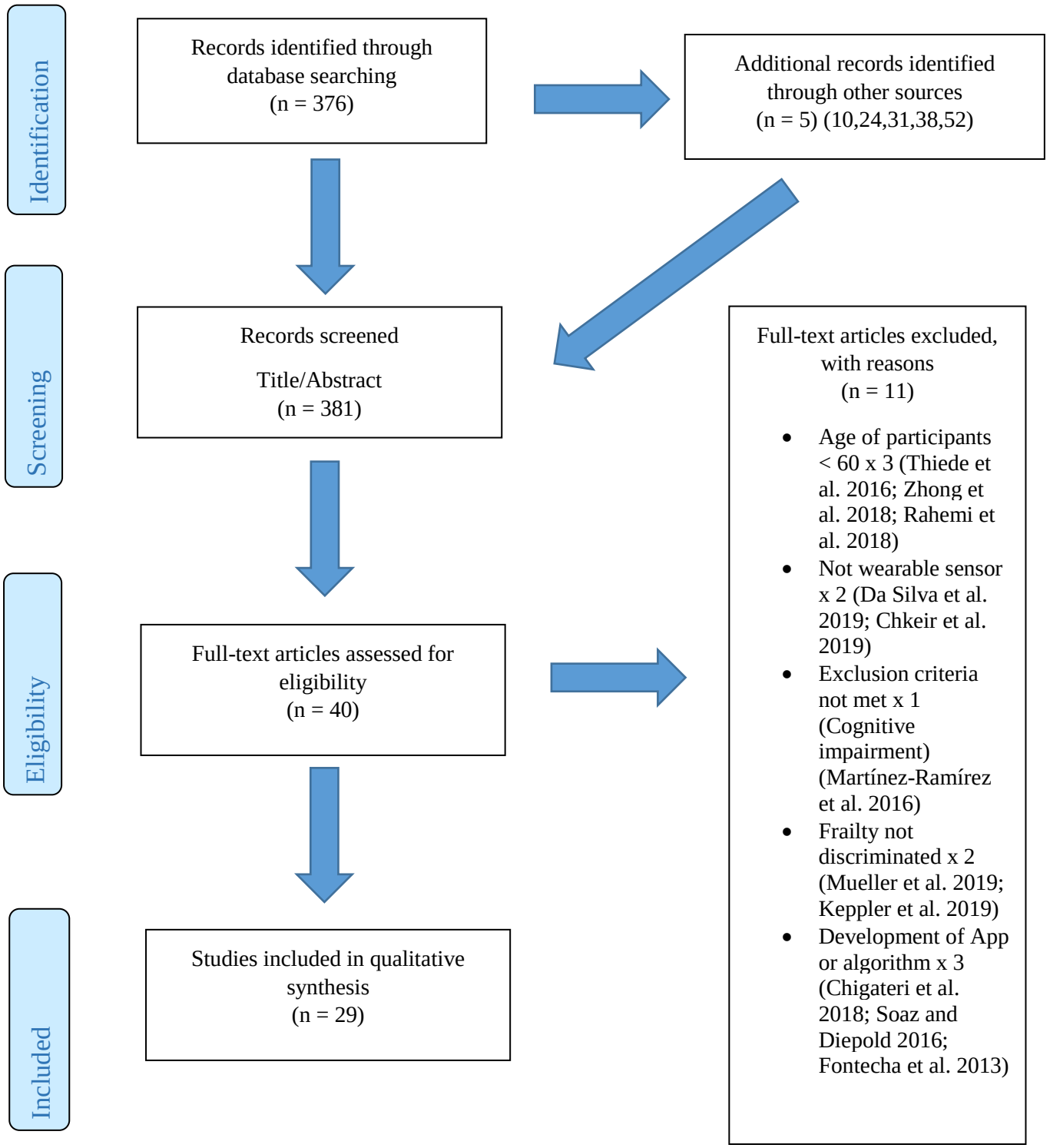


Fig. 1 PRISMA 2009 Flow Diagram

3.3.2 Study characteristics

All studies included in the review were either validation (<25%) or observational cross-sectional design. One study (Castaneda-Gameros et al. 2018) was a mixed methods design but only the objective quantitative results were included in the report. The studies were carried out in varying settings; home n = 14 (Schwenk et al. 2015a; Jansen et al. 2019; Toosizadeh, Mohler and Najafi 2015; Parvaneh et al. 2017; Razjouyan et al. 2018; Castaneda-Gameros et al. 2018; Mulasso et al. 2019; Theou et al. 2012; Jansen et al. 2015; Chen et al. 2015; Ziller et al. 2020; Huisingh-Scheetz et al. 2018; Kikuchi et al. 2020; Yuki et al. 2019), laboratory n = 8 (Martınez-Ramırez et al. 2011; Millor et al. 2013; Galán-Mercant and Cuesta-Vargas 2013; Mulasso et al. 2019; Lepetit et al. 2019; Greene et al. 2014; Greene et al. 2014; Galán-Mercant and Cuesta-Vargas 2013), hospital in-patient n = 2 (Lee et al. 2018; Toosizadeh et al. 2016), hospital out-patient n = 2 (Zhou et al. 2019; Ziller et al. 2020), community centre n = 1 (Chen et al. 2020), and not specified n = 4 (Martínez-Ramírez et al. 2015; Toosizadeh, Mohler, Wendel, et al. 2015; Millor et al. 2017; Apsega et al. 2020). Participant numbers included in the studies examined ranged from n = 30 to n = 718. Criteria of frailty classification included; Fried's Frailty Phenotype (n = 19) (Martınez-Ramırez et al. 2011; Millor et al. 2013; Galán-Mercant and Cuesta-Vargas 2013; Galán-Mercant and Cuesta-Vargas 2013; Greene et al. 2014; Greene et al. 2014; Chen et al. 2015; Schwenk et al. 2015; Martínez-Ramírez et al. 2015; Toosizadeh, Mohler, Wendel, et al. 2015; Toosizadeh, Mohler and Najafi 2015; Millor et al. 2017; Parvaneh et al. 2017; Razjouyan et al. 2018; Castaneda-Gameros et al. 2018; Jansen et al. 2019; Zhou et al. 2019; Ziller et al. 2020; Apsega et al. 2020), the modified Frailty Phenotype (n = 3) (Huisingh-Scheetz et al. 2018; Chen et al. 2020; Kikuchi et al. 2020), Rockwood's Frailty Index (n = 2) (Theou et al. 2012; Lepetit et al. 2019) Trauma-Specific Frailty Index (n = 2) (Toosizadeh et al. 2016; Lee et al. 2018), Identification Seniors At Risk-Hospitalized Patients' questionnaire (ISAR-HP) (n = 1) (Jansen et al. 2015), and Tilburg Frailty Indicator (n = 1) (Mulasso et al. 2019).

Of the studies included, 13 different body-worn sensor brands were used in eight different body-locations. Details of sensors are provided in Table 3.1. One study used an iPhone as a body-worn sensor by affixing it to the chest and was thus included in the study, data from which is presented in

two separate articles (Galán-Mercant and Cuesta-Vargas 2013; Galán-Mercant and Cuesta-Vargas 2013). Sensor placement included; the lumbar spine (L3) (n = 8), chest (n = 7), shin/ankle (n = 7), wrist and upper-limb combination (n = 3), wrist (n = 2), waist (n = 3), hip (n = 3), thigh (n = 3), and foot (n = 1). Sensor placement was not specified in three studies. Nineteen studies used just one body location (Lepetit et al. 2019; Mulasso et al. 2019; Castaneda-Gameros et al. 2018; Razjouyan et al. 2018; Parvaneh et al. 2017; Millor et al. 2013; Millor et al. 2017; Martínez-Ramírez et al. 2015; Greene et al. 2014; Galán-Mercant and Cuesta-Vargas 2013; Martınez-Ramırez et al. 2011; Jansen et al. 2015; Ziller et al. 2020; Zhou et al. 2019; Galán-Mercant and Cuesta-Vargas 2013; Huisingh-Scheetz et al. 2018; Chen et al. 2020; Kikuchi et al. 2020; Yuki et al. 2019), three studies, measuring elbow kinetics specifically, used a combination of above elbow and wrist (Lee et al. 2018; Toosizadeh et al. 2016; Toosizadeh, Mohler and Najafi 2015), while six others used multiple body-locations of L3 and shin (Toosizadeh, Mohler, Wendel, et al. 2015), and chest, L3, thigh, shin and foot (Schwenk et al. 2015; Jansen et al. 2019; Greene et al. 2014; Theou et al. 2012; Apsega et al. 2020).

Table 3.1. Details of sensors

Author (Reference.)	Sensor Type, Location and properties, where provided	Acquisition, Processing and Analysis
Martinez-Ramirez et al., (2011)	MTx XSENS (Xsens Technologies B.V. Enschede, Netherlands). Tri-axial accelerometer, gyroscope & magnetometer worn at L 3 combines nine individual MEMS sensors to provide drift-free 3D orientation as well as kinematic data: 3D acceleration, 3D (rate gyro) and 3D magnetometers.	A wavelet-based algorithm using Fourier Technique, Wavelet Decomposition, Principal Component Analysis
Theou et al., (2012)	ActiTrainer (ActiGraph LLC, Fl., USA). Uni-axial accelerometer worn on waist Records data in 1-minute epochs Polar WearLink (Polarlink Technologies Ltd., KH, Taiwan). HR monitor worn on chest Garmin forerunner405 (Garmin International Inc., KS, USA). GPS worn on wrist Biometrics DataLOG P3X8 (Gwent, UK). EMG worn on Vastus Lateralis and Biceps Brachii	Data downloaded or wirelessly transmitted to Custom Software EMG sampling frequency 1000Hz
Millor et al., (2013)	MTx XSENS (Xsens Technologies B.V. Enschede, Netherlands). Tri-axial accelerometer, gyroscope & magnetometer worn at L3	Sampling frequency 100Hz, Automated raw data analysis using Matlab (Mathworks Inc., MA., USA).
Galan-Mercant and Cuesta-Vargas (2013)	iPhone4 secured to chest (Apple Inc., CA, USA). Tri-axial accelerometer, gyroscope & magnetometer. Apple uses a LIS302DL accelerometer in iPhone4	Sampling frequency 32Hz. Data obtained through the use of an application, xSensor Pro(Crossbow Technology Inc., CA., USA) available from Apple *AppStore*
Greene et al., (2014)	Shimmer (Dublin, Ireland). Tri-axial accelerometer & gyroscope worn on each shin Sensor axes aligned with the vertical, medio-lateral and anterior-posterior axes of the body,	Sampling frequency 102.4Hz, Low-pass filtered with zero-phase 2nd order Butterworth filter, 20Hz corner frequency. Raw data analysis using Matlab (Mathworks Inc., MA., USA).
Greene et al., (2014)	Shimmer (Dublin, Ireland). Tri-axial accelerometer & gyroscope worn on each shin, lateral aspect of right thigh, Sternum above L5	Inertial sensor Sampling frequency 102.4Hz, 2nd order Butterworth filter. Pressure sensor 40Hz. Raw data analysis using Matlab (Mathworks Inc., MA., USA).
Chen et al., (2015)	Active Style Pro, HJA350-IT (Omron Healthcare Co. Ltd, Kyoto, Japan). Tri-axial accelerometer. Location not specified	Details not provided
Schwenk et al., (2015)	LEGSys™, BalanSens™, PAMSys™ Locomotion Evaluation and Gait System (BioSensics, MA, USA). Tri-axial accelerometer, gyroscope, magnetometer sensors worn on shanks, thighs, and L.	Sampling frequency 100Hz Custom software LEGSys™, BalanSens™, (BioSensics, MA, USA).
Martinez-Ramirez et al., (2015)	MTx XSENS,(Xsens Technologies B.V. Enschede, Netherlands). Tri-axial accelerometer, gyroscope & magnetometer worn at L3	Gait features were detected using automatic peak detection and identified using wavelet decomposition (Coif5 level 3)
Toosizadeh, Mohler, Wendel et al., (2015)	BalanSens™ BioSensics LLC. (MA., USA). Triaxial accelerometer, gyroscope, magnetometer worn at shank and trunk	Sampling frequency 100Hz Real time quaternions were converted to Eular angles
Toosizadeh, Mohler and Najafi (2015)	BioSensics LLC (MA., USA). Tri-axial gyroscope worn on Upper Arm near Biceps muscle and wrist.	Sampling frequency 100Hz Further details of sensor-data extraction not provided
Jansen et al., (2015)	ActiGraph GT3X+ (ActiGraph LLC, FL., USA) and BT-Q1000XT (QStarz International Co., Taipai, Taiwan). Tri-axial accelerometer and GPS receiver worn on waist	ActiLife v5.8.3 Firmware v2.2.0, (ActiGraph LLC, Fl., USA) was used to process accelerometer data
Toosizadeh et al., (2016)	BioSensics LLC (MA., USA). Tri-axial gyroscope worn on Upper Arm near Biceps muscle and wrist.	Sampling frequency 100Hz. Further details of sensor-data extraction not provided
Millor et al., (2017)	MTx Orientation Tracker (Xsens Technologies B.V., Enschede, Netherlands). Tri-axial accelerometer, gyroscope & magnetometer worn at L3	Sampling frequency 100Hz. Nine individual MEMS sensors provided kinematic data. Drift-free orientation data was also provided using Kalman filters. Automated data analysis using Matlab (Mathworks Inc., MA., USA)
Parvanneh et al., (2017)	PAMSys™ (BioSensics LLC, MA, USA), Tri-axial accelerometer worn at Sternum	Sampling frequency 50Hz. Custom software / algorithm (PAMWare, BioSensics MA, USA)
Huisingh-Scheetz et al., (2018)	ActiWatch Spectrum (Philips, Amsterdam, Netherlands). Tri-axial piezo-electric accelerometer worn on wrist	Sampling frequency 32Hz. Data processed using Actiware® software (Philips, Amsterdam, Netherlands).
Lee et al., (2018)	LEGSys™ (Biosensics LLC, MA. USA). Tri-axial gyroscope worn on wrist and Upper arm	Sampling frequency 100Hz, Automated raw data analysis using Matlab (Mathworks Inc., Natick, MA., USA). An algorithm was developed using zero crossing technique, with no filtering, to automate phenotype extraction.

Razjouyan et al., (2018)	PAMSys™ (BioSensics LLC, MA, USA). Tri-axial accelerometer worn at sternum	Sampling frequency 50Hz. The raw data were processed with a band-pass filter at cut-off frequencies of 0.1953 Hz and 12.5 Hz
Castaneda-Gameros et al., (2018)	Actigraph GT3X accelerometer (ActiGraph LLC, FL., USA). Worn on hip. Programmed to record activity in 60-second epochs	Data were cleaned and scored using ActiLife software V6.2 (ActiGraph LLC, Fl., USA).
Jansen et al., (2019)	LEGSys™ (BioSensics, MA., USA). Tri-axial accelerometer, gyroscope, magnetometer worn on shanks, thighs, and L.	Algorithm based on accelerometer data with low-pass filtering (as described in author's earlier publication)
Zhou et al., (2019)	LEGSysTM (BioSensics, MA, USA) Tri-axial accelerometer, gyroscope, magnetometer worn on both shins	Quaternion components of ankle rotation were converted to Eular angles. Sampling frequency 100Hz
Mulasso et al., (2019)	ADAMO System (Caretek SRL.,Turin, Italy). Tri-axial accelerometer worn on wrist	Embedded step-count algorithm. Sampling frequency 50Hz
Lepetit et al., (2019)	APDM (Opal, Portland, USA) Tri-axial accelerometer, gyroscope, magnetometer worn on chest	Fusion algorithm. Sampling frequency 128Hz
Yuki et al., (2019)	Lifecorder (Suzuken, Aichi, Japan) Uniaxial accelerometer. Body-location not specified	Data recorded in 4-second epochs. No further information available
Ziller et al., (2020)	ActiGraph wGT3x-BT, (ActiGraph, LLC., FL., USA). Tri-axial accelerometer worn at hip	Sampling frequency 100Hz, 10-second epochs. Data processing using ActiLife Software 6, (ActiGraph LLC., FL., USA)
Chen et al., (2020)	Active style Pro HJA- 350IT, (Omron Healthcare, Kyoto, Japan). Triaxial accelerometer worn at the waist	Data recorded in 60-second epochs. No further detail available
Kikuchi et al., (2020)	Active style Pro HJA-750C, (Omron Healthcare, Kyoto, Japan). Triaxial accelerometer worn at the hip	Data recorded in 60-second epochs. Analysis using application developed by Omron Healthcare, Kyoto, Japan) to read METs data from accelerometer.
Apsega et al., (2020)	Shimmer, (Dublin, Ireland). Tri-axial accelerometer & gyroscope worn on each thigh, shin and dorsum of foot	Sampling frequency 256 Hz. Butterworth second order low pass filter with an 8 Hz cut-off and an additional least square method 25th order filter with a 10 Hz cut-off for composite foot acceleration data. A gait event detection algorithm was developed.

Seven different measures of mobility and PA were reported. Mobility measures included; temporal-spatial gait parameters of speed, total steps, double support, stride length, time and variability (Apsega et al. 2020; Galán-Mercant and Cuesta-Vargas 2013; Greene et al. 2014; Greene et al. 2014; Martínez-Ramírez et al. 2015; Schwenk et al. 2015; Theou et al. 2012; Zhou et al. 2019), postural transitions: acceleration counts of sit to stand (STS), stand to walk, stand to sit (Greene et al. 2014; Lepetit et al. 2019; Millor et al. 2017; Millor et al. 2013; Parvaneh et al. 2017; Razjouyan et al. 2018; Theou et al. 2012), trunk angular velocity (Galán-Mercant and Cuesta-Vargas 2013; Greene et al. 2014), upper limb kinematics (Lee et al. 2018; Toosizadeh, et al., 2015; Toosizadeh et al. 2016), intensity of PA and percentage of time in walking, standing, sitting and lying (Castaneda-Gameros et al. 2018; Chen et al. 2020; Huisingh-Scheetz et al. 2018; Jansen et al. 2015; Jansen et al. 2019; Kikuchi et al. 2020; Mulasso et al. 2019; Parvaneh et al. 2017; Razjouyan et al. 2018; Schwenk et al. 2015; Theou et al. 2012; Yuki et al. 2019;). Two studies examined PA intensity with the aim to objectively define and compare with the low PA criterion of a frailty classification tool (Chen et al. 2015; Ziller et al. 2020). Balance parameters included sway of ankle, hip and centre of mass (Greene et al. 2014; Martınez-Ramırez et al. 2011; Schwenk et al. 2015; Toosizadeh et al. 2015) and chair-stand kinematics including number of STS cycles, acceleration and trunk displacement (Greene et al. 2014; Lepetit et al. 2019; Millor et al. 2013; Millor et al. 2017).

3.3.3 Participant characteristics

Participants ranging in age 63 – 90 years were recruited from community, assisted-living or hospital environments. Four studies (Lepetit et al. 2019; Martınez-Ramırez et al. 2011; Millor et al. 2013; Zhou et al. 2019) included a healthy young cohort (age range 18-54 years) for comparison. For those studies that reported sex there was an overall predominance of females.

3.3.4 Quality assessment

With the exception of one study that scored 12, the methodological quality of studies demonstrated a minimum result of 70% (14 out of a possible 20, range 14 - 20) using the AXIS tool (Appendix 3.5). Quality appraisal of all 29 studies is presented in Table 3.2. The tool used does not apply a numerical score or rating because of the author's assertion of the non-linear weighting of each aspect of the

assessment and each section (Downes et al. 2016b). No study was excluded based on methodological score.

Table 3.2 AXIS Methodological Quality Assessment
AXIS Methodological Quality Assessment (Yes = 1, No = 0, Not known = 0)
*Q 13 "Does the response rate raise concerns about non-response bias?" *Q19 "Were there any funding sources or conflicts of interest that may affect the authors' interpretation of the results? 'No' is a positive response, therefore 'No' counts as '1'

Study	Q1	2	3	4	5	6	7	8	9	10	11	12	13*	14	15	16	17	18	19*	20	Total
Martinez-Ramirez et al., (2011)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	15
Theou et al., (2012)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16
Millor et al., (2013)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	0	1	1	14
Galan-Mercant and Cuesta-Vargas (2013)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	0	1	1	14
Galan-Mercant and Cuesta-Vargas (2013)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	14
Greene et al., (2014)	1	1	1	1	1	0	0	1	1	1	1	0	0	0	1	1	1	1	0	1	14
Greene et al., (2014)	1	1	0	1	1	0	0	1	1	1	1	0	0	0	0	1	1	1	0	1	12
Chen et al., (2015)	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	18
Toosizadeh, Mohler, Wendel et al., (2015)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16
Toosizadeh, Mohler and Najafi (2015)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16
Schwenk et al., (2015)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	15
Martinez-Ramirez et al., (2015)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	15
Jansen et al., (2015)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
Thiede et al., (2016)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	15
Parvanneh et al., (2017)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	15
Millor et al., (2017)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	14
Huisingh-Scheetz et al., (2018)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
Lee et al., (2018)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	14
Castaneda-Gameros et al., (2018)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16

Razjouyan et al., (2018)	1`	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	14
Mulasso et al., (2019)	1	1	0	1	0	0	0	1	1	1	1	1	0*	1	1	1	1	1	0	1	14
Zhou et al., (2019)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	14
Lepetit et al., (2019)	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	15
Jansen et al., (2019)	1	1	0	1	0	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	14
Yuki et al., (2019)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16
Ziller et al., (2020)	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	19
Chen et al., (2020)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	20
Kikuchi et al., (2020)	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	18
Apsega et al., (2020)	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	16

3.4 Discussion

This systematic review was undertaken to examine which parameters of mobility and PA obtained from a wearable sensor have been used to assess and quantify frailty, which type of body-worn sensors and specific body-locations have been used, and how different parameters are associated with discriminating the stages of frailty. Of the 29 studies included in the review, seven distinct aspects of mobility and PA with a multiplicity of subdivisions were examined, using 13 different sensor brands on eight different body-locations. Some studies use a combination of body-locations. This heterogeneity makes comparison and analysis difficult and thus precludes recommendations on devices. It is worth noting however that while brands of sensors reported differ, the properties are comparable. Studies will be discussed under headings referring to the various mobility and PA parameters, sensors used and body-location of sensors.

3.4.1 Parameters of Mobility and Physical Activity

3.4.1.1 Physical Activity Parameters

Time spent in non-sedentary activity is the most commonly examined parameter of mobility and PA in the literature reviewed. Subdivisions of PA patterns and PA behaviour examined include time spent in non-sedentary activity; time spent in various intensities of activity; number of postural transitions,

number of bouts, length of unbroken bouts and variability in bouts of the different measurements of PA.

There was some commonality of metrics among the 12 studies in this group (Castaneda-Gameros et al. 2018; Chen et al. 2020; Huisingh-Scheetz et al. 2018; Jansen et al. 2019; Jansen et al. 2015; Kikuchi et al. 2020; Mulasso et al. 2019; Parvaneh et al. 2017; Razjouyan et al. 2018; Schwenk et al. 2015; Theou et al. 2012; Yuki et al. 2019) and some consensus. Razjouyan et al., (Razjouyan et al. 2018) agree with earlier findings of (Theou et al. 2012) that total time spent in non-sedentary activity correlates well with a frailty index, demonstrating significant differences between levels of frailty. This is supported by (Jansen et al. 2019) in a study which examines the effect of frailty levels on motor capacity and mobility performance. The authors suggest that capacity does not necessarily determine performance or function but there is a strong association between the two and frailty. These findings are contradicted by (Schwenk et al. 2015a) who suggest that percentage of time spent walking is a poor discriminator of frailty levels. These authors (Schwenk et al. 2015a) suggest variability in walking bouts described as more static and less complex PA combined with shorter walking bouts as a more sensitive measure of frailty. Similarly, it is suggested that sedentary time is associated with frailty (Kikuchi et al. 2020; Razjouyan et al. 2018) but this is refuted in another study (Castaneda-Gameros et al. 2018).

Some studies measured intensity of PA, but as is common with many of the parameters in the studies included in this review, there is little consistency in how the metrics are defined or measured. Categories of PA intensity are consistent insofar as they are referred to as variations of low, medium or high (Castaneda-Gameros et al. 2018; Chen et al. 2015; Chen et al. 2020; Jansen et al. 2015; Kikuchi et al. 2020; Mulasso et al. 2019; Razjouyan et al. 2018; Yuki et al. 2019; Ziller et al. 2020;) but how each category is defined differs from measurement of acceleration counts per minute (Castaneda-Gameros et al. 2018; Jansen et al. 2015) to metabolic equivalents (MET) (Chen et al. 2020; Jansen et al. 2015; Kikuchi et al. 2020; Razjouyan et al. 2018; Yuki et al. 2019) and magnitude of mobility e.g., lying, sitting, walking pace (Mulasso et al. 2019). Counts per minute as a metric of

PA intensity are not universal and there is marked disparity between the scales used (Castaneda-Gameros et al. 2018; Huisingh-Scheetz et al. 2018; Jansen et al. 2015; Ziller et al. 2020).

There is some agreement that moderate to vigorous activity is inversely related to frailty. Those studies that differentiate between levels of frailty agree that PA intensity discriminates non-frail from pre-frail and to a lesser extent pre-frail from frail (Castaneda-Gameros et al. 2018; Chen et al. 2020; Kikuchi et al. 2020; Razjouyan et al. 2018; Yuki et al. 2019). This is refuted by (Jansen et al. 2015) who found no significant between-group differences. The much lower counts per minute used in this study may account for this finding. Acceleration counts as measured in one study (Theou et al. 2012) are referred to as postural transitions or counts per minute (CPM) in others (Huisingh-Scheetz et al. 2018; Yuki et al. 2019; Ziller et al. 2020). One study (Parvaneh et al. 2017) in which postural transitions are further defined as STS, stand to sit, stand to walk etc. purports the ability of the number of postural transitions to discriminate between levels of frailty while the others suggest discrimination between frail and non-frail only (Huisingh-Scheetz et al. 2018; Ziller et al. 2020).

Within the literature included in the review, the most common correlation between frailty levels and PA demonstrated are moderate – vigorous PA (MVPA) (Castaneda-Gameros et al. 2018; Chen et al. 2020; Kikuchi et al. 2020; Razjouyan et al. 2018; Yuki et al. 2019) , bouts of PA (Chen et al. 2020; Jansen et al. 2019; Razjouyan et al. 2018; Schwenk et al. 2015) and total number of steps (Chen et al. 2020; Jansen et al. 2019; Razjouyan et al. 2018; Theou et al. 2012; Yuki et al. 2019).

3.4.1.2 Temporal-Spatial Parameters of Gait including Trunk kinematics

Seven studies (Jansen et al. 2019; Martínez-Ramírez et al. 2015; Millor et al. 2017; Mulasso et al. 2019; Schwenk et al. 2015; Theou et al. 2012; Zhou et al. 2019) examined gait speed, velocity, or time to complete a walk test as part of their research. Five included gait speed with temporal-spatial parameters including step time, regularity, stride time, length regularity, percentage of time in double support, and trunk kinematics of angular velocity and trunk displacement (Apsega et al. 2020; Greene et al. 2014; Greene et al. 2014; Martínez-Ramírez et al. 2015; Schwenk et al. 2015;). One study examined trunk kinematics only, during the STS, Stand to Sit and turn transitions of the 10-m Timed

Up and Go (TUG) test (Galán-Mercant and Cuesta-Vargas 2013; Galán-Mercant and Cuesta-Vargas 2013). While there is consensus regarding the association between gait speed/velocity and the identification of frailty (Theou et al. 2012; Schwenk et al. 2015; Galán-Mercant and Cuesta-Vargas 2013; Zhou et al. 2019; Apsega et al. 2020) there is disparity in the significance of the results. All agree on the ability of gait speed/velocity to discriminate between non-frail and frail however the effect size varies considerably, even between studies using the same body-location (Schwenk et al. 2015a; Zhou et al. 2019). Variation in the methodology of gait speed measurement may be a contributory factor in the disparity, with distance over which speed was measured varying from 3m to 20m. One study suggests that the ability to distinguish between pre-frail and frail, arguably a more important distinction, lies within the development of models including capacity and performance (Jansen et al. 2019). This study included measures of normal and fast walking speed as measures of capacity.

3.4.1.3 Balance

Balance is measured in different ways throughout the literature varying in the nature of the assessment, the conditions under which the assessment took place and duration of each task. Those that assessed balance during a period of quiet standing did so over different time periods ranging from 10 – 40-seconds (Greene et al. 2014; Martınez-Ramırez et al. 2011; Schwenk et al. 2015; Toosizadeh, Mohler, Wendel, et al. 2015) . Conditions varied between participants standing with feet together, feet semi-tandem, eyes open and/or eyes closed while another measured balance during a 30-second chair-stand exercise (Millor et al. 2013). Balance was evaluated by examining displacement of trunk (Greene et al. 2014; Martınez-Ramırez et al. 2011; Millor et al. 2013; Schwenk et al. 2015), hip and ankle (Schwenk et al. 2015a; Toosizadeh, Mohler, Wendel, et al. 2015) in anteroposterior and medial-lateral directions and during different phases of the task (Millor et al. 2013).

Studies that investigated the effect of balance parameters on the identification of frailty agree on a greater anteroposterior sway in frail groups under conditions of feet together, eyes closed but no between-group significance (Martınez-Ramırez et al. 2011; Toosizadeh, Mohler, Wendel, et al. 2015; Schwenk et al. 2015a). Millor et al., (Millor et al. 2013) concur to some extent in their assessment of

lateral sway. However, synthesis of data is difficult because of the study characteristics. These studies varied in their methodology and analysis. One study (Martınez-Ramırez et al. 2011) proposes analysis of the orientation and acceleration signal-intensity as a novel and perhaps more appropriate approach to discriminating between frailty levels than sway or power variables of balance tests. Results of this study indicate that the higher frequencies of orientation and acceleration signals obtained through wavelet decomposition analysis in healthy populations are distinguished from the lower frequencies typical of a frail population.

One study that examined a broad range of variables suggests that the predictive validity of balance parameters is inferior to those of gait and PA parameters (Schwenk et al. 2015a). Subsequently it has been suggested that kinematics of STS have greater sensitivity, specificity, accuracy and precision values than those of gait parameters, specifically velocity (Millor et al. 2017). This is supported by one study which, using a model combining data from balance, PA and chair kinematics, yields a higher accuracy percentage in identifying frailty than each of the individual tests (Greene et al. 2014).

3.4.1.4 Upper Limb Kinematics

Three studies (Lee et al. 2018; Toosizadeh, Mohler and Najafi 2015; Toosizadeh et al. 2016) examined kinematics of the upper limb, specifically the elbow, in the development of a frailty assessment tool that does not rely on gait. All agree on the ability of the variables derived from an elbow flexion/extension task to distinguish between levels of frailty.

3.4.2 Sensors and Body- Location

With the exception of two studies (Theou et al. 2012; Yuki et al. 2019) in which a uni-axial accelerometer was used, all studies report the use of either a tri-axial accelerometer, gyroscope or a combination of both, with the inclusion of a tri-axial magnetometer reported in eight studies (Apsega et al. 2020; Galán-Mercant and Cuesta-Vargas 2013; Lepetit et al. 2019; Martınez-Ramırez et al. 2011; Martínez-Ramírez et al. 2015; Millor et al. 2013; Millor et al. 2017; Zhou et al. 2019). The uni-axial accelerometer was positioned at the waist and used to record steps in conjunction with acceleration counts (Theou et al. 2012) and total number of steps with PA intensity (Yuki et al. 2019).

The most common body-location for the tri-axial sensors was the lumbar spine (Greene et al. 2014; Jansen et al. 2019; Martınez-Ramırez et al. 2011; Martínez-Ramírez et al. 2015; Millor et al. 2013; Millor et al. 2017; Schwenk et al. 2015; Toosizadeh, Mohler, Wendel, et al. 2015), but in other studies, these sensors were positioned at the chest (Galán-Mercant and Cuesta-Vargas 2013; Greene et al. 2014; Lepetit et al. 2019; Parvaneh et al. 2017; Razjouyan et al. 2018; Theou et al. 2012), shins (Toosizadeh, Mohler, Wendel, et al. 2015; Zhou et al. 2019; Greene et al. 2014; Schwenk et al. 2015; Greene et al. 2012; Jansen et al. 2019; Apsega et al. 2020), wrist (Mulasso et al. 2019; Toosizadeh, Mohler and Najafi 2015; Toosizadeh et al. 2016; Lee et al. 2018; Huisingh-Scheetz et al. 2018), waist (Jansen et al. 2015; Chen et al. 2020), hip (Castaneda-Gameros et al. 2018; Kikuchi et al. 2020) thigh (Schwenk et al. 2015a; Apsega et al. 2020) and foot (Apsega et al. 2020)

There was some commonality with the body-locations used and metrics obtained, for example all balance parameters were obtained using a tri-axial gyroscope positioned at the L3 (Martınez-Ramırez et al. 2011; Millor et al. 2013; Toosizadeh, Mohler, Wendel, et al. 2015; Schwenk et al. 2015a; Greene et al. 2012). However, in some studies a sensor positioned at the L3 was used to examine temporal-spatial parameters of gait (Martínez-Ramírez et al. 2015; Millor et al. 2017). One study used a combination of L3 and shin to measure balance parameters, presumably because the study examined open-loop and closed-loop postural control strategy (Toosizadeh, Mohler, Wendel, et al. 2015).

Body-location of sensors measuring PA included chest (Schwenk et al. 2015; Razjouyan et al. 2018; Parvaneh et al. 2017; Greene et al. 2012; Jansen et al. 2019; Galán-Mercant and Cuesta-Vargas 2013), wrist (Mulasso et al. 2019; Huisingh-Scheetz et al. 2018), hip (Castaneda-Gameros et al. 2018; Kikuchi et al. 2020) and waist (Theou et al. 2012; Chen et al. 2020). One study in this group (Schwenk et al. 2015a) used a combination of body-locations but reports that data for PA was retrieved from only the sensor located at the chest.

Correlation between accelerometer counts and step-counts in one study (Theou et al. 2012) was less in the higher frailty index cohort, which is surprising considering both were obtained from the same device. This perhaps suggests less sensitivity in accelerometers in detecting lower intensity of movement. This supports the idea mooted that activity below a cut-off point considered in some

research as non-wear time may in fact reflect low intensity activity (Gorman et al. 2014). The same study (Theou et al. 2012) found that minute-by-minute accelerometer-derived step-count and acceleration-counts correlated positively with heart rate values. This is interesting considering as referred to previously, heart rate monitors capture indications of physical activities that do not require trunk displacement and can be used to indicate energy expenditure and PA behaviours e.g., sedentary time.

3.5 Limitations

While every effort has been made to ensure a thorough search of the relevant databases, it is possible that some literature was missed. An updated search performed prior to thesis submission reduces the risk of any over-sight. The inclusion of English-only publications may have resulted in omission of some relevant studies. Applying the age profile criteria of >60 years in the inclusion may be perceived as a limitation but this was done to optimise the literature included and is in accordance with the World Health Organization and the United Nations who have adopted >60 years in reference to older adults as opposed to the arbitrary 65 years commonly adopted (WHO 2015). Due to the heterogeneity of metrics, the variation in body-location of sensor placement and the difference in methods of analysis among the studies included in the review, meta-analysis was not possible. This however does not invalidate the findings. Many studies involved small numbers of participants and some combined frail and pre-frail cohorts for statistical analysis. This reduces the potential to discriminate between levels of frailty, which is considered an important objective.

3.6 Conclusions

Despite its limitations, this review, the first to comprehensively synthesise data from the last decade of research in this field, makes a valuable contribution to identifying how wearable sensors have been utilised to assess frailty in older adults, the body-locations of sensor-placement used and the parameters of PA and mobility that best assist in the discrimination of frailty levels. The review highlights the heterogeneity of parameters examined in relation to frailty identification and the body-locations used. Measurements of PA have proved to be the most frequently used parameter when all variations of number of postural transitions, number of steps, percentage of time in PA and intensity

of PA are considered. Only one study failed to demonstrate an association between PA and levels of frailty. Gait-speed was found to be the next most prevalent parameter examined, with all studies included in the review demonstrating a correlation between walking speed and levels of frailty. A higher sensitivity compared with other mobility parameters is noted.

Considering the facts that up to 95% of older adults are community-dwelling, that not all older adults develop frailty, and that research suggests older adults can transition between levels of frailty, this review highlights the need for further research to identify a feasible, user-friendly device and body-location that can be used to independently, objectively measure and identify signs of pre-frailty in community-dwelling older adults. This could facilitate early identification and targeted intervention to reduce the burden of frailty in an ageing population. Future reviews could focus on important open research questions related to wearable technology and older adults including acceptance, feasibility and facilitation of ageing in place.

This chapter has presented a systematic review demonstrating how wearable sensors have been used to identify and distinguish between levels of frailty in older adults. The findings were used to inform the research of sensor positioning and parameters of gait, mobility and PA to capture in an effort to facilitate early recognition of risks of frailty among community-dwelling older adults. The following chapter reports on a laboratory-based study which was conducted to compare measurements of mobility and PA obtained from body-worn sensors placed in different locations on the body.

Chapter Four - Laboratory-Based Study

Introduction

The previous chapter presented a systematic review which was conducted to examine how parameters of gait, mobility and PA obtained from wearable sensors have been used to evaluate frailty among older adults. As demonstrated, there are many studies to support the use of wearable sensors to detect activity levels among older adults, for example in measuring walking, running, sitting, lying, ascending or descending stairs (Pannurat et al. 2017; Cleland et al. 2013; McCullagh et al. 2016). However, there is little consensus within the literature regarding the best placement of a sensor to accurately and reliably monitor each different activity (Theou et al. 2012; Tedesco et al. 2017; Pannurat et al. 2017). Ankles, thigh and waist sensor placements have demonstrated high accuracy of step detection at different gait-speeds. The wrist has been proposed as a location for sensor placement that is convenient and accessible for use by older adults (Kolasinska et al. 2018) however, the systematic review presented in chapter three identifies just two studies which evaluated the wrist as a body location for sensor placement (Huisingh-Scheetz et al. 2018; Mulasso et al. 2019). Only one of these studies includes the wrist as the body-location for a single sensor to capture parameters of PA (Huisingh-Scheetz et al. 2018). The other study evaluating a wrist-worn sensor involved a remote monitoring system which composed of a wrist-watch to collect data pertaining to daily activity which was then transmitted to a base station in the user's home for off-site monitoring and analysis (Mulasso et al. 2019).

This chapter reports on a laboratory-based study comparing measurements of gait obtained from body-worn sensors placed in different locations on the body in two groups, a cohort of healthy older adults and of healthy younger adults. It also compares step-count obtained from body-worn sensors with a criterion measure of direct observation, and with a validated inertial sensor and software system. Parameters of gait and PA have been identified in chapter 3 as indicators of frailty risk and adverse health outcomes. The ankle and waist are selected to confirm the literature supporting the accuracy of data from sensors positioned at these body-locations (Schwenk et al. 2015a; Zhou et al. 2019). The wrist is included to examine if data obtained from a sensor positioned at body-location

deemed conveniently accessible for use by older adults i.e. the wrist (Kolasinska et al. 2018) compares with that obtained from the waist and ankle.

The remainder of the chapter is outlined as follows; section 4.1 outlines the aims and objectives of the study, section 4.2 describes the materials and methodology, section 4.3 presents the results that are discussed in section 4.4. Sections 4.5 and 4.6 present the limitations and conclusion of the study.

4.0 Background

In a climate where health services are struggling to meet the needs of older adults (Abdi et al. 2019), mitigating the risks associated with ageing must be a priority of health care providers to reduce the physical and socioeconomic burden and reduce the demand on health care resources (Faller et al. 2019). Most older adults wish to remain at home and ageing in place is a key goal of national ageing strategies worldwide (World Health Organization 2017). The changes associated with ageing are not consistent among older adults however, and are influenced by extrinsic factors including an individual's behaviours and the environment (WHO 2015; Singer et al. 2019).

Gait is an indicator of health status; changes in gait parameters are associated with age (Schimpl et al. 2011), and have been identified as a key prognostic indicator for disability (Fortune et al. 2014; Perera et al. 2014; Studenski et al. 2011). Parameters of gait commonly measured include speed, step-length, stride-length, and variability. Gait-speed has been identified as the strongest predictor of disability, prolonged hospital-stay and quality of life (Bair et al. 2019; Bortone et al. 2021; Pamoukdjian et al. 2015), while variability in gait has been shown to negatively associate with levels of PA (Ciprandi et al. 2017). Walking is considered the main contributor to PA in adults, therefore it is important to measure gait parameters as part of an assessment of mobility and PA. Accurately measuring step-count is an important first step in measuring walking and PA (Bassett et al. 2017). PA has traditionally been measured in either self-reported estimates or structured, supervised measurements of gait (Phillips et al. 2018). Historically these objective measurements involved costly, complicated, and time-consuming laboratory-based assessments. Self-reported estimates of PA by their nature are subjective with a risk of bias (Razjouyan et al. 2018) and have poor validity (Phillips et al. 2018).

The proliferation of wearable sensors and their anticipated evolution over the coming years suggests more proactive solutions to healthcare, ageing and functional decline with new developments from the user's perspective (Ometov et al. 2021). This will enable older adults to take on a more independent, proactive role in monitoring and addressing risk factors thereby developing self-regulation and self-efficacy. Self-regulating is the monitoring and controlling of ones behaviours to achieve a goal, and is influenced by the perception of self-efficacy, the belief that one can achieve a goal (Clark and Dodge 1999; McAuley and Blissmer 2000). Both self-monitoring and self-efficacy have been identified as determining factors in exercise behaviours, with higher levels of self-monitoring and self-efficacy associating with better health outcomes (Clark and Dodge 1999).

4.1 Aims and Objectives

To address the second objective of this thesis, the aim of this study was to conduct a laboratory-based study to establish how measures of mobility and PA obtained from a single sensor positioned at different body locations compare with each other; with a criterion measure; and with a validated medical-grade sensor and software system.

The objectives of this study were;

1. To collect sensor data from inertial sensors positioned at three different body-locations (the ankle, the waist, and the wrist) in two different cohorts; a healthy younger adult group aged 18-65 years and a healthy older adult group aged >65 years, during a Timed Up and Go (TUG) test performed under different conditions, and during a 3-minute treadmill walk at a slow speed.

2. To compare step-count obtained from the inertial sensors positioned at each body-location during a three-minute treadmill walk with that of criterion measure, direct observation.

3. To compare step-count obtained from a validated sensor and software system during each of the TUG tests, with that obtained from inertial sensors positioned at different body locations, and with a criterion measure.

4. To compare temporal parameters of gait obtained from the validated research-grade inertial sensors positioned at the ankle during the treadmill walk with that obtained from the waist and the wrist and identify if one is more accurate than the other.

4.2 Materials and Methods

4.2.1 Study design

A laboratory based cross-sectional study was conducted to compare sensor data collected from different body locations in two cohorts of adults during a series of mobility and PA tests. Inertial sensor data collected from sensors positioned at the waist, wrist and ankles were compared with each other, with a criterion measure and with that of a validated sensor system.

The study protocol received institutional ethics approval (Appendix 4.1).

4.2.2 Participants

Participants were recruited through advertisements in a local golf club, tennis club and physiotherapy department (Appendix 4.2). Inclusion criteria were 18 - 65 years of age, or > 65 years of age, healthy, independently mobile, physically capable of performing a series of mobility and PA tests, have no cognitive or neurological deficits and have no history in the past 12 months of orthopaedic trauma or surgery. Healthy individuals were selected for convenience during the COVID-19 pandemic when level 5 travel restrictions were in place nationally (gov.ie 2020). It was deemed conceivable that the incidence of pre-frailty among the older participant sample recruited from the community could reflect that of the general population. It is acknowledged that the incidence of frailty was less likely as participants were recruited from sports clubs. As gait characteristics e.g. gait speed and step length change with age (Schimpl et al. 2011; Oberg et al. 1993) a younger cohort was included to examine any differences between the two cohorts in the accuracy of the data obtained from the sensors and criterion measures. Healthy young participants have been included in studies within the literature for comparative purposes and to provide a healthy benchmark (Zhou et al. 2018; Hafer and Zernicke 2020; Pang et al. 2019; Soaz and Diepold 2016). Those interested were assessed for eligibility, and fully informed about the study by telephone when potential participants contacted the researcher. A

participant information leaflet (PIL) was then provided either by email, by post or by hand (Appendix 4.3).

A convenience sample of twenty community-dwelling volunteers was recruited (n = 10 aged > 65 years of age and n = 10 aged 18 – 65 years). Many earlier studies (Tedesco et al. 2019b; Lee et al. 2020) have included similar sample sizes for validation purposes as demonstrated in a systematic review by Ngueleu 2019 (Ngueleu et al. 2019). The first ten volunteers in each group available to contact by phone, willing to participate and fitting the inclusion criteria were enrolled in the study. There were those who enquired about the study but declined participation for reasons including concerns regarding the activity required being unsuitable, reluctance to travel to the test centre and fears of COVID-19 risks.

All participants signed a written informed consent form prior to participation (Appendix 4.4). Participants also fulfilled COVID-19-specific requirements including a COVID-19 questionnaire (Appendix 4.5), temperature check and hand hygiene prior to data collection.

4.2.3 Data collection

The study was carried out in two different sites for logistical reasons. All participants in the over-65 years of age group were assessed at site one while all those in the 18-65 years of age group were assessed at a separate site (site two). The set-up in both sites were comparable except for the floor surface; a carpet-tile surface at site one and a wooden floor at site two. Measurements of height and body mass were taken along with demographic details of date of birth, sex, past medical history, and current medications. These data were recorded on a case report form (CRF) (Appendix 4.6). The PA and mobility tests consisted of a TUG test under three different conditions and a treadmill walk.

Prior to the beginning of the study, the inertial sensors (Shimmer 3, Shimmer Research, Dublin, Ireland) were calibrated according to the Shimmer 9DoF Calibration procedure (Shimmer 2013). Prior to each participant instrumentation, sensors were configured according to the same application with sampling rate 102.4Hz; acceleration signal range ± 2g; wide range accelerometer, gyroscope and magnetometer sensors enabled; Gyro on the fly calibration and 9DoF algorithms set.

4.2.3.1 Timed Up and Go (TUG) Tests

The TUG test is a reliable and valid test of functional balance and mobility that measures in seconds (s), the time taken by a participant to stand up from a standard chair seat height, walk a distance of 3-meters (m) (10 feet), turn 180 degrees, walk back to the chair and sit down (Podsiadlo and Richardson 1991). A TUG-cognitive or TUG-manual further tests functional balance and mobility through the performance of concurrent tasks (Lundin-olsson et al. 1998; Shumway-Cook et al. 1997). A TUG-Cognitive test involves the inclusion of either a language or visual spatial task while performing a standard TUG test. A TUG-Manual test involves the inclusion of a second functional task. The TUG test under different conditions was selected to provide objective data representative of the short distances of mobility performed for functional activities in a real world setting of community-dwelling older adults (Deblock-Bellamy et al. 2022; Kumar et al. 2020). It is suggested that dual-task walking is comparable with everyday walking in older adults (Hillel et al. 2019)The Kinesis QTUG sensor and software system (QTUG) (Kinesis Health Technologies, Dublin, Ireland) is a validated tool which measures temporal-spatial parameters of gait and uses proprietary algorithms to provide a quantitative falls and frailty risk score obtained during a standard TUG test. It is designed as a clinician-administered performance test for clinical evaluation.

Prior to performing the TUG test participants were instrumented with the Kinesis QTUG sensors, one positioned on each shank as per manufacturer's instruction. Each sensor was aligned with the vertical, medio-lateral and anterior-posterior axes of the body and contained a tri-axial accelerometer, tri-axial gyroscope and a magnetometer. The Kinesis QTUG sensors were secured over outer clothing with reusable straps (Fig. 5.2). The data derived from the QTUG sensors were streamed via Bluetooth to a handheld tablet (Samsung Galaxy Tab A 2016) which automatically calculated a frailty risk based on analysis of temporal-spatial gait parameters. Data were saved on board the tablet in text form for offline analysis. The QTUG was used during each TUG test performed under different conditions. The QTUG sensors collected data during the TUG tests only.

4.2.3.2 Three-minute Treadmill walk

Shimmer inertial sensors containing a tri-axial accelerometer, gyroscope and magnetometer providing 9DoF inertial sensing were used to collect data during the three-minute treadmill walk. Only the accelerometer data were used in the analysis. A treadmill walk was selected to control the gait speed to reflect that of older adults (Abellan Van Kan et al. 2009). The three-minute duration was selected to capture multiple gait cycles for analysis, and steady state treadmill walking has been recommended for laboratory-based evaluation of wearable sensors (Johnston et al. 2020).

Participants performed the set of TUG tests first, rested in sitting for a minimum of 1-minute and then performed the three-minute treadmill walk. Prior to the TUG tests and the treadmill walk, participants were instrumented with Shimmer inertial sensors, one each placed at waist level, above the third lumbar vertebra (L3), bilateral ankles 5-centimeters (cms) above the lateral malleolus, and bilateral wrists 2cms proximal to the ulnar styloid (Fig. 4.1). Each sensor was aligned with the vertical, medio-lateral and anterior-posterior axes of the body. Ankle sensors were secured over socks or tights and wrist sensors were secured beneath outer clothing, with elastic tubular bandage and tape. The waist sensor was secured over outer clothing with a strap and tape. The raw accelerometer data from the sensors were captured and stored onto the on-board memory. On completion of each participant's sensor data collection, these data were transferred onto a personal computer (PC) via USB-C connection, labelled and stored as excel files using the participant's ID code, for post processing and analysis.

The body-locations for positioning of the Shimmer sensors were selected based on previous studies (Apsega et al. 2020; Chen et al. 2020; Jansen et al. 2019; Millor et al. 2017; Schwenk et al. 2015; Toosizadeh, Mohler, Wendel, et al. 2015; Zhou et al. 2019). The ankle has been recommended for accurate gait-event detection at slow speeds (Soaz and Diepold 2016) that may reflect the self-selected pace of older adults. As acceleration signals increase in magnitude from the head to the ankle, highest activity recognition accuracy is anticipated from a sensor positioned at the ankle (Cleland et al. 2013). As a body-location for sensor-positioning the ankle is the most frequently recommended location (Prasanth et al. 2021). However, with ageing comes a reduction in fine motor

skills and dexterity which can create barriers to the use of wearable sensors (Takemoto et al. 2018). While the ankle sensor-placement may provide the best quality data, it may not be the most convenient location for use by older adults. It was therefore deemed important to compare data from different sensor-placements including those more easily accessed by older adults. A study of acceptability and usability of wearable sensors among older adults investigating the preferred body-location of wearable sensors among this cohort found that incorporating a sensor into familiar accessories was the preferred option (Kolasinska et al. 2018). The most common placements of accessories included the wrist and waist. Identifying a body-location that can be used by older adults to independently capture objective measurements of mobility and PA will assist in a more proactive approach to self-care and preventative measures. This will play a significant role in supporting healthy ageing and promoting independent living (Baig et al. 2019).

Participants first performed a TUG test under three different conditions with a minimum of 1-minute rest between tests; at normal pace, at normal pace while counting in 3s backwards from 100 (TUG-cognitive) (Shumway-Cook et al. 1997), and at normal pace while carrying a glass of water (TUG-manual) (Lundin-olsson et al. 1998).

The chair used was without armrests, with a seat-height of 45cms. In the seated position, the participant's feet rested on the floor with toes positioned behind a floor-mark which indicated the start of the 3m distance. A second floor-mark at 3m distance indicated the turning point. The manual start-stop function of the QTUG system was operated to coincide with the signal to start and with the finish of each TUG test and therefore used to manually time each TUG test. The instruction given to each participant was "on the count of 3-2-1-Go, on 'Go' you will stand up, walk at your own pace to and around the tape on the floor, back to the chair you stood up from and sit down. The test will start when I say 'Go' and finish when your bottom reaches the chair. You can use your arms or hands on the chair for support as you like". For the TUG-cognitive, the participants were instructed to start counting backwards as soon as they heard 'Go' and to finish counting when they had sat down completely. For the TUG-manual, the participants were instructed to stand, pick up the glass of water

positioned on a table beside the chair, complete the walk and replace the glass on the table before sitting down.

The three-minute treadmill walk test which followed the TUG tests after a minimum 1-minute rest, was timed using the treadmill timer (Sole Fitness S77, Salt Lake City, USA). The three-minute timing started when the treadmill reached the appointed speed (0.8m/s i.e., 2.9km/hr) at approximately10-seconds (s). A speed of 0.8 m/s was adopted because it is reflective of the speed of community-dwelling older adults and is a useful cut-off point for prediction of adverse outcomes (Abellan Van Kan et al. 2009). Participants were instructed to hold the handrail if preferred, to take long steps toward the front of the moving belt and to keep walking on completion of the three-minutes until the treadmill belt came to a standstill. The three-minute time ended the recording of sensor-steps. The extra steps taken were not included in the manual or the sensor step-count and therefore not analysed. All participants reported being familiar with treadmill use so no period of familiarisation was given. Data from the treadmill walk was collected using the Shimmer sensors only.

The criterion measurement of steps taken during the TUG tests was determined by a manual step-count performed by direct observation by the researcher in real-time with the 18-65 years of age group, while retrospective observation of video-recordings was used to obtain the criterion measurement of step-count during the TUG tests in the > 65 years of age cohort. The rationale for not video-recording the TUG tests performed by the younger cohort was the sole decision of the researcher. This decision was based on the perception that there would be less need to be engage with the younger cohort during the test and so the multi-tasking of counting steps directly while monitoring the QTUG system could be managed. Non-identifiable video-recordings of the treadmill walk test in each cohort and the TUG tests performed by the older cohort were taken using a smartphone (Samsung Galaxy A4, Samsung Electronics Co., Ltd, South Korea).

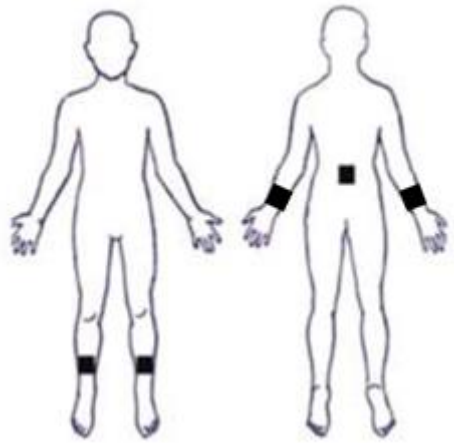


Figure 4.1. Schematic illustration of Shimmer sensor placement

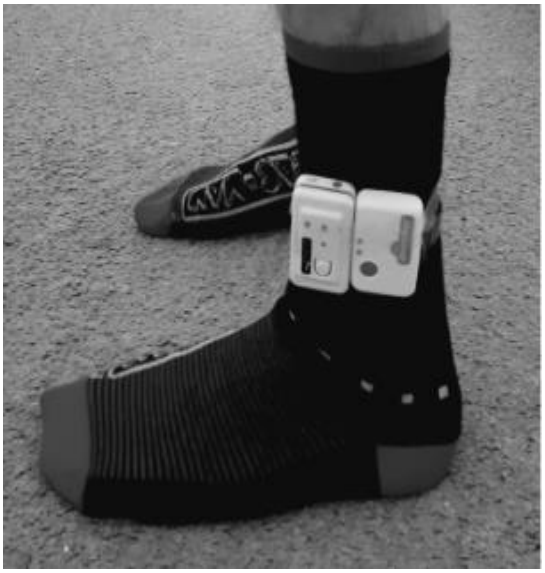


Figure 4.2. Illustration of QTUG and Shimmer sensor placement

4.2.4 Data Management

All participant data was pseudonymised. A data dictionary was created for all the data collected in the study (Appendix 4.7). Data were exported into a Microsoft Excel spreadsheet (Microsoft Office Excel, 2016, Microsoft Corporation, Redmond, CA, USA) and recorded using the coding created in the data dictionary. Data from the QTUG sensors were saved as PDF files. Video-recordings were exported to a PC as MP4 files. All data files were password protected and stored on a password protected PC. COVID-19 data and paper-based case report forms were stored in a locked cabinet as per data management plan (Appendix 4.8).

As part of a collaborative research agreement, Shimmer sensor data were shared with external collaborators for processing. A Data Protection Impact Assessment (DPIA) was completed to identify and address any risks to personal data of participants, as required by general data protection regulations (GDPR). This document was accepted by the data protection officer (DPO) of Dundalk Institute of Technology (Appendix 4.9).

4.2.5 Data Processing

4.2.5.1 TUG tests

Step-count data were obtained from the QTUG sensor and software system tablet where it was live-streamed and stored during each of the TUG tests.

4.2.5.2 Three-minute Treadmill walk

To measure temporal features of the gait cycle (step-count, step/stride time, step time variability, and stride asymmetry), accelerometer data obtained from the Shimmer sensors positioned at the waist and both ankles during the treadmill walking test were used to estimate initial contact and final contact times using the Teager-Kaiser gait event detection algorithm (TK_{GED}) (Flood et al. 2020; Flood et al. 2020). The TK_{GED} algorithm first transforms the acceleration signal in the anterior-posterior axis using the Teager-Kaiser energy operator and then applies a two-step peak finding method to identify initial and final contact events (Flood et al. 2020). Amplitude and temporal threshold scaling factors of the TK_{GED} algorithm were chosen with respect to step time and stride time for data from the waist-mounted and ankle-mounted sensors, respectively. From the estimated initial and final contact times, step-count, mean step/stride time, step time variability, and stride asymmetry features were derived for both waist-mounted and ankle-mounted sensors (Flood et al. 2020). Step Time Variability was calculated as standard deviation of step times. Stride asymmetry was calculated as the absolute difference between left and right mean stride times. Both are measured in seconds (s). This data processing was performed using MatLab 2020a (MathWorks, Natick, USA). The TK_{GED} algorithm was applied to the accelerometer data from the wrist but was found to be not suitable. Other algorithms (Bui et al. 2018; Cho et al. 2016) were considered however, examining the performance of these was beyond the scope of this thesis.

4.2.6 Data analysis

Statistical data analysis was performed using Microsoft Excel-16, and SPSS-26 (IBM Corporation, Armonk, NY, USA). Descriptive statistics of continuous variables age, height and body mass are presented as mean and standard deviation (SD). Data were tested for normality using the Shapiro-

Wilk test. A p value of < .05 was considered statistically significant. Because of the small sample size, the relation between sensor-based step-count and criterion and between data obtained from ankle and waist sensors were analysed using Spearman's rank correlation coefficient. Spearmans rank correlation coefficient is used to describe the strength and direction of non-normally distributed data and is measured on a scale of -1 to +1, where 0 indicates there is no linear association. The association is stronger as the coefficient nears -1 or +1 (Schober and Schwarte 2018). Conventional values for interpreting a correlation coefficient as very strong (0.9 – 1.0), strong (0.7 – 0.89), moderate (0.4 – 0.69) or weak (0.10 – 0.39) were used in the analysis (Schober and Schwarte 2018). Many studies within the literature have included correlation coefficients when examining the same output measure from different devices or tools. Using Spearman's rank correlation coefficient (r_s) Tully et al (Tully et al. 2014) report on the relationship between the step-count obtained from a Fitbit Zip, ActiGraph GT3X accelerometer and a Yamax CW700 pedometer, while Mandigout et al (2019) use r_s to examine the relationship between step-count obtained from activity trackers positioned at the waist and at the hip (Mandigout et al. 2019). The relationship between total sleep time obtained from two different activity trackers has been reported (Gruwez et al. 2017) while the relationship between energy expenditure as measured by a Fitbit Charge HR2 and an Apple Watch has been reported using correlation coefficient (Nuss et al. 2019).

Bland Altman plots (BAPs) are presented to demonstrate the strength of agreement between the criterion and sensor data. The x-axis of the BAP represents the mean of both measurements using the formula:

criterion + new sensor data/2'

while the y-axis represents the difference between each method using the formula:

criterion - sensor data (Giavarina 2015).

Mean bias represents the over or under-estimation of step-count or parameters of gait by each sensor compared to the criterion. Mean difference between the methods of measurement should not be

significantly different from zero (Bland and Altman 1986). It is also expected that 95% of differences should fall between ± 1.96 SD. This is referred to as limits of agreement (LOA) and computed as

mean bias ± 1.96 SD.

These LOA provide sample estimates only, which may especially for small sample sizes be biased estimates of the population and considerably inaccurate (Carkeet 2015). Calculating confidence intervals (CIs) for sample LOA is a way to estimate their reliability, is necessary to examine how precise the estimates are and to estimate the 95% probability that results apply to the population (Bland and Altman 1986; Mantha et al. 2000). Carkeet (2020) suggests CI's are not commonly reported and while their use is increasing since 2015 in recognition of their importance, the percentage of published articles including CI's for LOA remains low (Carkeet 2020). It has been suggested that BAPs should not be interpreted without the inclusion of CI's (Hamilton 2007). In this study CI's for LOA were calculated using the formula

observed value – t(se)

where *t* is the student's T distribution and se is the standard error of the LOA (Bland and Altman 1986). The BAP defines the limits but does not indicate whether or not the limits are acceptable or appropriate. For a sensor location to be deemed appropriate, the limits of agreement should be within a range that maintain clinical relevance and should be defined a priori (Giavarina 2015). Agreement of between 3 and 20% of the mean of the criterion step count or measures of physical activity has been proposed as acceptable (Simpson et al. 2015; Bai et al. 2016; Schneider et al. 2003; Thorup et al. 2017). An error margin of ±10% of the mean criterion was selected a priori as an acceptable agreement for step-count during the TUG tests and step-count and parameters of gait during the treadmill walk test.

As a measure of accuracy between methods of data collection mean absolute error (MAE) and mean absolute percentage error (MAPE) were calculated between step-count obtained from the observed count and each sensor location and between temporal parameters of gait obtained from each sensor location. The following formula was used to calculate MAPE.

criterion – sensor / criterion x 100

When comparing sensor data from each location with each other the ankle was taken as the criterion. Based on previous studies the MAE and the MAPE would be within 1 unit and 10% respectively of the mean of the criterion (Simpson et al. 2015; Kooiman et al. 2015; Bai et al. 2016, Tedesco 2019). Intra-rater reliability for the observed step-count during each of the TUG tests and the treadmill walk test in the older age group was assessed using the intraclass correlation coefficient (ICC) (2-way mixed-model single measure) with 95% Confidence Intervals (95% CIs). ICC values range from 0 to 1 where 1 corresponds to perfect agreement. An ICC of 0.80 or higher was considered high, 0.60–0.79 moderate and less than 0.60 was considered to be poor relative reliability (Olsen and Bergland 2017).

4.3 Results

Twenty participants were enrolled in the study; 10 healthy older adults aged > 65 years (age 68.7 ± 3.68 years, height 164.85 ± 7.45cm, weight 71.75 ± 11.52kg, female n = 5) and 10 healthy young adults aged 18 – 65 years (age 47.7 ± 11.49 years, height 173.5 ± 8.76cm, weight 75.5 ± 13.91kg female n = 5). Researcher-error configuring the Shimmer sensors, with a consequent error in timestamps resulted in missing data from n=2 participants in the >65 years of age group therefore data from eighteen participants were included in the analysis of the parameters of gait as measured on the treadmill. Video-recording of one male participant in the healthy older adult group was of poor quality and not deemed usable therefore data from nine participants from this cohort were included in the analysis of step-count as measured during the TUG tests. Data from all 10 participants in the younger cohort were included. The results of the Shapiro Wilk test in each age group indicated a significant departure from normal distribution of variables, however skewness fell within acceptable range of ± 2 at p value <.05 (Ghasemi and Zahediasl 2012).

The TK_{GED} algorithm proved to be unsuitable for use in the analysis of data obtained from the sensors positioned at the wrist during the treadmill and TUG tests. This same algorithm proved unsuitable for use in the analysis of data obtained from the sensors positioned at the waist during the TUG tests, possibly due to the turn element of the TUG test interfering with the algorithm. Therefore, only data obtained from the sensors positioned at the waist and ankles are presented for the treadmill test. Both the QTUG and shimmer sensors contain inertial sensing via accelerometer, gyroscope and

magnetometer and were positioned at the same body-location therefore, shimmer sensor data obtained from the ankle were not further examined. Data obtained from the QTUG sensors and from the criterion measure are presented for the TUG tests.

4.3.1 TUG tests

The mean criterion step-count for the TUG, TUG-cognitive and TUG-manual in the younger age group was 12, 13.4 and 12.9 respectively; and 14.66 for each TUG test in the older age group. The criterion refers to the observed step-count. Results of the Spearman's rank correlation coefficient indicated that in the older adult cohort there was a very strong positive correlation between the criterion measure of step-count and that captured by the QTUG sensor and software system in the TUG test and the TUG-manual (r_s .920, and .914, p<.001 respectively). There was a strong positive correlation in the TUG-cognitive for this group (.824, p<.01). Intra-rater reliability for each of the TUG tests was between perfect and excellent for each of the TUG tests in the older adult group (ICC .993 CI's .970-.999, p<.001; .893 CI's .433-.979, p=.006; 1.0 for the TUG, TUG-COG and TUG-MAN respectively.

In the younger cohort here was a moderate positive correlation in the 1st TUG test (r_s .633, p<.05) and a strong positive correlation in the TUG-cognitive and TUG-manual tests (r_s .776 and .809, p<.01). (Table 4.1). Video-recording of the younger age group was not captured and so intra-rater reliability could not be examined.

Mean absolute error ranged between 0.4 and 1 in the younger group (MAPE 3.3% to 7.75%) and from 0.3 to 1.3 (MAPE 2.25% to 8.9%) in the older adult cohort. All MAE and MAPE values are within the pre-defined acceptable limits of error (Table 4.1).

The BAPs demonstrate the mean bias, LOA and 95% CI'S between the criterion and QTUG sensor (Fig. 4.3). In the younger cohort the QTUG sensor on average under-estimated step-count (mean bias 0.4, 0.9 and 1, LOA -1.4 to 2.2; -0.15 to 1.9; -.5 to 2.5; 95% CI's -2.5 to -0.24 and 1.4 to 3.4; -0.83 to 0.5 and 1.27 to 2.6; -1.5 to .45 and 1.5 to 3.5 for the 1st TUG, TUG-cognitive and TUG-manual respectively). In the older adult cohort the QTUG sensor under-estimated step-count by 1.3, 0.3, and

0.7; LOA -.05 to 2.7; -2.7 to 3.4; -1.7 to 3.3; 95% CI's -1.4 to 0.4 and 1.8 to 3.6; -4.9 to - 0.7 and 1.3 to 5.5; -3.5 to -0.05 and 1.6 to 5 for the 1st TUG, TUG-cognitive and TUG-manual respectively (Table 4.2). The upper LOA are beyond the pre-defined acceptable range of ±10% of the mean criterion step-count. The 95% CI's are wide and exceed the pre-defined ±10% range of acceptance. There was no apparent relationship between the difference and the magnitude of the step-count. There was no significant correlation between the difference and the mean of each step-count.

There are a different number of data points visible on each BAP. This is because of overlap of measurements e.g. in the 1st TUG <65 years of age there are three measurements of 11.5, in the TUG-cognitive BAP there are two measurements each of 12.5 and 13. 5, while in the TUG-manual there are two measurements of 13.5.

Table 4.1 Comparing step-count from QTUG with criterion

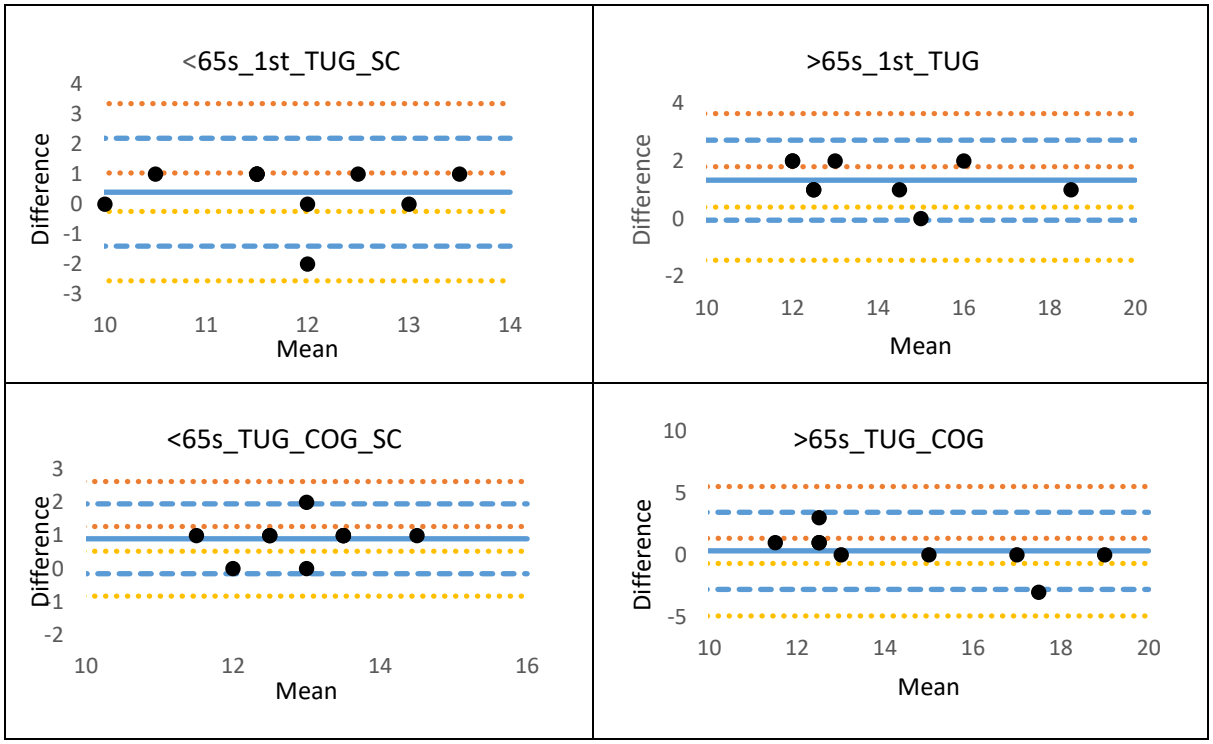
Group	**Test**	**Observed step-count**	**QTUG step-count**	**Mean Absolute Error**	**Mean Absolute % Error**	**r_s**
Age 18-65 years	TUG	12 (1.15)	11.6 (1.17)	0.4	3.33	0.633*
	TUG-cognitive	13.40 (0.96)	12.5 (0.84)	0.9	7.50	0.776**
	TUG-manual	12.90 (1.37)	11.90 (1.19)	1.0	7.75	0.809**
Age >65 years	TUG	14.66 (2.12)	13.33 (2.34)	1.33	8.90	0.920***
	TUG-cognitive	14.66 (3.27)	14.33 (3.27)	0.33	2.25	0.824**
	TUG-manual	14.66 (1.93)	13.88 (2.57)	0.78	5.32	0.914***

Data are presented as Mean (SD). Abbreviations: Percentage (%),Spearman's rank correlation coefficient (r_s), Standard deviation (SD). *$p<.05$; **$p<.01$; ***$p<.001$

Table 4.2. Mean bias, Limits of Agreement, Standard error and 95% Confidence intervals for step-count measured by QTUG and criterion during the TUG tests in >65 and <65 years of age cohorts

	Variable	Mean Bias	Limits of agreement Lower	Upper	Standard error of LOA ($\sqrt{3s^2/n}$)	95% Confidence intervals of LOA Lower	Upper
Age 18-65 years n = 10	1st TUG	0.4	-1.4	2.2	0.5	-2.5 to -0.24	1.4 to 3.4
	TUG-cog	0.9	-0.15	1.9	0.3	-0.8 to 0.5	1.27 to 2.6
	TUG-man	1.54	-0.5	2.5	0.4	-1.5 to 0.45	1.5 to 3.5
Age >65 years n = 9	1st TUG	1.3	-0.5	2.7	0.4	-1.4 to 0.4	1.8 to 3.6
	TUG-cog	.33	-2.7	3.4	0.9	-4.9 to - 0.7	1.3 to 5.5
	TUG-man	.77	-1.7	3.3	0.75	-3.5 to -0.05	1.6 to 5

Abbreviations: Limits of Agreement (LOA); Standard deviation (s); Sample size (n); Timed Up and Go cognitive (TUG-cog); Timed Up and Go manual (TUG-man).



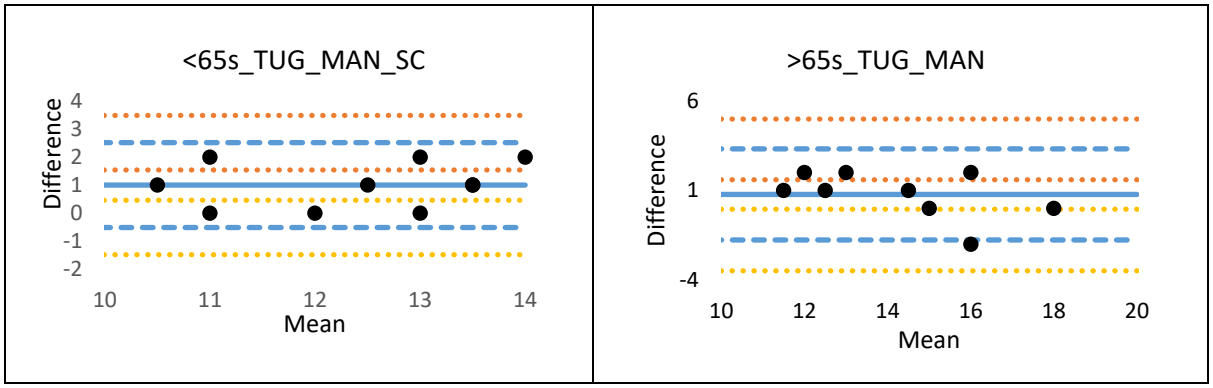


Figure 4.3 Bland-Altman Plots demonstrating level of agreement between counted and sensor-obtained step-count for each age group and each TUG test. Abbreviation: >65 years of age cohort (>65s); 18-65 years of age cohort (<65s); Timed Up and Go (TUG); Cognitive (COG); Manual (MAN)
••• Upper Limit of agreement (LOA); **- - -** Lower LOA; —— Bias. **…** Upper Confidence Interval range; **…** Lower Confidence Interval range.

4.3.2 Three-Minute Treadmill Walk Test

The Spearman's rank correlation coefficient indicated there was a strong positive correlation between step-count measurement from the data recorded from both the ankle and waist Shimmer sensors and the criterion measure during the treadmill walk (r_s 0.912, 0.875 p<.01 and 0.802, p<.05; 0.878 p<.01) in the younger group and older group respectively (Table 4.3). Intra-rater reliability for the criterion step-count as measured in the older age group during the treadmill walk test was excellent (ICC .997, CI's.986-.999 p<.001). There was a strong positive correlation between ankle and waist sensor step-count, mean step-time and mean stride time in both the younger and older group (.964, .988, .988, p<.01) (.982, 1.0, 1.0 p<.01) respectively. There was a moderate, not statistically significant correlation between the step-time variability obtained from the ankle and waist sensors in the >65 years of age group (.405, p>.05) and poor correlation in the younger age group (.200). Stride asymmetry showed poor correlation between the two locations in both cohorts (.176 and .286 respectively) (Table 4.3). Bland-Altman plots demonstrating mean bias, LOA and 95% CI's for each strongly correlated variable are presented in Fig. 4.4. On average, compared to the criterion measure the ankle shimmer sensor under-estimated step-count in the treadmill walk test in the younger cohort and over-estimated in the older age group (mean bias 6.6 and -16.4 respectively). The waist sensor under-estimated step-count compared to the criterion in both groups but agreed with the sensor positioned at the ankle in step-count, mean step and stride time. There was no significant correlation

between the difference and the mean of any variable. There was no apparent relationship between the difference and the magnitude of each variable apart from one outlier in the younger cohort. The 95% CI's are wide and exceed the pre-defined ±10% range of acceptance.

The difference in the MAPE between step-count obtained from criterion measure of observed count and that from the ankle and waist sensors was less than 5% in each age group (Table 4.3). The MAE between mean step time and mean stride time obtained from each sensor-location in each age group was negligible. The MAE and MAPE for asymmetry and variability between each sensor location was large in each cohort (Table 4.3).

Table 4.3 Comparing step-count obtained from ankle and waist-mounted sensors with criterion during the three-minute treadmill walk test.

Group	**Sensor Location**	**Sensor Step-count**	**Observed Step-count**	**Mean Absolute Error**	**Mean Absolute Percent Error**	**r_s**
Age 18-65 years	Ankle	300.60 (48.53)	307.20 (47.75)	6.60 (9.33)	2.16 (3.08)	.912**
	Waist	301.10 (48.63)		6.10 (9.30)	2.37 (3.09)	.875**
Age >65 years	Ankle	294.88 (17.31)	311.25 (38.96)	16.37 (28.80)	4.56 (7.11)	.802*
	Waist	295 (16.89)		16.25 (29.20)	4.50 (7.21)	.878**

Data are presented as Mean (SD). Abbreviations: Spearman's rank correlation coefficient (r_s), Standard deviation (SD). **p<.01, *p<.05

Table 4.4. Comparing gait parameters between inertial sensors positioned at two different body-locations during the three-minute treadmill walk test.

Group	Parameter	Ankle Sensor	Waist Sensor	Mean Absolute Error	Mean Absolute Percentage Error	r_s
Age 18-65 years	Step-count	300.60 (48.53)	301.1 (48.63)	0.7 (.94)	0.16 (.38)	.964**
	Mean Step Time (s)	.614 (.088)	.613 (.087)	0.01 x 10^{-2} (.002)	0.16 (.290)	.988**
	Mean Stride Time (s)	1.22 (.176)	1.22 (.176)	0.19 x 10^{-2} (.003)	0.15 (.270)	.988**
	Stride Asymmetry	2.15 x 10^{-3} (2.80 x 10^{-3})	1.20x10^{-3} (0.7x10^{-})	0.09 x 10^{-2} (.003)	206 (305)	.176
	Step Time Variability	.07 (.04)	.06 (.02)	0.98 x 10^{-2} (.05)	36.67 (27.80)	.200
Age >65 years	Step-count	294.88 (17.31)	295 (16.89)	0.38 (0.51)	0.05 (.22)	.982**
	Mean Step Time (s)	.62 (.04)	.62 (.039)	0.01 x 10^{-2} (.09 x 10^{-2})	0.01 (.16)	1.0**
	Mean Stride Time (s)	1.23 (.08)	1.23 (.08)	0.02 x 10^{-2} (.002)	0.01 (.17)	1.0**
	Stride Asymmetry	0.08 x 10^{-2} (0.07 x 10^{-1})	0.07 x 10^{-2} (0.08 10^{-1})	0.01 x 10^{-2} (.001)	149 (165)	.286
	Step Time Variability	.08 (.03)	.04 (.01)	0.04 (.03)	40 (23.80)	.405

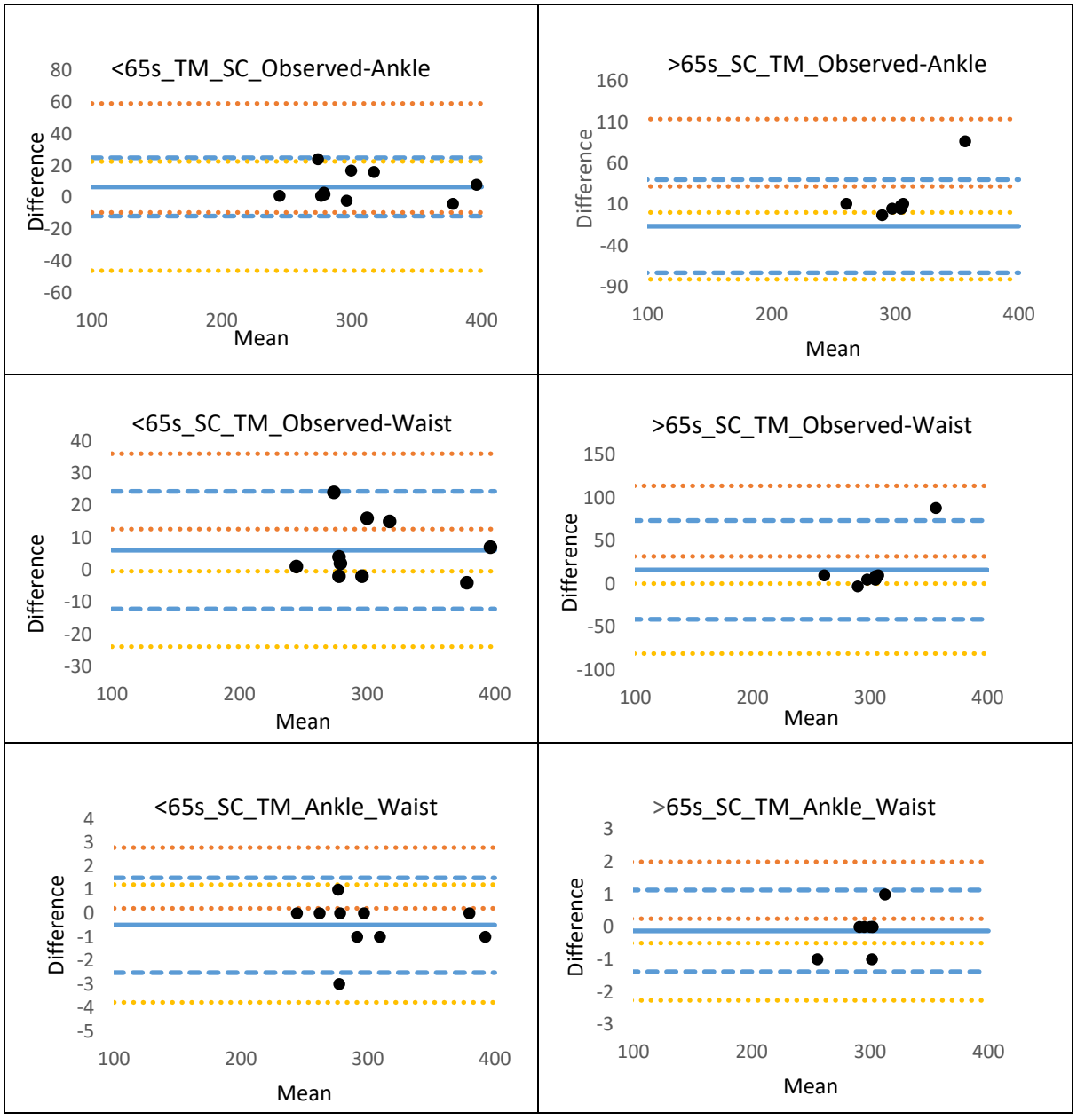
Data are presented as Mean (SD). Abbreviations: Spearman's rank correlation coefficient (r_s), Standard deviation (SD). **p<.01

Table 4.5. Mean bias, Limits of Agreement, Standard error and 95% Confidence intervals for variables measured by ankle and waist shimmer sensors during the treadmill walk test in >65 and <65 years of age

			Limits of agreement			95% Confidence intervals of LOA	
	Variable	Mean Bias	Lower	Upper	Standard error of LOA ($\sqrt{3s^2/n}$)	Lower	Upper
Age 18-65 years n = 10	SC Observed-Ankle	6.6	-11.69	24.89	14.9	-45.97 to 22.57	-9.4 to 59
	SC Observed – Waist	6.1	-12.13	24.33	5.09	-23.8 to -.423	12.63 to 36.03
	SC Ankle – Waist	-.5	-2.5	1.49	.5608	-3.78 to -1.21	.207 to 2.78
	Mean Step Time Ankle - Waist	.0013	0	.0036	.0009	-.0023 to .0023	.0013 to .0059
	Mean Stride Time Ankle - Waist	.0024	-.0065	.0065	.0018	-.0107 to -.0024	.0024 to .0107

Age >65 years n = 8	SC Observed - Ankle	-16.37	-40.25	72.99	17.68	-80.90 to .41	32.33 to 113.65
	SC Observed – Waist	16.25	-41.17	73.67	17.94	-82.43 to .09	32.41 to 115
	SC Ankle – Waist	.125	-1.38	1.13	.39	-2.26 to -.5	.25 to 2.0
	Mean Step Time Ankle - Waist	.0001	-.0018	.0020	.0005	-.0006 to -.003	-.0032 to -.0008
	Mean Stride Time Ankle - Waist	.0002	-.0038	.0041	.0012	-.0066 to -.001	.0069 to .0013

Abbreviations: Limits of agreement (LOA); Sample size (n); Step-count (SC).



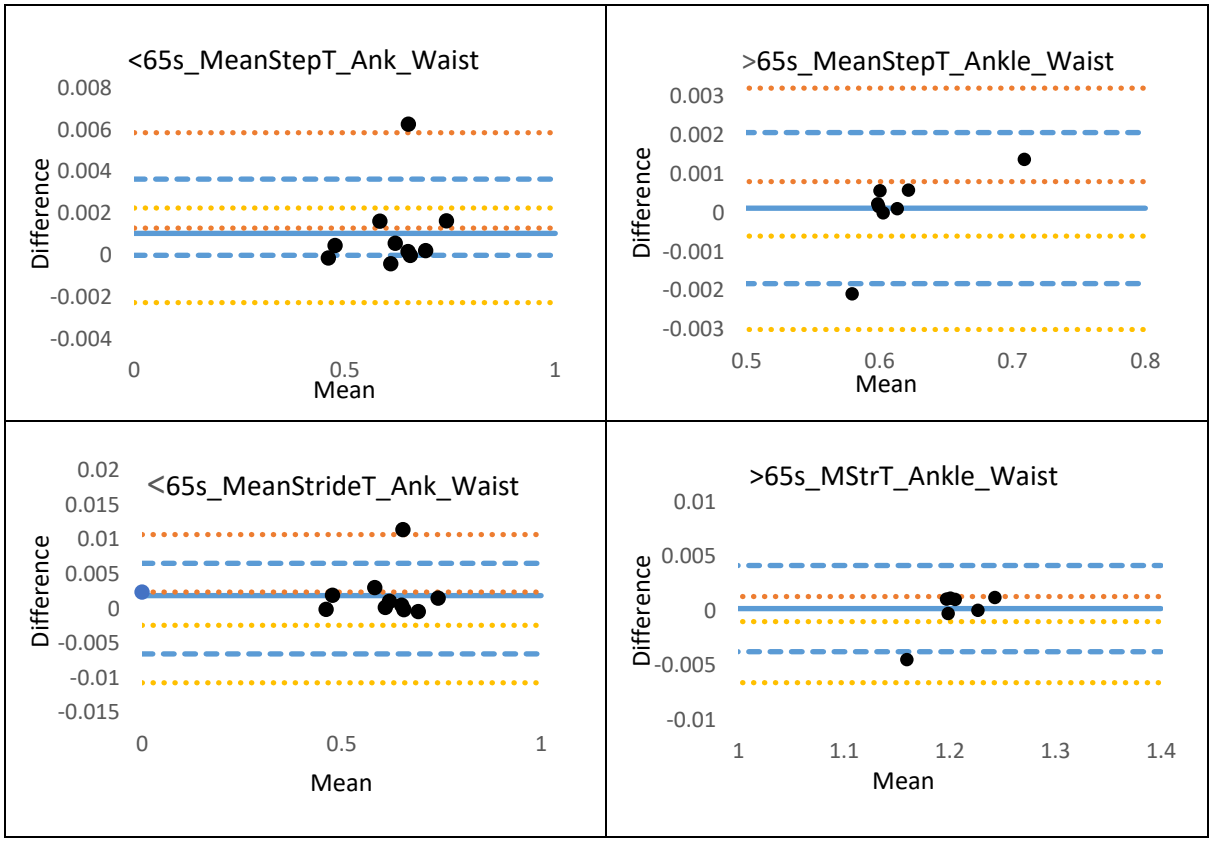


Figure 4.4. Bland-Altman Plots demonstrating level of agreement between; ankle-sensor and manual step-count; waist-sensor and manual step-count; ankle and waist sensor step-count; ankle and waist sensor mean step time; ankle and waist sensor mean stride time. Abbreviation: >65 years of age cohort (>65s). 18-65 years of age cohort (<65s). Manually observed step-count (Manual); Step-count (SC); Mean (M); Time (T). Treadmill (TM). Mean Stride Time (MStrT).
••• Upper Limit of agreement (LOA); - - - Lower LOA; —— Bias.••• Upper Limit of agreement (LOA); - - - Lower LOA; —— Bias; ... Upper Confidence Interval range; ... Lower Confidence Interval range

4. 4 Discussion

This study examined the correlation and agreement between step-count obtained from a criterion measure of direct observation with that obtained from research-grade wearable sensors positioned on the ankles and the waist in a cohort of healthy older adults and young adults during a 3-minute treadmill walk and during TUG tests performed under different conditions. Additionally, gait features obtained from sensors positioned on the ankle and waist were compared. Bland Altman plots were used to examine the strength of agreement between the different methods. For a method to be replaced with another, a strong agreement between both methods is necessary, with differences falling within an acceptable, pre-determined range. A high correlation between methods of measurement can conceal a considerable lack of agreement (Bland and Altman 1986). The BAP allows us to examine the

difference between the two methods (on the y-axis) and the assumed true value i.e. the average of the two methods represented on the x-axis (Mantha et al. 2000).

Walking accounts for the largest proportion of leisure and everyday activities and so it makes sense to measure it as part of an assessment of mobility (Bassett et al. 2017; Tudor-Locke and Rowe 2012). Accurately measuring step-count is an important first step in measuring mobility and PA (Hurt et al. 2019). A young cohort was included for comparison, to examine if the outcomes observed were specific to either age group. This comparison is reflected in previous literature where a healthy younger cohort is included to compare results between different cohorts and to provide a healthy benchmark (Zhou et al. 2018; Pang et al. 2019).

Results suggest a strong relationship between the criterion measure of step-count, and step-count obtained from the QTUG sensor system during the TUG tests and between each sensor-location in both cohorts during the treadmill walk test. Strong correlations were also observed between gait parameters of mean step time and mean stride time obtained from both ankle and waist sensors during the treadmill walk. Agreement was demonstrated between all variables as indicated by the MAE and MAPES (Tables 4.1 and 4.4) and mean bias which all fell within the pre-defined limits of acceptable difference between the two methods. However, limits of agreement illustrated in the BAPs between which 95% of the values are expected to fall are not within the ±10% range pre-defined and do not represent a clinically acceptable difference between the two methods. While the 95% CI's do contain the LOA in each of the BAPs, the range of the intervals is wide, reflective of the small sample size. This further disparages the LOA and thus limits the external validity of the findings (Olofsen et al. 2015). The approximate method for calculating the 95% CI'S was employed (Bland and Altman 1986). The exact method may have been more appropriate (Carkeet 2015).

Spearman's correlation for step-count between the ankle sensor and criterion, while significant in both cohorts, was less so in the older age group (rs .912 and .802 for younger and older cohorts respectively). This is reflected in the mean bias (6.6 and -16.37) and LOA (-11.7 to 24.9 and -40.25 to 73) for younger and older cohorts respectively as presented in the BAPs (Fig. 4.4). This is consistent with previous studies which suggest reduced accuracy of sensor-derived measures of PA in an older age group with reduced gait-speed (Evenson et al. 2015; Tedesco et al. 2019b). In this present

investigation, while gait speed was controlled with the use of a treadmill, the difference in cadence between younger and older adults is evident in the mean step-count. The discrepancy in the correlation and agreement between the criterion and each sensor-location may be due to reduced accuracy of the gait features extracted from data recorded at the waist compared to the ankle as suggested in earlier studies (Cleland et al. 2013; Storm et al. 2016). One such study acknowledges the difference in accuracy between sensor locations is significant statistically but argues the results are close and therefore the difference is marginal in practical or clinical terms (Cleland et al. 2013). The discrepancy between the observed and sensor step-count may also be due to the accuracy of the observed step-count. Intra-rater reliability in the older cohort was excellent but inter-rater reliability was not established. Video recording was not undertaken in the younger cohort and so reliability could not be evaluated.

Within each cohort, the MAE between the criterion measure of step-count and step-count obtained from each sensor is similar suggesting the accuracy of step-count extracted from accelerometers in both sensor-positions are comparable. The values of the MAE are small (Table 4.4) suggesting that in both cohorts, each sensor-location is acceptable in terms of accuracy of step-count. This is supported by an earlier study which found negligible differences in accuracy of measured step-count between ankle and waist-mounted sensors during free-living walking (Storm et al. 2016). Similarly, a study examining the accuracy of waist and ankle-mounted sensors in gait analysis at speeds reflective of older adults found < 10% error between ankle sensor and waist sensor derived step-count (Simpson et al. 2015). The MAPE between ankle and waist sensor derived step-count in the current study of younger and older adults was 1.6% and 5% respectively.

Because the study was not carried out with frail adults who would be expected to demonstrate different gait characteristics including gait speed (Bortone et al. 2021; Apsega et al. 2020; Martínez-Ramírez et al. 2015), the correlation and agreement would possibly be even lower in a frail cohort and results cannot be extrapolated to such a population. The magnitude of the step-count measured within the older adult cohort is somewhat higher than that reported in a study examining cadence of older adults 61 – 85 years of age (Tudor-Locke et al. 2021).

Temporal parameters of stride asymmetry and step time variability could not be accurately derived from the waist-mounted sensor as illustrated by high MAPE values in both age groups (Table 4.4). Variability in parameters of gait can be affected by arm swing (Bailey et al. 2022). Video-recording of the treadmill walk test included footage of the lower limbs only, and whether or not a participant held the handrail of the treadmill was not recorded in real-time during the test and so the effect of arm swing on lower limb variability was not considered. However, temporal parameters of mean step time and stride time were consistent between ankle and waist-mounted sensors with MAPE values < 2% (Table 4.3). This is consistent with previous studies suggesting high accuracy of waist-mounted sensors for other applications such as fall detection (Ozdemir, 2016). The reported results could be promising for future examination of free-living walking and temporal parameters of gait in older adults as waist-mounted sensors are potentially more suitable for application by older adults than ankle-mounted sensors (Kolasinska et al. 2018) and may be more suitable for unsupervised monitoring outside of clinical settings (Rahemi et al. 2018).

In this study, accelerometer data were captured using research grade inertial sensors. The raw data from these Shimmer sensors requires processing to extract parameters of gait, and data from the sensors positioned at the wrist were not suitable for the selected algorithm. For this reason objectives number 2 through to number 4 as outlined in section 4.1 could not be fully evaluated. Other algorithms were considered but their application was deemed beyond the scope of this thesis. While the results of this study demonstrate that the research-grade wearable sensors used can produce accurate data, this work also highlights the potential difficulties for both clinicians and their clients/patients in monitoring parameters of gait and PA using research grade devices. These barriers include the need for specific algorithms, specialised data extraction and analysis - all of which complicates extracting useful, actionable information from them. The reliance to date on researchers within a specific field of expertise for the analysis of data is acknowledged in the literature (Tolley et al. 2021). This demonstrates the need for further research to establish if parameters of mobility and PA related to frailty could be captured using an alternative, commercial, less research-based sensor system that can be monitored and interpreted by older adults, their family members / carers and/or GP.

4.5 Limitations

Limitations to this study include the small sample size, the method of data collection and the securing of the sensors above outer clothing as opposed to adhering directly to the skin. Each is discussed separately in this section. A small sample was selected for convenience but is supported in the literature (Alinia et al. 2017; Lee et al. 2020; Tedesco et al. 2019b). Data were collected in two different laboratory settings during a structured treadmill walk test. While not unique for data collection to occur in different settings (Bohannon and Wang 2019) in the interests of consistency, the one location for data collection is preferable. It has been suggested that treadmill walking may not reflect real-life walking patterns (Storm et al. 2016) and that laboratory-based gait analysis demonstrates less variability and higher cadence than free-living assessment thus reflecting participant's "best performance" (Brodie et al. 2015). However, treadmills have been widely used in similar type studies as they allow for collection of data at controlled speeds. The three-minute timeframe appointed in this study allowed for the capture and analysis of many gait cycles, examination of gait patterns of older adults and examination of any differences in the gait parameters between the two age groups. This work will contribute to future studies examining gait parameters in older adults in free-living conditions.

To accurately determine gait parameters, accurate detection of initial foot contact and final foot contact is necessary (Storm et al. 2016). Positioning of the sensors above outer clothing and not directly to the skin may have affected identification of the final contact point of the foot and thus influenced the results of the variability and asymmetry variables. This method was chosen for convenience and with reference to earlier studies (Cleland et al. 2013; Atallah et al. 2011). Future research should ensure sensors are affixed directly and securely to the skin to optimise integrity of the data collected.

4.6 Conclusions

Most assessment tools for identifying frailty or functional dependence incorporate a measurement of mobility (Fried et al. 2001; Gill et al. 1995; Rockwood K 2005). As people age there is a tendency to move less. Having an objective method for older adults to measure their mobility and thus be alerted to

any decline in PA may facilitate early intervention and reduce the associated risks. This study has demonstrated a strong relationship between step-count, a parameter of mobility and PA obtained from body-worn sensors, and a criterion measure of direct observation in a group of healthy older and healthy young adults in a laboratory setting. It is a first step in identifying the potential for a wearable sensor positioned on a body location conveniently accessible for older adults use, to record a single parameter of mobility in older adults that can indicate a risk of functional decline. Other studies have included step-count as one of a multitude of parameters to examine frailty (Razjouyan et al. 2018; Yuki et al. 2019) but not, to the author's knowledge as a stand-alone parameter. The wrist has been suggested as an ideal location for measuring PA, a potentially convenient, accessible location for use by older adults. However, this study has demonstrated the obstacles encountered using research-grade devices including the need for a specific, suitable algorithm and a specialist analyst to extract and process data from the wrist. It asks the question if community-dwelling older adults, their family members or carers can independently capture and interpret parameters of mobility and PA related to frailty risk using an alternative, consumer-grade sensor. The home-based study presented in the next chapter investigates whether community dwelling older adults can capture relevant data unsupervised during a structured mobility assessment, using a consumer-grade device.

Chapter Five - Home-Based Study

Introduction

The previous chapter outlined the strong correlation and agreement between body-worn sensor data and a criterion measure in parameters of mobility and PA among older adults in a laboratory setting. The results suggest the potential for a single wearable sensor positioned on either the waist or the ankle to capture a single parameter of mobility that can indicate a risk of functional decline. Only the data from the sensors positioned at the waist and ankles were presented in the results because data from the wrist sensor could not be analysed with the selected algorithm. Research grade wearable sensors were used in this study, and while the results show they can produce accurate data, this work also highlighted the difficulty that clinicians/patients/ those without expertise in data science may have in extracting useful, actionable information from them.

This chapter reports on a study conducted to investigate if community-dwelling older adults can capture objective, quantitative measures of mobility and PA unsupervised in their own home, and if the data captured correlates with frailty risk. While the waist has been identified in chapter 4 as a suitable body-location for positioning of a single sensor to collect parameters of mobility and PA relevant to frailty, the difficulties associated with a research-grade wearable device have been discussed. The results of the laboratory based study were inconclusive. The study used research grade devices which needed specialist data analytics to extract meaningful information from the raw data collected and the application of an algorithm different to the one selected. The wrist has been identified in the literature as a convenient location for use by older adults and a watch is an accessory older adults may routinely wear. For these reasons, the home-based study aimed to explore the potential of a consumer grade device positioned at the wrist, a potentially more accessible body-location for use by older adults than the ankle or the waist. It aimed to investigate if a wrist-worn consumer-grade device could replace the use of a research-grade sensor in the capture of parameters of mobility and PA, to provide meaningful, actionable data with sufficient detail to discriminate

between stages of frailty and would remove the need for specialist analytics. This study also aimed to examine if older adults could capture this data unsupervised.

The remainder of the chapter is outlined as follows; section 5.1 outlines the aims and objectives of the study, section 5.2 describes the methodology, section 5.3 presents the results that are discussed in section 5.4. Sections 5.5 and 5.6 present the limitations and conclusion of the study.

5.0 Background

Wearable sensors have been successfully used to collect objective, quantifiable parameters of mobility and PA that have been shown to distinguish between levels of frailty (Vavasour et al. 2021). The majority of studies examined were carried out in laboratory or under test conditions however, due to the insidious onset of frailty the signs of which are reflected in the decline of every day functions, the collection of continuous data in the home setting is considered more appropriate (Brodie et al. 2015; Mueller et al. 2019).

A recent systematic review identifies that body-worn sensors are the most commonly used technology in the identification of frailty in non-clinical settings (Bian et al. 2020). The previous chapter identified the difficulties associated with a research grade wearable sensor including the necessity for the selection and sourcing of an appropriate algorithm, which, in turn requires specialist application for data processing and analysis. Data captured by consumer grade devices are processed instantaneously on board the device and presented via the device or accompanying application. This facilitates interpretation by the user and eliminates the need for specialised processing and analysis. The proliferation of consumer grade wearable sensors provides an opportunity to capture parameters of mobility and PA in real-world, non-clinical/laboratory settings over an extended period. The literature demonstrates the use of technology among older adults ranging from mobile phone use to smartwatches and technology for telehealth, social media and online activity (Yap et al. 2022; Keogh et al. 2020). Facilitating older adults to engage with the capture of PA data independently, unsupervised in their own home could provide them with an indication of reduced activity, potentially alter the development or progression of frailty and thus lessen the associated physical, psychosocial and economic burden. The use of technology to monitor PA has shown positive outcomes in terms of

self-efficacy and subsequent increase in levels of PA (O'Brien et al. 2015; Nyman et al. 2016). According to market research in the US, adults over the age of 55 years are the fastest growing group of wearable sensor users (eMarketer 2019) suggesting that this cohort are ideally placed to benefit from such an initiative.

The goal of this study is to contribute to the literature on how wearable sensors can be used to discriminate between levels of frailty in community dwelling older adults; to establish if older adults can capture parameters of mobility and PA relevant to frailty risk, unsupervised in their own home; and to explore older adult's attitudes to the use of technology to capture such data.

5.1 Aims and Objectives

To address the thesis objectives numbered 3 through to 5 outlined in chapter 1, the aim of this study was to establish if community-dwelling older adults can capture unsupervised, in their own home, objective measures of mobility and PA that correlate with frailty. These include but are not limited to total step-count, number of bouts of activity or postural transitions, time spent in sedentary activity and parameters of gait (Theou et al. 2012; Schwenk et al. 2015a; Parvaneh et al. 2017; Razjouyan et al. 2018; Huisingh-Scheetz et al. 2018; Ziller et al. 2020).

To achieve this the following objectives were identified;

1. To measure mobility and PA in community-dwelling people >65 years of age using wearable sensors and validated functional assessment tools.
2. To examine the correlation between sensor-data captured during supervised and unsupervised mobility tests.
3. To examine the correlation between sensor-data obtained during unsupervised and free-living PA with traditional functional and frailty assessment tools.
4. To explore the usability of a wearable sensor system among community-dwelling older adults for independent capture of activity data during a mobility test, following a period of training and education.

5. To examine the experience and attitudes to the use of technology for ongoing monitoring of physical activity among this cohort.

5.2 Methodology

5.2.1 Study Design

A mixed methods cross-sectional design was deemed appropriate for this study to investigate older adult's ability to capture sensor data independently and to examine the perceptions and experience of older adults in the use of such technology. A 48-hour study duration was selected as a planned longitudinal study was not possible due to the uncertainty surrounding the COVID-19 pandemic. Data collection for this study was opportunistically scheduled immediately following the relaxation of travel and home-visiting restrictions (gov.ie 2020) and took place during October – December 2020. A 48-hour period is supported in the literature for the collection of mobility and PA data (Theou et al. 2012; Schwenk et al. 2015b; Parvaneh et al. 2017; Razjouyan et al. 2018; Jansen et al. 2019). Studies of longer duration, up to one week, have more often focused on measures of intensity of PA rather than parameters measured in this study (Castaneda-Gameros et al. 2018; Mulasso et al. 2019; Kikuchi et al. 2020). A combination of supervised test conditions and unsupervised free-living data collection was selected to capture both objective functional assessments and everyday activity. While it has been suggested that laboratory or test conditions correlate well with free-living activity (Portegijs et al. 2019), this particular study reported on association rather than the more appropriate measure of agreement between each setting. A more comprehensive study found significantly better performance in parameters of gait measured in laboratory conditions compared with a free-living environment with wide limits of agreement and confidence intervals (Hillel et al. 2019). The collection, analysis and integration of qualitative and quantitative data is illustrated in Fig. 5.1.

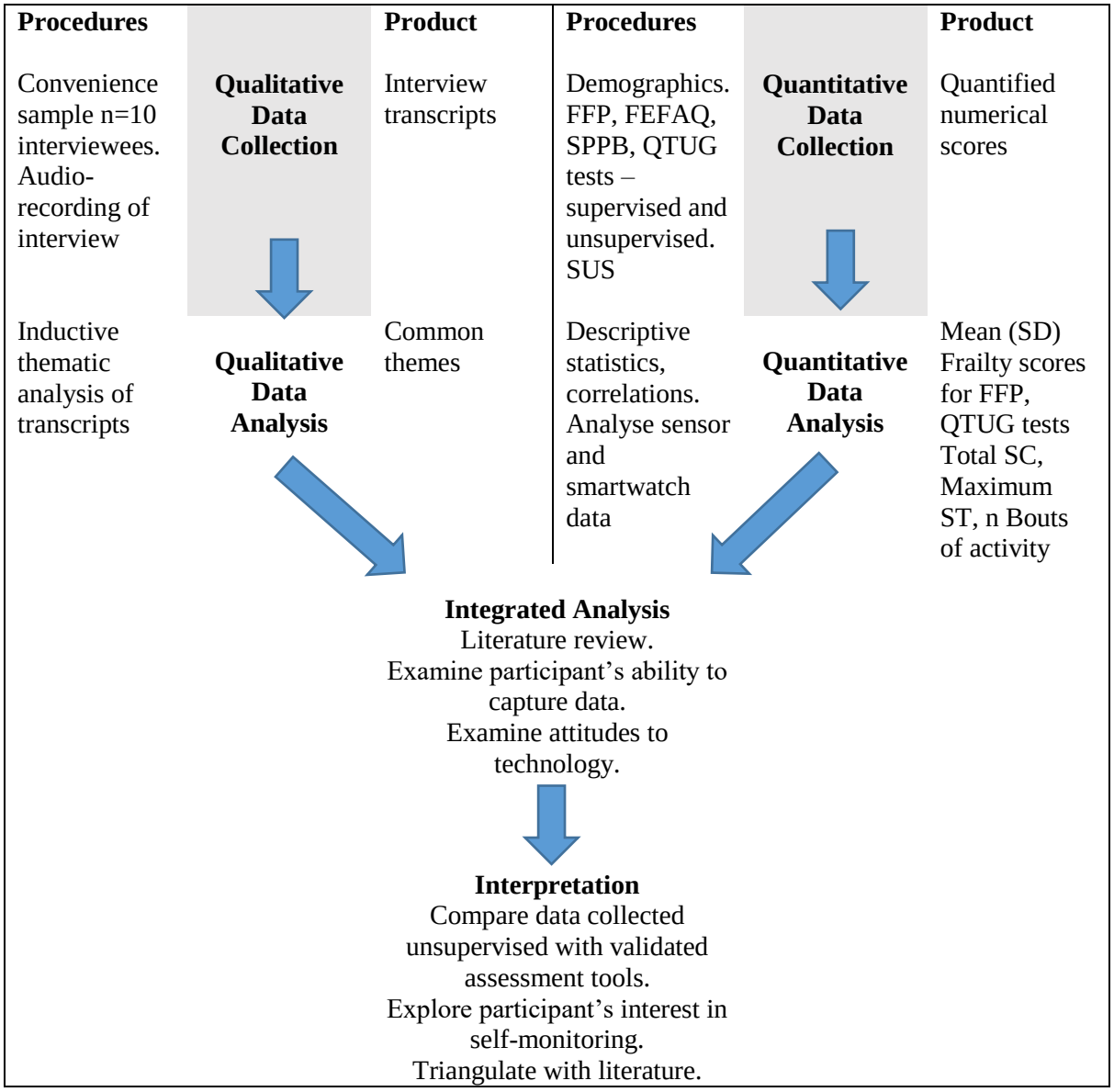


Figure 5.1 Study diagram showing data collection, analysis and integration of qualitative and quantitative data

5.2.2 Participants

Participants were recruited through advertisements in local golf, bridge and church community groups between August and November 2021(Appendix 5.1). Upon receipt of Health Service Executive (HSE) ethics approval on October 14th, advertisements were also placed with a gate-keeper in an outpatient ortho-geriatric clinic and an outpatient musculoskeletal clinic in two local hospitals from October 15th until November 16th, 2021.. Those interested were fully informed about the study and assessed for eligibility by the primary researcher. Screening for inclusion / exclusion criteria took place by

telephone when potential participants contacted the researcher in response to the advertisements. Interested parties were provided with written information either by email or by hand (PIL Appendix 5.2). Participants were enrolled in the study when they subsequently contacted the researcher to indicate their interest. Those included were; > 65 years of age, independently mobile, physically capable of performing a series of mobility and physical activity tests, had no cognitive or neurological deficits and no history in the past 6 months of lower limb orthopaedic trauma or surgery that would interfere with the ability to exercise. A sample of 52 was based on power 0.8, effect size 0.8, *p* value 0.05 (AI-Therapy Statistics 2018). This is justified in the literature with previous studies including similar sample sizes (Apsega et al. 2020). Every effort was made to ensure gender balance among the participant group. The study protocol received institutional and HSE ethics approval (Appendices 5.3 and 5.4), and all participants signed a written informed consent form prior to participation (Appendix 5.5). Participants also fulfilled COVID-19-specific requirements (COVID-19 Protocol - Appendix 5.6).

5.2.3 Data Collection

Participants were visited by the primary researcher in their homes for data collection on two occasions, 48-hours apart, between September 2021 and December 2021. A summary of the activities performed, and the data collected at each point is presented in Table 5.1.

Table 5.1 Summary of activities performed and data collection

Timeline	**Activities**			
1st visit by researcher to participant's home	Temperature check, COVID-19 questionnaire, Consent signed, Demographics recorded.	FFP, FEFAQ, SPPB completed.	Supervised QTUG performed. Data stored on-board tablet for offsite analysis.	QTUG and Smartwatch instruction. Booklet and support contact provided
48-hours between researcher visits	Smartwatch data collected during waking hours	Day 1 Unsupervised QTUG performed by participants in their own home	Day 2 Unsupervised QTUG performed by participants in their own home	Frailty scores from QTUGs stored on-board QTUG.
After 48-hours: 2nd visit by researcher to participant's home	SUS completed.	Interview of convenience sample n=10.	Technology collected from participant	
Offsite Data Collection	QTUG frailty scores retrieved from QTUG system and recorded in CRF	SC, ST and n bouts of activity retrieved from smartwatch via manufacturer's web application		

Abbreviations: Fried's Frailty Phenotype (FFP); Frail Elderly Function Assessment Questionnaire (FEFAQ); Short Physical Performance Battery (SPPB); Quantified Timed Up and Go test (QTUG); System Usability Scale (SUS); Number (n); Case Report Form (CRF); Step-count (SC); Sedentary Time (ST).

5.2.3.1 First visit

During the first visit signed consent was obtained and measurements of height and weight were taken along with demographic details of date of birth, sex, past medical history and current medication. The researcher performed a frailty assessment with each participant based on Fried's Frailty Phenotype Frailty Assessment tool (FFP) (Fried et al. 2001) (Appendix 5.7), and The Frail Elderly Functional Assessment Questionnaire (FEFAQ) (Gloth et al. 1999) (Appendix 5.8). Participants were also requested to perform two PA tests, namely; the Short Physical Performance Battery of tests (SPPB) (Guralnik et al. 1995) (Appendix 5.9) and a Timed Up and Go (TUG) (Podsiadlo and Richardson 1991). These data were recorded on a case report form (Appendix 5.10). Selection of mobility and PA tests were selected based on previous similar-type studies (Galán-Mercant and Cuesta-Vargas 2014; Apsega et al. 2020; Rodríguez-gómez et al. 2021).

The FFP is a clinical frailty assessment tool validated for use with community-dwelling older adults (Fried et al. 2001) selected for use as it is recognised as the most frequently adopted frailty assessment tool (Buta et al. 2016). It consists of five phenotypes of weight loss, exhaustion, low level of activity, weakness as measured by grip strength, and gait speed. Weight loss scored one point for unintentional weight loss >4.5kg in the previous year or a body mass index (BMI) <18.5kg/m^2. Exhaustion was assessed subjectively through two questions regarding perception of energy and how regularly one had rested in bed during the day over the previous four weeks – one point was scored if the answer to the first question was negative and 'every day' for the latter. Low level of activity scored one point if self-reported frequency of high *and* moderate activity was "never or hardly ever". Handgrip strength and gait speed were measured objectively and scored according to pre-determined cut-off points (Fried et al. 2001) and (Www.cgakit.com 2015) respectively. One point was scored for weakness if handgrip strength was less than a pre-determined cut-off weight (in kg) for sex and BMI categories. One point was scored for slowness if time to complete the TUG test was equal to or exceeded 19 seconds. Individuals are considered non-frail or robust if they fulfil none of the criteria, pre-frail if they fulfil one or two and frail if they meet three or more of the five criteria.

The FEFAQ is a reliable instrument for measuring function in frail older adults and is sensitive to changes in functional status. The 19-item clinician-applied questionnaire focuses on lower-level activity with a higher score indicating greater functional impairment (Gloth et al. 1999). Items include transfers, mobility, activities of daily living (ADLs), household tasks and higher order functional tasks such as managing finances. It has demonstrated content and construct validity in the measurement of frailty and was selected because it is reported to score positively on ceiling and floor effects (De Vries et al. 2010). This was considered important as participant recruitment from both community-based social groups and geriatric clinics suggested there could potentially be a wide spectrum of functional abilities.

The SPPB is a series of tests to assess balance; side by side, semi-tandem and tandem standing, walking speed; time taken to walk 3-m, and the ability to rise from a chair repeatedly. It was selected for inclusion because it tests important domains of physical function including balance, strength and

gait speed. It covers the requirements for screening as suggested by ADVANTAGE JA (Rodríguez-Laso et al. 2020) insofar as it has been validated to predict frailty and disability (Verghese et al. 2013; Bandinelli et al. 2006), is quick to implement and requires no special equipment. The SPPB has been used in many studies examining frailty or comparing frailty assessment tools (Pritchard et al. 2017; Checa-López et al. 2019; O'Hoski et al. 2019; Rodríguez-gómez et al. 2021). Each section is scored from zero or one to four with a final cumulated score between one and 12, the higher score indicating higher function. A TUG test is a reliable and valid test of functional balance and mobility, selected for its ubiquitous use and high sensitivity for identifying frailty (Clegg et al. 2015). It has been described in detail in chapter 4. The chair used was without armrests, with a seat-height of 45cms. Each home visited had a chair without armrests, of 45cm seat height available for use. It must be noted however, some chair seats were cushioned while others were not. This detail was not recorded. Another difference encountered during the home-visits was the floor surface which varied between carpet, tile and linoleum covering. This detail was recorded but not included in the analysis.

In the seated position for the TUG test and in the standing position for the walk part of the SPPB, the participant's feet rested on the floor with toes positioned behind a floor-mark that indicated the start of the 3m distance. A second floor-mark at 3m distance indicated the turning point (TUG test) or finish point (SPPB). For the purpose of the TUG test, participants were allowed to use their upper limbs to assist with standing up. For the purpose of the repeated chair stand in the SPPB, participants were instructed to place their arms across their chest. The 3m walk test in the SPPB is repeated twice and the fastest time is included in the calculations.

Prior to performing the TUG test participants were instrumented with the Kinesis QTUG sensors, one positioned on each shank as per manufacturer's instruction. Each sensor was aligned with the vertical, medio-lateral and anterior-posterior axes of the body and contained a tri-axial accelerometer, tri-axial gyroscope and a magnetometer. The Kinesis QTUG sensors were secured over outer clothing with reusable straps (Fig. 5.2). The data derived from the QTUG sensors were streamed via Bluetooth to a handheld tablet (Samsung Galaxy Tab A 2016) which automatically calculated a frailty risk based on analysis of temporal-spatial gait parameters. Data were saved on board the tablet in text form for

offline analysis. The Kinesis QTUG sensor and software system (QTUG) (Kinesis Health Technologies, Dublin, Ireland) as described in chapter 4 is a validated tool which measures temporal-spatial parameters of gait and uses proprietary algorithms to provide a quantitative falls and frailty risk score obtained during a standard TUG test. It is designed as a clinician-administered performance test for clinical evaluation of frailty and falls risk. It was selected for use as an example of a validated sensor and software system to explore if after a period of instruction and supervised use, older adults could use it independently to capture a frailty risk score. The theory was that experience with technology would enhance future use (Choi et al. 2022) and if participants could use a system designed for clinician administration after a brief instruction, using an accompanying guidance booklet, there would be potential to successfully use another form of technology(Jin et al. 2019). The format and duration of the education was driven by the restrictions of the COVID-19 pandemic, which created uncertainty regarding a window of opportunity to access participants and which limited the time the researcher could spend in the company of participants. The education session was delivered individually as person-centred implementation of technology has shown to have positive benefits (Ollevier et al. 2020). Support was provided in the form of an information booklet and off-site phone support where required.

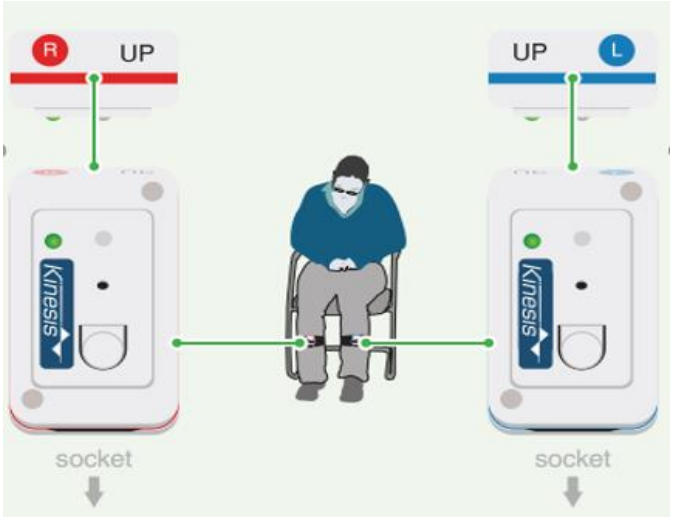


Figure 5.2 Image of QTUG sensor system and placement

5.2.3.2 Unsupervised 48-hour period

Following the supervised, researcher-administered activity and mobility tests and on removal of the sensors, participants were instructed in the use of the Kinesis QTUG sensor system and a consumer-grade smartwatch (Withings ScanWatch, Issy-les-Moulineaux, France). Challenges are associated with consumer grade wrist-worn devices for example when walking with a mobility aid or at slow gait speed (Tedesco et al. 2019a). However, strong correlation between a Withings smartwatch (Withings Pulse O_2) and a criterion measure of step-count has been demonstrated in healthy young adults in free-living conditions (Gruwez et al. 2017). Strong intra-device reliability has been demonstrated for a Withings smartwatch (Withings Pulse O_2) for step detection in a young cohort over a prescribed walking route (O'Connell et al. 2016). No studies examining reliability in an older cohort were identified for the Withings ScanWatch specifically however, good reliability for wrist-worn activity trackers has been demonstrated among older adults, including those walking with a mobility aid and at self-selected pace (Martinato et al. 2021; Floegel et al. 2017). The Withings ScanWatch was selected based on an evaluation framework designed and developed to aid selection of wearable activity monitors (Connelly et al. 2021; Byrom et al. 2018) and includes scoring several commercial smartwatches and activity trackers on domains including everyday use, functionality and infrastructure / support (Appendix 5.12).

Participants were requested to repeat the QTUG test unsupervised, in their own home along the same course and using the same chair as in the supervised test, once each day over the following 48-hours and to apply the QTUG sensor system for the duration of each test. Participants were provided with an illustrated information booklet (Appendix 5.11) and a support contact if needed. Participants were also requested to wear the smartwatch on their non-dominant wrist during waking hours for the 48-hour study duration. It is suggested that positioning of a wearable sensor on the non-dominant wrist improves the accuracy of activity detection during daily activities compared to the dominant wrist (Chen et al. 2016) and its use is supported by other studies (Huisingh-Scheetz et al. 2018; Koolhaas et al. 2017; Minici et al. 2022). Participants did not need to interact with the smartwatch but were

instructed in the use of its functions should they wish to investigate and use them. Participants were not provided with access to the accompanying application.

5.2.3.3 Final visit

5.2.3.3.1 System Usability Score

The researcher visited each participant a second time for collection of the technology not less than 48-hours after the initial visit. Participants were asked to complete the system usability score (SUS) (Appendix 5.13), a validated outcome measure which measures the usability of a system (Brooke 2020). It consists of a 10-item questionnaire with five response options for respondents ranging from strongly disagree to strongly agree, resulting in a score between 0 and 100. Usability is defined by the International Organisation for standardisation (ISO) as the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction within a specified context (ISO 2013). The system usability score was used to examine the participant's perception of the QTUG system. Because the participants were not specifically asked to engage with the ScanWatch or provided with details or access to the accompanying application, its usability was not scored. However, participants were asked to record on a 5-point scale if they thought they would like to use the smartwatch frequently. The response was recorded separately to the system usability score.

5.2.3.3.2 Interview

A convenience sample of ten participants were selected to answer questions relating to their previous experience with technology. The participants were randomly selected for interview using a computer-generated number system (https://www.calculator.net/random-numbergenerator.html) (Calculator.net 2008). Initially their responses were not audio-recorded. However, it became apparent that the questions asked generated discussion and required more probing. It was agreed to select another sample, ten different individuals for interview, to adopt a semi-structured approach to questioning, and to audio-record these interviews. This subsequent sampling process took place after the study had commenced when most of the participants had already completed the trial, therefore a random sample was not possible. The interview protocol was designed and developed with a member of the

supervisory team. It was piloted on one participant who had already completed the study and no subsequent changes to the protocol were deemed necessary. All of the last 15 participants yet to take part in the data collection were invited to take part in the interview. The first ten who agreed to participate were interviewed. Three participants declined to take part and the last participant was not interviewed as the proposed quota of ten had been reached and it was anticipated that data saturation would be achieved with n=10. The analysis of interview data included the second group of participants only.

A semi-structured interview approach was chosen to explore and focus on each individual's experience. Questions included participant's previous experience with technology (type, frequency and reason for use), their interest and perception of their ability using the new technology, their perception of its usefulness, and their ability to complete each test independently. Questions were guided by the overarching research aim using the Technology Acceptance Model (Davis 1989) and are listed in Appendix 5.14. According to the literature (Yap et al. 2022) the Technology Acceptance Model is one of the most commonly used theories for predicting technology acceptance at an individual level, identifying attitude, perceived ease of use and perceived usefulness as indicators for an individual's acceptance and engagement with technology. According to (Davis 1989) perceived ease of use refers to the degree to which the prospective user expects the target system to be free of effort and perceived usefulness is the prospective user's perception that using the system will increase his or her performance within a specific context. The number of participants selected to take part in the semi-structured interview was justified by the literature that suggests 10 interviewees will reveal >80% of the issues around usability of a system; The interview was used to examine participant's perceptions of both the smartwatch and the QTUG system.

For convenience and to comply with COVID-19 precautions, the primary researcher was the only interviewer present. The risk of interview bias as a result of subjectivity, interviewer expectations or pre-conceptions is higher when there is only one interviewer present (Kallio et al. 2016). This may result in selective data collection or leading questions on the part of the interviewer, or social desirability on the part of the participant where the participant responds with what (s)he might perceive the researcher wants to hear (Jager et al. 2020). The risk of bias was reduced through the use

of an interview protocol, designed with an experienced supervisory team member and field tested with a participant not subsequently included in the data analysis (Kallio et al. 2016). The audio-recording of this interview was checked by a member of the supervisory team as an additional quality step to ensure no leading or biased questions were included.

Audio-recordings of the interviews were transcribed verbatim by the primary researcher. A random sample of two transcripts were checked by a member of the supervisory team for accuracy.

5.2.3.3.3 Smartwatch Data

Measures of total step-count, number of bouts of activity and sedentary time were extracted from the smartwatch using the Withings' Health Mate web application (https://healthmate.withings.com). Parameters of mobility and PA that are easy to understand by a non-clinical / non-expert population, that are strongly associated with health and are reflected in the literature were selected for data collection. Step-count is strongly linked to health (Bassett et al. 2017), time spent in sedentary time has been shown to correlate strongly with frailty (Razjouyan et al. 2018) while number of bouts of activity and time spent in non-sedentary activity has been shown to negatively correlate with frailty (Theou et al. 2012; Razjouyan et al. 2018; Jansen et al. 2019). To standardise the data, only that collected between the hours of 8am and 8pm was included in the analysis. These hours were selected in an attempt to capture the majority of participant's waking time, an untestable assumption on the researcher's part, supported by previous studies (Leroux et al. 2019). Participants with data from these twelve hours of wear time for each of the two days were considered valid and were included in the analysis. The total step-count is the total number of steps detected by the smartwatch during the selected timeframe. A bout of activity is each unit of activity in 60-second epochs as identified by the smartwatch when activity is detected. Maximum number of bouts refers to the number of consecutive activity detections in 60-second epochs and reflects continuous activity during a break in sedentary time. Sedentary time is defined as the duration between each bout of activity and is recorded in hours, minutes, and seconds. The maximum sedentary time is calculated for each participant and is the longest uninterrupted sedentary time i.e., time between activity bouts when no steps are detected.

5.2.4 Data Management

All participant data were pseudonymised. A data dictionary was created for all the data collected in the study (Appendix 5.15). The ScanWatch data were downloaded from the Withings HealthMate web application and stored in a parent Microsoft Excel spreadsheet labelled with the ScanWatch identification code and dates of data collection. ScanWatch data for the selected hours of 8am – 8pm for each day were extracted from the parent excel file and stored in a separate excel file labelled with each participant's ID and recorded according to the data dictionary. The parent excel file was saved, unchanged. Data from the QTUG sensors were saved as PDF files. Audio-recordings were exported to a PC as MP3 files. All data files were password protected and stored on a password protected PC. COVID-19 data and paper-based case report forms were stored in a locked cabinet as per data management plan (Appendix 5.16).

A Data Protection Impact Assessment was completed to identify and address any risks to personal data of participants, as required by GDPR. This document was accepted by the data protection officer of Dundalk Institute of Technology (Appendix 5.17).

5.2.5 Data Analysis

5.2.5.1 Quantitative Analysis

Statistical analysis was performed using Microsoft Excel-16, SPSS-26, and WEKA V3.8.6 (University of Waikoto, New Zealand). Descriptive statistics of continuous variables are presented as mean and standard deviation (SD). Quantitative data from the QTUG and smartwatch were tested for normality using the Shapiro-Wilk test. A p value of $< .05$ was considered statistically significant. Independent t-tests and Mann-Whitney U tests were used to examine the variance in total steps, number of bouts of activity and maximum sedentary time between frailty groups as identified based on the FFP. Because of the relatively small sample size and the non-normally distributed data, the relationships between the researcher-administered and the unsupervised QTUG frailty risk scores, the unsupervised QTUG frailty risk and results of the SPPB / FEFAQ and free-living PA data were analysed using Spearman's rank correlation coefficient. Conventional coefficient values for very

strong (0.9 – 1.0), strong (0.7 – 0.89), moderate (0.4 – 0.69) or weak (0.10 – 0.39) were used in the analysis (Schober and Schwarte 2018). To further investigate the influence of each variable in the prediction of frailty, machine learning classifiers were used to establish optimum thresholds for the QTUG frailty risk estimate and for each parameter obtained from the smartwatch. The thresholds are the proposed levels of activity for each variable, activity below which, predicts a risk of frailty as classified using the FFP. The mean of each variable was used as the starting point for threshold selection and the highest accuracy percentage indicated the optimum threshold selected. Random forest models were then fitted separately with all variables using information gains attribute evaluation ranker and a 10-fold cross validation mode. Ten-fold cross validation divides the data randomly and trains the model using 10 (–1) folds and tests it on the remaining 9. This process is repeated 10 times, with each fold used as a training fold to optimise the robustness of the model (Sajeev et al. 2022). The system usability score for the QTUG system was calculated using standard methodology (Brooke 2020).

5.2.5.2 Qualitative Analysis

For qualitative interview data, thematic analysis was used to identify common themes, topics and patterns across the interview data set. Inductive thematic analysis involved line by line coding of the transcripts and followed a six-step process of familiarisation, coding, generating themes, reviewing themes, defining and naming themes, and writing up (Braun and Clarke 2006). A description of the analytical steps undertaken is presented in Table 5.2. Familiarisation involved reading and re-reading the transcripts to achieve a sense of the whole. Repeated reading facilitated line by line open coding of units of meaning to capture an overview of the main points of interest relevant to the research question. These codes were then collated into categories and sub-categories from which common themes became apparent. These themes along with the transcripts were reviewed to ensure they were an accurate reflection of the data. Two researchers separately coded two interviews to ensure consistency and guarantee a systematic, inclusive approach to the data analysis. Given the small data set, two interviews was deemed sufficient. It is generally accepted that due to resource limitations, not

all interviews are examined for inter-coder reliability (O'Connor and Joffe 2020). Agreement was met through discussion rather than using statistics to determine reliability. This approach is not unique. While it is apparent from the literature that a quantitative approach to inter-coder reliability is widely accepted there is controversy and debate around the idea of applying a quantitative measure to an interpretive methodology (Whittemore et al. 2001; O'Connor and Joffe 2020). It is suggested that the credibility of qualitative research can be demonstrated through the reporting of a transparent process of methodology and analysis (Tong et al. 2007; Johnson et al. 2020).

Table 5.3 outlines how individual codes were grouped to determine sub-categories and categories.

Table 5.2. Analytical steps (Braun and Clarke 2006)

Familiarizing yourself with your data	Verbatim transcription of all the interviews by the researcher. This provided an opportunity for initial familiarisation. The interview transcripts were read through several times. Initial thoughts and pre-codes were documented.
Generating initial codes	Data-driven codes were documented until no new codes were identified.
Searching for themes	Final coding was examined for themes and sub themes in relation to the research question and the studies' goals.
Reviewing themes	The interview audios were listened to once more to ensure that all relevant themes had been captured during the analytic process.
Defining and naming themes	Discussion between the researcher and supervisor to ensure themes were relevant to the research questions. Applying relevant names to describe the core of the theme.
Producing the report	Discussion between the supervisory team about the themes and how to describe them in a report.

Table 5.3. Individual codes ascribed to each category and subcategory

Categories	**Previous experience with technology**	**Attitude to technology**	**QTUG**	**Smartwatch**	**Interest in future use**
Subcategories	**Frequency of use**	**Technology in general**	**Perceived ease of use**	**Perceived ease of use**	**QTUG frailty risk indicator**
"codes"	*"Every day" #39* *"several times a day" #40* *"Never" #47* *"not very often" #48*	*"I'm more interested in the crochet" #50* *"I'm not all that interested …I'm more the arty type" #48* *"If only you had enough time to spend on it" #45* *"…. I usually go to the other one (feature-phone)…lazy!" #47*	***"****With the help, I had help" #50* "*It was fine, I was a little bit scared of it because there were so many bits to remember but once I got the hang of the bits it was very simple really" #40* *"…once I had somebody to read it because between the magnifying glass... I found it fine" #43* *"It was… alright"* (tentative) *"I had help" #48* ***"*** *a lot of pieces you had to remember and the sequence" #49* ***"****Very difficult…the sequence and the actual use…I studied the paper and tried to divide them*	*"The watch was marvellous, keeping track, I even did my ECG" #39* "*Yes, I checked my steps and my heartbeat. I tried to check my ECG once but I couldn't really read it (ECG) anyway so I gave up" #40* *"It was comfortable" #45* *"I think I didn't keep my hand over it (the timer) for long enough" #40* *"I found it hard to manipulate" #50*	***"****yes, maybe a simplified version for users…" #40* *"Probably I would but at the moment I feel I can manage…" #43* *"If there was somebody monitoring… I think it would be helpful" #45* *"there seems to be a lot more on it than I understand and really wouldn't be necessary for me…" #46* *"if there was a hcp monitoring and giving the feedback…yes" #50* *"I think I'd go by how I feel" #43* *"Not rea… I deal with people who are all nearly worse off than I am myself so I wouldn't*

			out, did one section at a time…complex" #49 *"No problem" #51* *"We did think a lot of people wouldn't remember or would definitely be challenged" #39* *"… I couldn't have done it without (the booklet)" #45*		*really think it would be useful for them, but for ordinary people it would be useful, it's good to know where you are…" #49* *"I suppose, yeah… but as I say you just have to be careful yourself"* *"Yes.. maybe in 10 years" (laughs)#51*
	Type of device	**Technology used in study**	**QTUG Challenges**	**Smartwatch Challenges**	**Interest in future use Smartwatch**
	"Phone, laptop, ipad, computer, the whole lot" #51 *"I use the old fashioned Nokia" #50* *"and an internet radio…" #40*	"*I didn't even try, I just asked my friend" #47* *"I don't think anything would influence my activity.. I am as I am…" #51* *"I never looked at it" #47* *"like a fun toy"… #40* "*marvellous" #39, #50*	**"***I found the Velcro on the straps difficult, the actual sensor technology wasn't a problem… the velcro isn't easy to manage" #46* *"so many bits to remember*" *"…it was really the sequence and the number of steps involved" #49* *"but now I'm very slow and my typing is quite bad…" #49* "*But it takes me time to get used to it…" #45*	*"something simpler would be better…" #48*	*"Yes and I was telling a couple of friends of mine…" #39* *"Probably not. It was interesting but … probably not"#40* *"I just check it myself, without technology" #46* *"At my age now, what would I be doing with it?" (laughs) #47* *"Yes"* *"Yes I think I would, as a stimulus, a motivation"*

			"having a tracker might help…" #48 *"I don't think anything would influence my activity.. I am as I am…"* *#51*
	Reason for use	**Perceived usefulness QTUG**	**Perceived usefulness Smartwatch**
	"playing solitaire or candy crush" #49 "*watching films, playback, Netflix, shopping, historical research, gambling…" #51* *"for sending messages, and Facebook because they (family and friends) send me messages on it. I use Whatsapp quite a bit" #43* *"just calls" #48*	*"I think It's of great use.. to alert people how frail they are" #40* *"I think it will be…when I saw 100% fragility, that's very high, I didn't think I was anything near that" #45* "*the information it has given me is very interesting to me" #46*	*"No, I looked at the time once, that was all" #47* *"what's the point in counting the steps, you just keep going anyway…" #50*
		Perceived confidence	
		"I got help straight away … I felt I wouldn't do it right, you wouldn't have information if I'd	

	been left alone with it (laughs)" #50 *"I remembered but called someone just in case" #39* *"I suppose I am a little bit alright on technology" #40* *"I'm fairly ok on the computer" #39* *"not confident exactly" #40* *"I use an ordinary phone for texts, I can use that one well. The other one is more complicated, I can get a message if it comes in and if I can find the keyboard I can answer but…. I usually go to the other one …lazy!" #47* *"I googled once but whatever I did it didn't work…" #47* *"I'm not very good at them (computers), still learning" #45*

5.3 Results

Of the 52 participants recruited, 51 are included in the analysis (age 77.45 ± 8.38 years, height 163.56 ± 8.36cm, weight 72.04 ± 13.53 kg, female 76%; n=39). There was one withdrawal prior to complete data collection due to ill health, unrelated to the study. Assistive walking aids were used by n=3 participants. No persons from the hospital-based clinics fulfilled the inclusion criteria within the recruitment timeframe. Potential reasons for this are the absence of the consultant geriatrician during the month of recruitment and the presence of ongoing COVID-19 restrictions. Both conditions resulted in reduced attendance at each clinic.

According to the FFP, 12% of participants were classified as frail (n=6), 61% pre-frail (n=31), and 27% non-frail (n=14). There was a strong correlation between frailty status as identified by the FFP and the SPPB assessment tool (r_s .626, p<.001), but a weak positive correlation between the FFP and the FEFAQ (r_s .340, p 0.01).

Smartwatch data from six participants were not available for analysis due to: lost data due to researcher error (n=2), incomplete data obtained from the manufacturer's web application (n=2), and smartwatch not provided to participants (n=2) due to the presence of a permanent pacemaker, a contraindication for the smartwatch selected. All remaining participants had twelve hours wear time between the hours of 8am and 8pm for each day and were thus included in the analysis.

5.3.1 Quantitative Results

5.3.1.1 Usability

Sixty-three percent (n=32) of participants (mean age 74.34; SD 7.83) (86%, 55% and 50% of NF, PF and F cohort respectively) successfully obtained a frailty risk score unsupervised, in their own home using the Kinesis QTUG system. A further 29% (n=15) attempted to perform the QTUG test but were unsuccessful (mean age 82.68; SD 6.62) (14%, 45% and 50% of NF, PF and F cohort respectively). A total of 8% (n= 4) (mean age 82.5; SD 3.19) declined to take part in the training and the unsupervised test. Descriptive statistics of both successful and unsuccessful participants in each frailty group are presented in Table 5.4. The system usability score was completed by 80% of all participants (n=41)

with missing data due to participant unavailability on the day of collection of the sensor system and smartwatch. Percentile scores of the system usability score range from 2.5 to 92.5. Mean scores are presented by frailty group in Table 5.5. Fifty-three percent of participants (n=22) who provided smartwatch data and completed the system usability score reported an interest in the future use of a wrist-worn device similar to the ScanWatch as identified by a score ≥ 4 on a 5-point Likert scale.

Table 5.4. Number, percentage and age of successful and unsuccessful unsupervised QTUG by frailty status

	Frailty Group	n	% of each cohort	Age Mean (SD)
Unsuccessful [includes Declined; n=4; PF n=1; F n=3; Age 82.5 (3.19)]	NF	2	14	73.50 (6.36)
	PF	14	45	82.50 (5.67)
	F	3	50	89.67 (2.89)
	Total	19	37	82.68 (6.63)
Successful	NF	12	86	71.42 (7.14)
	PF	17	55	75.24 (7.76)
	F	3	50	81.00 (7.94)
	Total	32	63	74.34 (7.83)
Total	NF	14	27	71.71 (6.84)
	PF	31	61	78.52 (7.72)
	F	6	12	85.33 (7.15)
	Total	51	100	77.45 (8.39)

Abbreviations: number (n), non-frail (NF), pre-frail (PF), frail (F), percentage (%), standard deviation (SD).

Table 5.5. SUS Percentile score by Frailty status

		SUS Percentile Score		
Frailty Status	**N**	**Mean (SD)**	**Min**	**Max**
NF	12	65.41 (17.11)	45.00	92.50
PF	26	48.07 (30.30)	2.50	92.50
F	3	35.00 (26.10)	5.00	52.50
Total	41	52.19 (27.82)	2.50	92.50

Abbreviations: System usability score (SUS), number (n), non-frail (NF), pre-frail (PF), frail (F), standard deviation (SD).

5.3.1.2 QTUG

Results of the Spearman's rank correlation coefficient (r_s) between the QTUG frailty estimate and other variables indicate there was a very strong positive correlation between the supervised QTUG and the unsupervised QTUG tests for each of the two days (r_s .942 and .874 day 1 and day 2 respectively p<.001). There was an equally strong positive correlation between each of the two

unsupervised QTUG tests (r_s .938, p<.001). Estimates of agreement would be more appropriate for analysing the same variables however, the data violated the assumptions of normality necessary for creating and interpreting Bland Altman plots. Neither log transformation or taking the square root of variables resulted in normal distribution.

There was a moderate correlation between the FFP and each of day one and day two unsupervised QTUG tests (r_s.549 and .460, p <.02 respectively). There was strong correlation between the SPPB and each of day one and day two unsupervised QTUG tests (r_s -.789 and -.703, p <0.001) but no correlation between the QTUG tests and the FEFAQ. There was a moderate to strong correlation between the supervised QTUG and maximum sedentary time, total number of steps and total number of activity bouts (.507, -.611 and -.712 respectively p <.001). The unsupervised QTUG frailty estimate correlated best with the total number of bouts of activity. These results are presented in Table 5.6.

Predictive accuracy percentage, the number of correctly classified instances (CCI), sensitivity and specificity for each optimal threshold for each variable are presented in Table 5.7. Sensitivity is the ability of a test to correctly classify the presence of an outcome while specificity is the ability of a test to correctly classify the absence of an outcome (Parikh et al. 2008). When examined individually, the unsupervised QTUG performed well in the prediction of frailty, with a threshold frailty estimate of between 35 and 40% providing a predictive accuracy of 75.8%, (CCI 22/29) (sensitivity 54.5%; specificity 72.2%) (Table 5.7).

Confusion matrices and detailed accuracy for models incorporating PA data obtained from the unsupervised QTUG tests and the smartwatch are presented in (Table 5.8). The y-axis of the confusion matrix shows the actual classification of NF, PF and F. The x-axis indicates how participants were classified by the model. The detailed accuracy report gives an indication of the performance of the model or classifier. Precision, recall, F-Measure and ROC Area (receiver operating characteristic) are considered the most appropriate measures to include. Precision indicates the true positives i.e. of all the data classified into each frailty cohort, what percentage of data actually belong there. Recall indicates the percentage of positives that were captured in each cohort. The F-Measure provides a weighted average of precision and recall while the ROC Area indicates the

percentage of time the model would correctly classify a variable / participant. A measure of 0.8 is considered a strong result (Nahm 2022).

Because of the small sample size in the model incorporating the combined data, when classified into non-frail, pre-frail and frail there was only one participant in the frail group. For this reason, in the analysis of data from the QTUG and the smartwatch combined, frailty status was distributed into a binary classification of non-frail and frail, with the frail group consisting of participants classified as pre-frail and frail. Prior to applying the machine learning analysis in the prediction of frailty, the information gains attribute evaluator ranked variables as follows; age, total step-count, number of bouts of activity (n-Bouts), maximum sedentary time (MAX_ST), mean sedentary time (Mean_ST) and unsupervised QTUG frailty estimate percentage. This ranking was used in the development of the prediction models presented.

Table 5.6 Correlation between QTUG tests and other variables

	FFP	**SPPB**	**FEFAQ**	**SC**	**MAX_ST**	**n Bouts**
Supervised QTUG	.606**	-.833**	-	-.611**	.507**	-.712**
Unsupervised QTUG Day 1	.549*	-.789**	-	-.255	.289	-.407*
Unsupervised QTUG Day 2	.460*	-.703**	-	-.405	.309	-.522*

Data presented as Spearman's correlation coefficient (r_s). **Significant at $p < .01$; *Significant at $p < .05$.
Abbreviations: Fried's Frailty Phenotype (FFP); Short Physical Performance Battery (SPPB); Frail Elderly Function Assessment Questionnaire (FEFAQ); Step-Count (SC); Maximum Sedentary Time (MAX_ST); Number (n); Quantified Timed Up and Go test (QTUG).

Table 5.7 Predictive accuracy percentage and the number of correctly classified instances for each optimum threshold

Variable	**Threshold**	**% Accuracy**	**% Sensitivity**	**% Specificity**	**CCI n/29**
Unsupervised QTUG	40-49%	75	54.5	72.2	22
Step-Count	1300-1400	58.6	0	94.4	17
n-Bouts	150-200	51.7	18.2	27.8	15
MAX_ST (minutes)	55 – 58	68.9	27.3	83.3	20
Mean_ST (minutes)	8	72.4	9.1	100	21

Abbreviations: Correctly classified instances per total sample (CCI n /29), number of bouts of activity (n_Bouts), Maximum sedentary time in minutes (MAX_ST).

Table 5.8 Prediction models and confusion matrices and detailed accuracy using ScanWatch **and** QTUG data

Model 1 (n29)	**Model 2** (n29)	**Model 3** (n29)
Age Step-Count n-Bouts MAX-ST Mean-ST Unsupervised QTUG	Step-Count n-Bouts MAX-ST Mean-ST Unsupervised QTUG	Step-Count n-Bouts MAX-ST Mean-ST
Actual → / PF/F: TP n=13 72% (PF/F nCCI=13/18)	Actual → / PF/F: TP n=13 72% (PF/F nCCI=13/18)	Actual → / PF/F: TP n=15 83% (PF/F nCCI=15/18)
NF: FN n=5 (NF nCCI=7/11)	NF: FN n=5 (NF nCCI=8/11)	NF: FN n=3 (NF nCCI=8/11)
NF: FP n=4	NF: FP n=3	NF: FP n=3
PF/F: TN n=7 64%	PF/F: TN n=8 73%	PF/F: TN n=8 73%
Classified as →	Classified as →	Classified as →
Accuracy 68.9%	Accuracy 72.4%	Accuracy 79.3%
Precision 0.70	Precision 0.74	Precision 0.79
Recall 0.70	Recall 0.72	Recall 0.79
F1 Score 0.70	F1 Score 0.73	F1 Score 0.79
ROC Area 0.77	ROC Area 0.76	ROC Area 0.78

Abbreviations: Number of bouts of activity (n-Bouts), Maximum sedentary time (MAX_ST), Mean sedentary time (Mean-ST), Quantified Timed Up and Go test (QTUG). True positive (TP), False negative (FN), False positive (FP), True negative (TN), Correctly classified instances (CCI), Receiver operating characteristic (ROC).

5.3.1.3 Smartwatch

Data collected from the smartwatch for each participant during the timeframe selected from the 48-hour study duration (8am – 8pm on two consecutive days) were included in the analysis and consisted of total number of steps taken, total number of bouts of activity, mean and maximum sedentary time in hours and minutes. Table 5.9 presents the comparison of each activity by frailty status. There was significant variance between each frailty group in measures of total step-count and total number of bouts of activity ($p < .01$). Maximum sedentary time was not significantly different between groups. The sample size of the frail cohort was very small which increases the probability of an incorrect conclusion of between group difference, a family-wise type I error which should have been considered during the data analysis (Schwenk et al. 2015a).

The FFP and the SPPB significantly correlated with maximum sedentary time (r_s .403, -.498), total steps (r_s -.598, .653) and total number of bouts of activity (r_s -.654, .755) respectively (p <.01) (Table 5.10). Confusion matrices and detailed accuracy for models incorporating PA data obtained from the smartwatch are presented in (Table 5.11).

Table 5.9. Physical activity and sedentary time by frailty status

	NF (n=12)	**PF** (n=28)	**F** (n=5)
Step-Count	16772 (7543)	9942 (7297)	1018 (558)
Total bouts of activity n	536 (181)	322 (127)	108 (39)
Maximum Sedentary Time (hours)	1.01 (.47)	1.50 (.83)	1.70 (.44)

Data are presented as mean (SD). Abbreviations: Number (n).

Table 5.10 Correlation between the FFP and SPPB and Smartwatch variables

	Max ST	**Total SC**	**Total n Bouts**
FFP	.403**	-.598**	-.654**
SPPB	-.498**	.653**	.755**

Data presented as Spearman's correlation coefficient (r_s). **Significant at p < .01
Abbreviations: Fried's Frailty Phenotype (FFP); Short Physical Performance Battery (SPPB); Maximum Sedentary Time (Max ST); Step-Count (SC); Number of bouts of activity (n-Bouts).

Table 5.11 Prediction models, confusion matrices and detailed accuracy using Scanwatch data

Model 1 (n45)

Age
Step-Count
n-Bouts
MAX-ST
Mean-ST

CCI n33
Confusion Matrix

Actual→	**PF**	**NF**	**F**	**n CCI**
	23	3	2	**PF** n=23/28
	5	7	0	**NF** n7/12
	2	0	3	**F** n=3/5
classified as→				

Accuracy 73.3%
Precision 0.73
Recall 0.73
F1 Score 0.73
ROC Area 0.79

Model 2 (n45)

Step-Count
n-Bouts
MAX-ST
Mean-ST

CCI n31
Confusion Matrix

Actual→	**PF**	**NF**	**F**	**n CCI**
	23	4	1	**PF** n=23/28
	6	6	0	**NF** n=6/12
	2	1	2	**F** n=2/5
classified as→				

Accuracy 68.9%
Precision 0.68
Recall 0.69
F1 Score 0.68
ROC Area 0.80

Model 3 (n45)

Step-Count
n-Bouts
MAX-ST

CCI n28
Confusion Matrix

Actual→	**PF**	**NF**	**F**	**n CCI**
	23	3	2	**PF** n=23/28
	5	7	0	**NF** n=7/12
	2	0	3	**F** n=3/5
classified as→				

Accuracy 62.22%
Precision 0.61
Recall 0.62
F1 Score 0.61
ROC Area 0.77

Abbreviations: Number of bouts of activity (n-Bouts), Maximum sedentary time (MAX_ST), Mean sedentary time (Mean-ST), Correctly classified instances (CCI), Receiver operating characteristic (ROC).

5.3.2 Qualitative Findings

Qualitative data from the interviews of ten participants selected are included in the analysis (mean age 81.6 ± 6.78 years, range 71 – 90 years, male n = 1). All were pre-frail to some extent, scoring one or two out of five on the FFP. Demographics and associated participant identification (ID) are presented in Table 5.12. The duration of the interviews ranged between 3.25 and 13.25 minutes. Findings are discussed under the headings: Previous experience with technology, attitude to technology, perception of technology used during the study including perceived ease of use, perceived usefulness, challenges, confidence and interest in using a similar system or device in the future. Four categories and 11 sub-categories identified through coding are presented in Table 5.13

Table 5.12 Interview Participant demographics

ID	39	40	43	45	46	47	48	49	50	51
Gender	FM	FM	FM	FM	FM	FM	FM	FM	FM	M
Age	75	72	88	86	87	81	84	82	90	71
Frailty status	PF	PF	PF	PF	PF	PF	PF	PF	PF	PF

Table 5.13 Categories and subcategories identified through coding of interview transcripts

Category	**Subcategories**
Previous experience with technology	• Frequency of use • Type of device • Reason for use
Attitude to technology	• Technology in general • Technology used in study
Perception of technology used in the study (QTUG and Smartwatch)	• Perceived ease of use • Perceived usefulness • Challenges • Confidence
Interest in future use	• QTUG • Smartwatch

5.3.2.1 Previous experience with technology

Most participants (n= 9) reported the use of a smartphone, tablet device and/or a PC on a regular basis, most reporting at least daily use with a small minority (n=3) reporting weekly use or less. All reported owning a phone of some kind. Most (n=8) reported they use their phone for calls and text messages with one respondent reporting its use for games and another for shopping and other functions. One participant reported using the phone for calls only and this being a feature phone type (a feature phone is a mobile phone that incorporates features such as the ability to access the internet

but lacks the advanced functionality of a smartphone). Another participant reported having both a smartphone and a feature-phone but reported more frequent use of the feature-phone citing 'laziness' and ease of use as the reason.

> *"I use an ordinary phone for texts, I can use that one well. The other one is more complicated, I can get a message if it comes in and if I can find the keyboard, I can answer but…. I usually go to the other one…lazy!"(#47).*

Functions reported for laptop or PC use were broad and included shopping, email, research via Google or YouTube, games, gambling and attending mass on-line during the COVID-19 pandemic. Self-reported confidence with technology used on a regular basis varied from very confident to not so confident and still learning.

> *"I suppose I am a little bit alright on technology" (#40)*
>
> *"I'm fairly ok on the computer" (#39)*
>
> *"I'm not very good at them (computers), still learning" (#45)*
>
> *"…when the computers came….I was very good at it, but now I'm very slow …" (#49).*

5.3.2.2 Attitude to technology

Attitude refers to a viewpoint or frame of mind and is the cognitive process which influences positive or negative affection toward technology (Au and Enderwick 2000). Attitude is used in the context of this study to examine the participants' viewpoint regarding the technology. Attitudes to technology in general varied among the participants from

> *"I'm more interested in the crochet" (#50)* and *"I'm not all that interested …I'm more the arty type" (#48)*

to

> *"If only you had enough time to spend on it" (#45)* and (I use it for) "*everything!" (#40).*

Attitudes to the technology used in the study were equally diverse with a cohort agreeing that it was "*marvellous*" *(#39, #50),* "*like a fun toy" (#40)* and those who disregarded it completely

> "*I didn't even try; I just asked my friend" (#47).*

Overall, there was agreement that technology was necessary at the very least for communicating with family and friends, especially those "*abroad*" or "*away*". Attitudes are influenced by perception and perceptions are discussed in the following paragraphs.

5.3.2.3 Perception of the technology used during the study

Perception, defined as the way in which something is regarded, understood or interpreted is an opinion or belief that is influenced by past experience, education, values and culture, among others (Barnard et al. 2013). The consensus regarding the perception of the technology used for the duration of the study was that it was "*fine*" but further probing revealed a divide in participant's impressions. While the majority managed to complete the required task using the QTUG system, many reported seeking help before attempting the task. So, for some of the participants "fine" appeared to mean that they had no difficulty or anxiety regarding the task as they relied on someone else to do it for them

"It was easy – someone else used it, I just did the walk (laughs)" (#47)

Whereas for others "fine" meant they managed to use the system and complete the task without much ado.

"…once I got the hang of the bits it was very simple really" (#40).

Several factors influenced perceived ease of use of the sensor system, complexity being foremost. Those who managed to complete the task successfully and independently using the QTUG system varied in their responses to the perceived ease of using the system ranging from "*no difficulty at all"* (just one participant, *(#51)* to various degrees of challenge. The QTUG system was deemed manageable, but difficult to navigate by most despite the availability of the illustrated information booklet.

"*Very difficult…the sequence and the actual use…I studied the paper and tried to divide them out, did one section at a time…complex*" *(#49)*

"We did think a lot of people wouldn't remember or would definitely be challenged" (#39)

"I couldn't have done it without (the booklet)" (#45).

The perceived usefulness of the QTUG sensor system was more uniform than the perceived ease of use among the participants with the majority acknowledging they considered the information provided by the technology to be very useful, interesting and informative.

Responses regarding the perceived ease of use of the smartwatch were quite negative with few reporting full engagement with the functions available. Apart from one participant who was very enthusiastic;

"The watch was marvellous, keeping track, I even did my ECG" (#39)

the majority of participants struggled with the interface;

"I found it hard to manipulate" (#50)

"I think I didn't keep my hand over it (the timer) for long enough" (#40).

Perception as to the usefulness of the smartwatch was also less positive than for the sensor system, with participants agreeing for the most part that while it had a novelty factor, being able to interpret the information provided and failing to see its relevance to them reduced their perception of its usefulness.

"*Yes, I checked my steps and my heartbeat. I tried to check my ECG once but I couldn't really read (interpret) it (ECG) anyway so I gave up" (#40)*

"I didn't do the ECG or anything, I was just interested in looking at what it could do" (#49).

Not all the challenges experienced were related to the technology itself with some experiencing problems as a result of the biophysical restrictions associated with ageing including dexterity and eyesight.

"I found the Velcro on the straps difficult; the actual sensor technology wasn't a problem… the velcro isn't easy to manage" (#46)

"I found it alright once I had somebody to read it because between the magnifying glass... I found it fine" (#43)

"very difficult, now I'm very slow…" (#49).

Many participants who expressed confidence with regular use of technology did not demonstrate the same level of assuredness with the technology used in the study. Often those who sought help with the use of the QTUG system were frequent users of multiple devices. Reasons given for immediately seeking assistance were mainly lack of confidence in their ability to achieve the task independently or fear of doing it incorrectly and not capturing the data needed by the researcher.

"I got help straight away … I felt I wouldn't do it right, you wouldn't have information if I'd been left alone with it (laughs)" (#50)

"I remembered but called someone just in case" (#39)

"not confident exactly" (#40).

5.3.2.4 Interest in using a similar system or device

Participants overall responded positively to questioning about the perceived usefulness of the QTUG system and to a lesser extent of the smartwatch however, this positivity did not translate into an interest in future use of such tools. It seemed participants and family were interested in the information and the novelty but when asked about their interest in using the QTUG system or the smartwatch the majority of participants suggested it would be more suitable for 'others'. There were those who admitted to not exploring the functions or the information provided by the system or the smartwatch citing lack of interest or perceived relevance to their situation. Those who expressed an interest in future use were in the minority and did so with the caveat of the technology being simpler and easier to use. To further demonstrate a lack of real interest or intention to use, what could be described as adoption of the technology (Renaud and Van Biljon 2008), was participant's general perception of the extent to which the use of a smartwatch would influence their activity level;

"I think I'd go by how I feel" (#47)

"there seems to be a lot more on it than I understand and really wouldn't be necessary for me…" (#46)

"what's the point in counting the steps, you just keep going anyway…" (#50)

"Probably I would but at the moment I feel I can manage…" (#43)

"I don't think anything would influence my activity.. I am as I am…" (#51).

The main reasons given for lack of interest in future use were the challenges related to the complexity of the technology used in the study but also the idea that they (the participant) were either too old to benefit or too young.

"Yes... maybe in 10 years" (laughs) (#51)

"At my age now, what would I be doing with it?" (laughs) (#47).

Some alluded to an increase in interest if there was a clinician or health care professional monitoring the results, giving feedback and advising on appropriate intervention.

"If there was somebody monitoring… I think it would be helpful" (#45)

"if there was a health professional monitoring and giving the feedback…yes" (#50).

Two themes identified from the narrative are that of help being sought or deemed necessary, and acknowledgement of the usefulness of the technology but “for someone else”.

5.4 Discussion

This study examined the relationship between sensor data of mobility and PA obtained during both supervised and unsupervised, free-living activities among community-dwelling older adults, with traditional functional assessment using validated assessment tools and with frailty status as identified using a validated frailty assessment tool. The study also sought to investigate the usability of a wearable sensor system for independent and unsupervised capture of activity data during a mobility test and examine the experience and attitudes to the use of technology for ongoing monitoring of PA among this cohort.

A sample recruited from community-based hospital clinics and social groups was expected to represent of the target population of community-dwelling older adults. The small number of frail participants was possibly impacted by the COVID-19 pandemic, which influenced recruitment from hospital clinics and potentially from the community groups. However, the 73% prevalence of frailty and pre-frailty combined in the sample is comparable with other similar studies (Pradeep Kumar et al. 2021; O’Halloran et al. 2021; Roe et al. 2017) and reflects the population prevalence (Choi and Kim 2015).

Overall, the study found that the majority of participants were successful in obtaining a frailty risk score independently using a wearable sensor system; that parameters of PA obtained from the wrist-worn smartwatch significantly correlated with traditional functional tests and frailty assessment tools; and that models incorporating variables from both the unsupervised QTUG and the smartwatch were successful in the prediction of frail / pre-frail status. It is important to remember that correlation is a measure of the strength and direction of the relationship between the variables measured and not a measure of agreement (Bland and Altman 1986).

5.4.1 QTUG

The majority of the participants included in the study were successful in obtaining a frailty risk score independently using a wearable sensor system. It must be acknowledged that the Kinesis QTUG sensor and software system is designed for clinician-administration however it was used in this study as a validated tool for frailty assessment and to explore older adult's ability to capture quantified measurements of mobility and frailty independently. Body-worn sensors are the most commonly used technology to examine mobility and PA in older adults (Bian et al. 2020), but reliance to date has been on researcher analysis of the data obtained (Tolley et al. 2021). An established trend of individuals self-monitoring information pertaining to their health and/or PA is evident in the literature and illustrates the interest people have in monitoring and analysing their own data, referred to as quantified self-assessment (Rawassizadeh et al. 2015; Vijayan et al. 2021).

Those who were successful in obtaining a frailty score unsupervised were younger (mean age 74.34; SD 7.83) than those who failed to use the QTUG successfully (mean age 82.68; SD 6.62). However, the percentage of those in the pre-frail and frail cohorts was comparable (45% - 50% and 55% - 50% for PF - F cohort for successful and unsuccessful respectively).

Frailty estimates from the QTUG tests correlated with the results of the functional tests and frailty assessment tools. The QTUG frailty estimates captured by participants unsupervised correlated strongly with those of the supervised QTUG, the SPPB and had moderate correlation with the FFP. This outcome is promising, suggesting that many older adults can independently capture information relevant to their risk of frailty that does not depend on a clinician or researcher for analysis. The Kinesis QTUG sensor system provides an objective estimate of frailty in the form of a frailty risk score, which can potentially be understood by each individual user without further analysis or interpretation being necessary. With a more comprehensive educational component or with a less complex sensor system to capture parameters of mobility and PA, it is possible the 37% of participants who did not complete the self-assessment could be facilitated to do so. The QTUG sensor system is designed for clinician-implementation therefore no studies examining its use in unsupervised tests were found.

One reason for the less strong correlation between the unsupervised QTUG tests and the FFP could be the result of the cut-off point for gait speed in the FFP assessment tool at ≥19 seconds as proposed by the Comprehensive Geriatric Assessment (CGA) (Www.cgakit.com 2015). The cut-off point of 19 seconds could be considered quite high as other literature supports cut-off points as low as twelve seconds (Bischoff et al. 2003) and the QTUG algorithm uses a cut-off point of 13.6 seconds when estimating a frailty score (Kinesis 2023). If the algorithm is programmed with a higher cut-off time in seconds to detect gait speed indicative of frailty, subtle signs may be overlooked resulting in a lower frailty score.

There was no correlation between the unsupervised QTUG frailty risk estimate and function as predicted by the FEFAQ. There was also poor correlation between the FEFAQ and the FFP which is surprising considering the FEFAQ has scored positively on content and construct validity, reliability, responsiveness and floor / ceiling effects when compared with other valid questionnaires (De Vries et al. 2010; Gloth et al. 1995). This is in contrast to the strong correlation found between the SPPB and the FFP, a finding that is supported by the literature (Pritchard et al. 2017; Rodríguez-gómez et al. 2021). However, the FEFAQ is designed to assess function at very low levels of activity (Gloth et al. 1995) and because of the impact of COVID-19 resulting in recruitment exclusively from community-based social groups, the sample included lower frailty and higher functional levels. This is a limitation of the study and affects the generalisability of the results.

5.4.2 Smartwatch

A consumer grade wearable device in the form of a smartwatch positioned at the wrist was used to monitor parameters of PA during free-living activities because of its ability to continuously and unobtrusively collect data relating to PA, summarise the data and provide feedback in a way a user can interpret and understand. The wrist, selected for accessibility, has been found in a study of older adults and care-givers, to be one of the preferred body-locations for placement of a wearable sensor (Kolasinska et al. 2018). Consumer grade activity trackers positioned at the wrist have demonstrated validity and reliability in measuring step-count and activity duration in older adults (Straiton et al. 2018). There is an increasing body of evidence to support their use for continuous monitoring and

promotion of PA in older adults to improve activity behaviours and health (Brickwood et al. 2020; O'Brien et al. 2015; Straiton et al. 2018). Data obtained from activity trackers have been shown to increase users' awareness of their activity levels (Ehn et al. 2018) and to be successful in increasing their engagement with PA (Nyman et al. 2016). This supports the proposal that if older adults have a means of independently measuring PA that identifies a risk of frailty, the risk of frailty development could be mitigated. A smartwatch, specifically the ScanWatch was selected for use in lieu of an activity tracker as it performed better in the evaluation framework in terms of the use of the device controls, wearable display visibility, and interpretability.

Maximum sedentary time, total step-count and number of bouts of activity obtained from the smartwatch in the current study were found to be significantly correlated with frailty status as identified using a validated frailty assessment tool. Measures of sedentary time, step-count and number of bouts of activity selected as predictors of frailty are supported in the literature (Del Pozo-Cruz et al. 2017;Kim et al. 2020; Rodríguez-gómez et al. 2021). A large study examining sedentary time in community-dwelling older adults demonstrated a lower correlation coefficient between sedentary time and frailty (0.19 *p*.01) (Rodríguez-gómez et al. 2021). A smaller study of community-dwelling older adults in receipt of home care support demonstrated a correlation coefficient between step-count and frailty comparable with our study (-0.52 $p<.001$) (Kim et al. 2020). The significance in the correlation between parameters obtained from the smartwatch and frailty status are diminished when frailty groups are analysed separately because of the small sample size in each group. However, the findings reiterate those demonstrated in other studies (Del Pozo-Cruz et al. 2017; Mañas et al. 2019; Rodríguez-gómez et al. 2021) supporting a reduction in sedentary activity and the introduction of breaks in sedentary time to influence frailty status. The magnitude of the findings compare with earlier studies of sedentary time (Gorman et al. 2014; Jansen et al. 2015; Kehler et al. 2018). Step-count exceeds that observed in a previous study that reported a frailty prevalence of 35% (Kim et al. 2020), but the step-count captured by the frail cohort is comparable with that of a frail cohort in a study of nursing home residents (Chan et al. 2016). It is important to acknowledge that the smaller

sample size may influence the results and carries a risk of type I error. The true effect, if present will need to be confirmed in a larger sample size and longer period of data collection.

The use of a smartwatch is not without limitations. While providing feedback that can be interpreted without difficulty, accessing and engaging with the relevant application to obtain the information is necessary. The majority of participants who completed the usability questionnaire reported an interest in using a similar wrist-worn device in the future. This figure may be different if participants had been more comprehensively educated in the functions of the smartwatch, which may have also influenced the perceived usefulness. However, it may also have been different, either higher or lower if they had been required to access and engage with the accompanying mobile/web-based application. The outcome would very much depend on each participant's inclination toward the technology and on their interest in engaging with the accompanying application.

The use of a wrist worn device carries a risk that upper limb movement or activity may be erroneously misinterpreted and calculated as step-count (O'Connell et al. 2017) and reduced accuracy has been suggested during normal daily activities that involve upper limb movement (Chen et al. 2016; Tedesco et al. 2019a). Reduced accuracy is also suggested at varying gait speeds (Sears et al. 2017). Other body locations for sensor positioning may demonstrate higher accuracy in terms of step-count and PA detection (Chow et al. 2017) but the conveniently accessible wrist positioning has been shown to provide acceptable accuracy (O'Connell et al. 2016; Tedesco et al. 2019b) and the PA data is readily available without the need for pre-processing or specialised analysis.

5.4.3 Predictive Models

A machine learning classifier using 10-fold cross-validation was used to evaluate the performance of models derived from the parameters of PA obtained from the smartwatch and from the QTUG sensor system and smartwatch combined. It must be acknowledged that the sample size was powered based on t-test and correlation coefficients and is unlikely to be powered sufficiently for machine learning analysis. Previous studies using machine learning have included sample sizes ranging from 240 – 5000 (Balki et al. 2019). Therefore, although results are comparable with other similar studies which will be subsequently discussed, all results must be regarded cautiously.

All models incorporating the variables obtained from the unsupervised QTUG and the smartwatch combined, performed better in the prediction of frail/pre-frail than non-frail as demonstrated in the confusion matrices in Table 5.8 each with sensitivity and specificity ≥0.70. This is an important finding as it has been established that positive transition between stages of frailty is more successful if identified at the pre-frail rather than the frail stage (O'Halloran and O'Shea 2018; Kojima et al. 2019), thus identifying an opportunity for appropriate allocation of scarce resources for timely intervention. The QTUG data also performed well when analysed separately with the threshold of a frailty risk score between 35-40% providing a prediction accuracy of 75.8%. This is in keeping with the literature on the Kinesis QTUG system that supports its use in the classification of frailty (Greene et al. 2019). It is interesting to note however that despite the QTUG performing well in the prediction of frailty, when ranked using information gains evaluation for the development of prediction models, the QTUG variable was ranked last and the prediction model performed better when the QTUG data was omitted, with 79.3% accuracy, compared to 72.4% (Table 5.9). One explanation for this may be the fact that the QTUG, while performed by the participants unsupervised in their own home, was performed in what could be perceived as test-like conditions and may have inadvertently resulted in response bias. The PA data obtained from the smartwatch was done so continuously, without any active engagement by the participants being required thus minimising any bias. As not all participants' data were included in the analysis of the smartwatch data and not all participants successfully obtained a frailty score from the QTUG unsupervised, the sample size used in the predictive models incorporating data from both the QTUG and the smartwatch is reduced.

Models incorporating parameters of PA obtained from the smartwatch performed best in the prediction of pre-frail with CCI n23/28 i.e., accuracy of 82% in each model (Table 5.11). This is consistent with the favourable prediction accuracy for pre-frail in the models incorporating the QTUG data. Thresholds derived from simple machine learning methods on each smartwatch variable demonstrate predictive accuracy for frailty ranging between almost 52% for number of bouts of activity, 58% for total step-count and almost 70% for maximum sedentary time. A predictive accuracy percentage of 52% when analysed alone is of little value as chance is expected to achieve 50%

accuracy and the sensitivity of each individual variable was low (0 – 54.5%). However, when analysed as part of the confusion matrix, the value of each variable increases. The threshold proposed for total step-count is supported by an earlier study proposing a reduced risk of frailty for older adults walking ≥ 5000 steps per day (Yuki et al. 2019). While the QTUG provides a higher predictive accuracy at 75% it could be argued that the potential benefits of a smartwatch including its relative ease of use, make it an alternative worth considering. The collection of continuous data using a smartwatch as opposed to data collected by the QTUG sensor and software system during a specific mobility test could also be considered more suitable. The qualitative data analysis suggests older adult's preference for a simpler device to capture parameters of their activity.

This study has demonstrated that objective PA data associated with frailty can be monitored by older adults using a smartwatch, and some can capture an objective measurement of mobility and frailty using a sensor and software system. Activity monitors in the form of activity trackers or smartwatches provide users with real-time feedback about their PA, and do not require trained personnel to deliver or interpret the data (Brickwood et al. 2020). A smartwatch was selected for this study as a convenient, user-friendly method for continuous collection of activity data and demonstrated the ability of older adults to acquire continuous data of PA in free-living conditions.

5.4.4 Usability

The important question is if parameters of PA with sufficient predictive accuracy for frailty or pre-frailty can be captured with a smartwatch or sensor system and used independently by older adults to identify to them their risk of frailty. The results presented in this study demonstrate that the parameters of PA, specifically total step-count and number of bouts of activity obtained by the ScanWatch correlate well with frailty levels especially pre-frail, and that a threshold for sedentary time, predictive of frailty can be identified with levels of accuracy exceeding those that could be explained by chance (Brownlee 2021). This suggests that the combination of PA and sedentary activity can be monitored regularly and unobtrusively by older adults as a way of objectively identifying their risk of frailty.

These findings fit well with previous research demonstrating correlation between sensor-based data, traditional functional assessment, and frailty status (Huisingh-Scheetz et al. 2018; Kim et al. 2020; Mulasso et al. 2019) and provide new insights into the ability among community-dwelling older adults to capture a frailty risk estimate independently, unsupervised in their own home. As well as collecting PA data that correlates with frailty risk using a smartwatch, participants also demonstrated the ability to capture a more comprehensive frailty estimate, using the Kinesis QTUG sensor and software system. Overall, the system usability score for the QTUG system ranged from 2.5 to 92.5 demonstrating a wide variation in participants' perception of its usability. The mean SUS score was lower with each increasing level of frailty however, the lowest score was in the pre-frail group (2.5 in the PF group compared with a lowest score of 5 the frail group) indicating that some frail participants perceived the technology more usable than their pre-frail peers. This is consistent with earlier studies examining factors that influence technology acceptance among older adults which demonstrated a weak association between age and technology use (Ha and Park 2020; Peek et al. 2014).

The mean score of 52 falls below the score of 68 which is considered an average and acceptable score for the system usability score (Sauro 2011). Forty-four percent of those who completed the system usability score (n=18/41) scored ≥ 65 demonstrating that for many participants, the technology was deemed usable. The non-frail group came closest to the average of 68 (mean 65.4, range 45 – 92.5). The mean system usability score reduced in accordance with frailty status and age in keeping with previous studies (Bangor et al. 2009).

Four participants declined to take part in the unsupervised activity test using the QTUG system, citing lack of interest or lack of confidence in their ability to perform the test independently. Twenty-nine percent of the participants who attempted to use the sensor system independently were unsuccessful for reasons including system or battery failure, poor eyesight and self-reported lack of confidence to attempt the test without family support. The latter two reasons are related to biophysical restrictions and reduced confidence, both associated with ageing, and confirm the literature which identifies these as limiting factors to the use of technology among older adults (Wang et al. 2021). Help was reported as being sought regardless of participant's previous use of technology or self-reported ability. This, according to the participants was because of a lack of self-confidence in digital skills or a fear of not

providing the researcher with the necessary data. Lack of confidence in technology is referred to as digital anxiety in the literature and appears quite prevalent (Yap et al. 2022; Nimrod 2018; Di Giacomo et al. 2019). Self-confidence in digital skills is influenced by many factors including age, education and previous experience with technology, and in turn affects satisfaction, perceived usefulness and adoption or continued use of technology (Lee and Coughlin 2015). The predominant factor influencing self-confidence and consequent outcomes appears to be the training and support provided (Ehn et al. 2018; Neves and Mead 2020; Barnard et al. 2013).

Training sessions that allow older adults to learn at an individual pace, with ongoing support and provision of educational literature have been shown to instil confidence and facilitate problem solving resulting in acceptance and adoption of technology among older adults (Desai et al. 2022). It is recognised that older adults have the capacity and the interest to learn to use technology but again, the design of the training is important (Schlomann et al. 2022). The limited duration and once-off nature of the training provided in this study may have contributed to the participants not being equipped to manage system or battery failure. The training provided did not include the opportunity for participants to first engage with the technology and subsequently ask questions or experience success in tasks, both of which are understood to build confidence and facilitate successful adoption of technology (Lee and Coughlin 2015). The training did include one-to-one training and a reference manual, and the request to repeat the test on two consecutive days facilitated 'learning by doing', all of which have been reported as preferred learning strategies of older adults (Schlomann et al. 2022). The very strong correlation between the two consecutive unsupervised tests (r_s .938, p<.001) suggests that 'learning by doing' did not influence the outcome of the second unsupervised test. The system usability score is a validated and reliable tool for assessing the usability of a system but includes dimensions for learnability in two of the questions (four and eight) (Lewis and Sauro 2009; Sauro 2011). Learnability is defined as the ease with which something can be learned (Harrison et al. 2013). Considering the nature of the training provided and the short duration of the education, if analysed separately the learnability dimension score may have contributed to the understanding and interpretation of the system usability scores.

A recurrent theme evident from the qualitative interview analysis was the suggestion by the majority of participants that the technology would be useful for someone else, either older or younger, physically 'better off' or 'not as good'. Those who considered that the use of technology might influence their activity levels did so in a non-committal way *"I think it would…"* or *"it might help".* Self-monitoring of health and PA is recognised as an important factor in management and prevention of chronic disease and declining function (Rodríguez-gómez et al. 2021; Centre for Disease Control and Prevention 2022) however, patient's willingness to self-monitor is variable (Huygens et al. 2017). There are many potential explanations for the reluctance among the participants to adopt the technology presented in the study. The literature suggests perceived ease of use and perceived usefulness of a device or system are major contributing factors to the reluctance among older adults to adopt continued use of technology (Preusse et al. 2017). A study by (Keogh et al. 2020) found that perceived usefulness outweighed perceived ease of use, a finding that is supported throughout the literature (Yap et al. 2022) and supports the findings of the current study. This suggestion is refuted by (Chen and Chan 2014) who propose that self-efficacy, anxiety and social support outweigh the effect of perceived ease of use and perceived usefulness as influences of continued technology use. A study by (Keränen et al. 2017) identified that frailty status was directly associated with a negative opinion of the usefulness of technology. This may also have been a factor in the current study involving older adults with varying degrees of frailty.

Distinction has been made between acceptance of technology and adoption. Acceptance does not necessarily result in adoption which is defined as an individual embracing a technology and making full use of it (Renaud and Van Biljon 2008). Adoption and continued use of technology among older adults has been linked to their perception of the relevance of the technology to their lives and the perceived benefits (Vroman et al. 2015). Those who expressed interest in the QTUG system were generally positive regarding the smartwatch and equally, those who had little interest in the QTUG system had little interest in the smartwatch. It must be acknowledged that there was a lot more engagement required of the participant in the use of the QTUG system compared with the smartwatch. Participants were not uniformly instructed in the use of all the functions of the smartwatch and were

not given access to the accompanying application but rather requested to simply wear the device for the selected period of time. This may have influenced participant's perception of the usefulness of the smartwatch relative to the sensor system. Different responses may have been obtained if participants had to interact with the application or indeed if they had been given the opportunity to access it. As well as considering the design and delivery of technology to older adults, demonstrating its relevance in the role of disease prevention and management of health may influence and motivate older adult's adoption of technology to identify early signs or risk of frailty and should be included in future studies.

5.5 Limitations

The results of this study must be viewed in relation to its limitations. The sampling method for recruitment of participants resulted in a lack of gender balance and a lack of diversity in frailty status. While the prevalence of frailty in women is twice that of in men in Ireland (O'Halloran and O'Shea 2018) the percentage of men in the overall sample was just 25%. This is in contrast with other frailty studies where the gender balance has been more reflective of the population (Rodríguez-gómez et al. 2021; Xue et al. 2020) but not a unique occurrence (Buchman et al. 2021). There is the possibility this gender imbalance is a result of volunteer bias whereby people want to take part in the study to help others, in the hope of others benefitting from their input, and women are known to volunteer at a higher rate than men (Salkind 2010). The predominance of participants from community groups and the lack of recruitment from hospital clinics may have influenced the imbalance in frailty status among the participants. More successful recruitment from the ortho-gerontology clinic in non-COVID times may have resulted in a more balanced sample.

This gender imbalance is heightened in the sample of 10 participants selected for interview, as there was only one male included. Furthermore, the frailty status of all participants interviewed was pre-frail thereby omitting the contribution of the frail and non-frail participants. This potentially limits the truth value of the multiple perspectives that could be expected from different cohorts, which influences the dependability that ultimately relies on variability. This potentially impacts on the application and generalisabilty of findings (Whittemore et al. 2001). This imbalance can be explained

by the nature of the sample selected for interview, the fact that 75% of the sample population were female with a prevalence of 61% pre-frail. It is possible a purposive sample may have been more appropriate to ensure a better, more representative gender and frailty status balance.

The short time frame of the study which was influenced by the COVID-19 pandemic, and the once-off training session did not facilitate self-paced learning or provide the benefit of time to explore the technology with ongoing technical support, both of which have been identified by older adults as crucial to their ongoing engagement with technology (Desai et al. 2022). Participants may have benefitted from a follow-up training session to address questions and provide support prior to carrying out the unsupervised QTUG test, which may have influenced the responses and results. The limited duration of the training session and the study overall possibly did not adequately allow for learnability of either the sensor system or the smartwatch which precluded the opportunity to explore more meaningfully the potential for engagement and adoption. The average duration of the interviews was relatively short, which may be the result of the inexperience of the researcher in conducting the interview and following up with appropriate probing questions or prompts.

The restriction of the smartwatch data collection to between the hours of 8am and 8pm may be perceived as limitations to the study. Participants who engaged in activities or for example had a regular daily walk outside of the selected timeframe would not have been accurately represented in the data analysis. Older, more frail participants for whom activities of daily living may be the extent of their PA, may have had morning or bedtime routines omitted from the data analysis thus reducing their step-count or number of bouts of activity. Activities of daily living such as getting up and dressed or making breakfast are recognised as light intensity activity among older adults (NHS 2021). A small percentage of participants used a mobility aid such as a rollator frame or walking stick (n=3). The effect of the use of a mobility aid on the data was not analysed.

Usability was demonstrated following a brief education session and hands on experience with one mobility test. This prior knowledge of the system may be perceived as a limitation to the study of usability however, the time involved in an education session, which could possibly be delivered

during a routine clinical visit or in a group setting could mitigate the time needed for regular clinician-dependant, clinical-environment-based assessments.

The positive outcome following such brief intervention is promising for the potential to introduce a sensor system for continuous self-monitoring of data pertaining to frailty risk by older adults, unsupervised in their own home. This independently obtained data can provide actionable information, reducing greatly the need for clinician and clinical-based monitoring.

5.6 Conclusion

This study has demonstrated the ability among community-dwelling older adults to obtain a frailty risk score unsupervised in their own home using a QTUG system. It also demonstrated the validity of a wrist-worn smartwatch to capture data relating to frailty status among older adults. This information is important as it facilitates older adults to monitor their mobility and PA and identify their risk of developing frailty. Thresholds for activity levels predictive of frailty risk have been proposed. The study has introduced the use of a sensor and software system to independently capture parameters of PA relating to frailty risk, has examined the literature relating to technology use among older adults, and has triangulated the data by exploring through semi-structured interview, older adults' interest in engaging with such technology. Overall, participants demonstrated varying degrees of experience with technology, the minority being limited to the use of a phone, the majority reporting the use of multiple platforms including online functions. All, regardless of previous experience with technology were motivated to take part in the study. The majority undertook the training and endeavoured to use the smartwatch and QTUG system as required in this investigation. The results suggest researchers and manufacturers must continue to work together with older adult groups to develop devices suitable for use by this cohort.

Chapter Six - Concluding Remarks

Through the objectives outlined in chapter 1, this thesis has achieved its aim and demonstrated that quantitative measures of mobility and PA captured independently by older adults can be used to discriminate between frail and non-frail community-dwelling older adults.

Frailty is an avoidable and reversible biopsychosocial syndrome associated with ageing, resulting in adverse outcomes that are both life-changing and life-limiting, and which ultimately impacts on scarce healthcare resources. Current methods of screening for frailty involve traditional assessment tools which have inherent flaws, and wearable sensors which require expert analysis of data using specific algorithms that differ with each sensor-placement. Enabling older adults to recognise and monitor signs of frailty could influence mobility and PA behaviours, allow for earlier intervention and reduce the risk of developing frailty, thereby reducing the burden on the individual and society as a whole. The research presented in this thesis examines the parameters of mobility and PA associated with frailty, explores ways to collect this data and investigates if older adults could capture this data independently and unsupervised in their own home.

As identified in the first objective outlined in chapter 1, a review presented in chapter 2 examines the literature that has discussed the aetiology of frailty; its prevalence as identified using traditional assessment tools and the implications of frailty on both the individual and the health service. It introduces the concept of the use of technology in frailty screening and suggests an increasing acceptance among older adults in the use of technology. A systematic review of the literature presented in chapter 3 examining how wearable technology has been used to evaluate frailty in older adults highlights the heterogeneity in research methodologies, the parameters of mobility and PA examined in relation to frailty, and the variation in the body-locations of sensor positioning to capture data. This review highlighted the need for further research to identify a convenient, user-friendly device and body-location that older adults could potentially use to independently monitor and quantify frailty risk.

The following chapter in the thesis addresses the second objective and reports on the results of a laboratory-based study that sought to investigate the correlation between parameters of mobility and PA obtained from sensors positioned at different body locations. Results of the study demonstrated a strong correlation between step-count and parameters of gait which correlated with frailty, obtained from a body-worn sensor positioned at the waist with a criterion measure and that obtained from a wearable sensor and software system. It offers a single parameter that can be measured to indicate a risk of frailty. The research also highlighted the difficulties encountered analysing the raw data obtained from the research grade sensors, the need for specialised analysts and specific algorithms developed for data obtained from different body-locations. Therefore, the next stage of the research sought to explore if older adults could capture this data unsupervised in their own home using an alternative sensor system, and if the data obtained could be used to independently monitor the risk of frailty.

Results of the home-based study reported in chapter 5 address objectives 3 and 4 and demonstrate that older adults could indeed capture a frailty risk score independently, using a sensor and software system, and that parameters of PA that correlate with frailty could be obtained using a wrist worn smartwatch. Thresholds for the prediction of frailty were identified for each variable obtained from the smartwatch with varying predictive accuracy suggesting that a wrist-worn smartwatch can be used to obtain parameters of PA that could be used to indicate to them they are at risk of frailty. In fulfilment of the 5th and final objective of this thesis, the qualitative results of the home-based study identified older adult's willingness to engage with technology and their ability to capture data pertaining to mobility and PA independently. However, the results also suggest that the participants included in the study failed to see the relevance of capturing such data to their situation or stage in life.

Providing a user-friendly device for use by older adults to independently capture signs of frailty can mitigate the adverse outcomes of functional decline and disability. Results of this thesis will guide future work to highlight to community-dwelling older adults the importance of early frailty recognition, emphasise the relevance of its identification to their independence and quality of life, and

guide the development of a user-friendly device or sensor system suitable for use by older adults for continuous monitoring of data related to frailty risk.

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List of Appendices

5.4 Home-Based Study HSE Ethics Approval

5.5 Home-Based Study Participant Consent Form

5.6 Home-Based Study COVID-19 Protocol

5.7 Fried's Frailty Phenotype Frailty Assessment tool (FFP)

5.8 Frail Elderly Functional Assessment Questionnaire (FEFAQ)

5.9 Short Physical Performance Battery of tests (SPPB)

5.10 Case Report Form

5.11 Participant Information Booklet

5.12 Smartwatch Evaluation Framework

5.13 System Usability Score (SUS)

5.14 Home-Based Study Interview Questions and Protocol

5.15 Data Dictionary

5.16 Data Management Plan

5.17 Data Protection Impact Assessment Approval

Appendix 3.1 Systematic Review

Vavasour, G., Giggins, O.M., Doyle, J. *et al.* How wearable sensors have been utilised to evaluate frailty in older adults: a systematic review. *J NeuroEngineering Rehabil* **18,** 112 (2021). https://doi.org/10.1186/s12984-021-00909-0

Appendix 3.2 Systematic Review Search Strategy

Medline (Ebsco) Search strategy / terms

Search Alert: "AB (elderly OR aged OR older OR elder OR geriatric OR elderly people OR old people OR senior) AND AB (frailty OR frail OR "frailty syndrome") AND AB (wearable technology OR wearable devices OR body-worn sensor OR inertial sensor OR inertial measurement unit OR IMU OR accelerometer OR accelerometry OR actigraphy OR pedometer OR activity monitor OR daily steps OR GPS OR global positioning system OR activity tracker OR fitness trackers OR physical activity tracking OR physical fitness tracker OR biosensing OR biosensor) AND AB (physical activity OR physical function OR mobility OR gait OR walking OR ambulation OR function OR locomotion OR mobility OR speed OR postural transition OR sit to stand OR chair stand) AND AB (validity OR validation OR validation study OR reliability OR reliability study OR accuracy OR comparison OR comparison study) Date of Publication: 20100101-20201231 AND Apply equivalent subjects on 2020-03-31 06:13 AM"

	Concept 1	Concept 2	Concept 3	Concept 4
Key concepts	**Community-dwelling older adult Frail**	**wearable sensor**	**Measure of PA/Mob**	**Classify frailty**
Free text terms / natural language terms	Elderly Geriatric Aged Ageing Domicile Independent living In-place Frailty Frailty index Frailty syndrome	Wearables Wearable technology Wearable device Body-worn sensor Inertial sensor Inertial sensor unit (IMU) Accelerometer Accelerometry Pedometer Step counter GPS Activity tracker Physical Activity tracker Physical activity monitor Fitness tracker Bio-sensing Biosensor Ambulatory instruments	Physical activity Physical function Mobility Gait Speed Postural transition Sit to stand Chair stand	Validity Validation Validation study Accuracy reliability
Controlled vocabulary terms / Subject terms	Independent living (preferred term acc to MeSH) Aging in place (Narrower) Frailness Frailty (Preferred) Frailty syndrome(Narrower)	Activity trackers Physical fitness tracker		

Appendix 3.3 Systematic Review Excluded Articles

	Author & year	Reason for exclusion
1	Mueller 2019	Proof of concept. Not frailty
2	Keppler 2019	Not frailty
3	Chigateri 2018	Comparing algorithm with video
4	Soaz 2016	Validation of step-detection algorithm
5	Fontecha 2013	Development of app
6	Da Silva 2019	Not wearables
7	Chkeir 2019	Not wearables
8	Thiede 2016	< 60 yrs
9	Zhong 2018	< 60 yrs
10	Rahemi 2018	< 60 yrs
11	Martinez-Ramirez 2016	Participants cognitively impaired

Appendix 3.4 Systematic Review Included Articles

Author (Reference number) Year	Population, Frailty Classification, Setting	Objectives and Methods	Sensor and Location	Measure of Mobility / PA	Reported Findings	Quality Assessment Score
Martinez-Ramirez et al., (Martınez-Ramırez et al. 2011) 2011	N=56 community dwelling or assisted living volunteers (28 male, 28 female). FFP; 14 F (age: 79±4 years), 18 PF (age: 80±3 years), 24 NF (age: 40±3 years). Laboratory	To examine signals from a tri-axial sensor during quiet standing balance tests in a frail, pre-frail and healthy population. Participants were monitored during 10 s of quiet standing under 4 different conditions: FTO, FTC, FSO, FSC	MTx XSENS worn on lumbar spine (L3).	Postural sway (s)	Postural sway showed no significant differences among groups (NF, PF, F) under all conditions $p>0.05$ Frail group showed greater values in FTC $p<0.018$ compared with NF, PF.	15
Theou et al.,(Theou et al. 2012) 2012	N = 50 community dwelling female volunteers (age range: 63-90 years). FI (Deficit model); 17 high frailty tertile, 17 moderate frailty tertile, 16 low frailty tertile. Home	To examine the association of frailty with 5 PA assessment tools and determine if PA is different across levels of frailty. Participants wore all sensors simultaneously during normal daily activities at home for 10 hours. Maximum	ActiTrainer worn at the waist. Polar WearLink HR monitor at the chest. Garmin forerunner405 GPS at the wrist. Biometrics DataLOG P3X8 EMG on VL and BB.	Acceleration counts (n) Gait speed (m/s) Total step count (n) Time in non-sedentary activity (counts/min) Bursts of VL & BB	The FI was most significantly correlated with accelerometer steps ($r = -0.644$, $p<0.01$), PA minutes ($r = -0.617$, $p<0.01$) and MLTAQ ($r = -0.603$, $p<0.01$).	16

		voluntary exertions of Vastus Lateralis (VL) and Biceps Brachii (BB) were performed. A PA questionnaire was also administered.				
Millor et al., (Millor et al. 2013) 2013	N = 47 community dwelling or assisted living volunteers (26 male, 21 female). FFP; 13 F (age: 85±5 years), 16 PF (age: 78±3 years), 18 NF (age: 54±6 years). Laboratory.	To obtain kinematic measurements from 30 second chair sit to stand (CST) that can identify frailty. Participants were instructed to stand up and sit down from a standardised chair at their preferred speed as many times as possible within 30 seconds.	MTx XSENS worn on lumbar spine (L3).	Chair kinematics: Postural sway (s). Acceleration of STS (m/s^2). Velocity (m/s). No. of cycles of CST (n) Impulse phase duration (s).	Healthy participants performed a significantly greater n of STS cycles (22±7) compared with PF (15±5) and F (6±1). F participants had greater sway (30s) than PF (15s) or (Healthy (5s) $p<0.001$ Velocity of STS showed significantly greater values among PF (0.8m/s) compared with F (0.5m/s) Acceleration of STS and St-Si differentiated between levels of frailty when no. of cycles could not	14

<table>
<tr>
<td>Galan-Mercant et al (Al Galán-Mercant and Cuesta-Vargas 2013) 2013a</td>
<td>N = 30 volunteers aged > 65 years. Dwelling not specified.

FFP;
14 F (age: 83.72±6.37 years), 16 NF (age: 70.25±3.32 years).

Laboratory</td>
<td>To measure and describe variability in 3D acceleration, angular velocity and trunk displacement during the STS and St-Si transitions of 10-m Extended Timed Get Up and Go (ETGUG) test in F and NF participants and to analyse the difference between the two groups.

Participants performed a 10-m ETGUG test.</td>
<td>IPhone4 secured to chest.</td>
<td>Acceleration (m/s) in 3 axes. Angular velocity (deg/s) in 3 axes: Medial-Lateral (X),Vertical (Y) and Antero-Posterior (Z) of STS and St-Si transitions</td>
<td>Significant differences were found between the groups in accelerometry (P< 0.01) and angular displacement variables (P < 0.05) of both transitions

Mean (SD)
<table><tr><th>STS</th><th>F</th><th>NF</th><th>P value</th></tr><tr><td>X Axis Min Acceleration</td><td>-1.443 (1.211)</td><td>-3.136 (1.198)</td><td><0.001</td></tr><tr><td>Y Max</td><td>3.069 (1.240)</td><td>6.248 (1.913)</td><td><0.001</td></tr><tr><td>Y Min</td><td>-1.471 (0.788)</td><td>(-6.182 (2.415)</td><td><0.001</td></tr><tr><td>RV Max</td><td>7.065 (2.233)</td><td>8.962 (2.506)</td><td>0.025</td></tr></table>
Mean (SD)
<table><tr><th>St-Si</th><th>F</th><th>NF</th><th>P value</th></tr><tr><td>Y Axis Max Acceleration</td><td>3.567 (2.028)</td><td>6.200 (1.752)</td><td><0.001</td></tr><tr><td>Y Min</td><td>-2.950 (2.441)</td><td>-9.003 (4.334)</td><td><0.001</td></tr><tr><td>Z Min</td><td>-3.770 (1.928)</td><td>-6.645 (2.374)</td><td><0.001</td></tr><tr><td>RV Max</td><td>7.213 (2.566)</td><td>10.652 (3.510)</td><td>0.003</td></tr><tr><td>RV Min</td><td>0.364 (0.255)</td><td>0.808 (0.479)</td><td>0.002</td></tr></table>
Mean (SD)
<table><tr><th>STS</th><th>F</th><th>NF</th><th>P value</th></tr><tr><td>X Axis Max Angular Velocity</td><td>18.924 (8.843)</td><td>165.437 (120.989)</td><td><0.001</td></tr><tr><td>St-Si</td><td></td><td></td><td></td></tr><tr><td>X Axis Max Angular Velocity</td><td>38.146 (18.918)</td><td>145.150 (129.161)</td><td><0.001</td></tr></table></td>
<td>14</td>
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<table>
<tr>
<td>Galan-Mercant et al., (Alejandro Galán-Mercant and Cuesta-Vargas 2013) 2013b</td>
<td>N = 30 volunteers aged > 65 years. Dwelling not specified.

FFP;
14 F (age: 83.72±6.37 years), 16 NF (age: 70.25±3.32 years).

Laboratory.</td>
<td>To measure and describe variability in 3D acceleration, angular velocity and trunk displacement in the turn transition of 10-m Extended Timed Get Up and Go (ETGUG) test in F and NF participants and to analyse the difference between the two groups.

Participants performed a 10-m ETGUG test.</td>
<td>IPhone4 secured to chest.</td>
<td>Acceleration (m/s) in 3 axes. Angular velocity (deg/s) in 3 axes: Medial-Lateral (X),Vertical (Y) and Antero-Posterior (Z) Measurements of only the turning transition were examined.</td>
<td>Significant differences were found between the groups in accelerometry (P< 0.01) and angular displacement variables (P < 0.05) during the turn transition

Mean (SD)
<table>
<tr><th></th><th>F</th><th>NF</th><th>P value</th></tr>
<tr><td>X Axis Min Acceleration</td><td>-2.05 (0.962)</td><td>-5.77 (2.43)</td><td><0.003</td></tr>
<tr><td>Y Max</td><td>26.332 (9.271)</td><td>112.81 (147.91)</td><td>0.022</td></tr>
<tr><td>Y Min</td><td>-2.04 (0.945)</td><td>-9.448 (6.937)</td><td><0.001</td></tr>
<tr><td>Z Min</td><td>-1.815 (1.619)</td><td>-7.204 (2.438)</td><td><0.001</td></tr>
<tr><td>X Axis Max Angular Velocity</td><td>25.5 (14.21)</td><td>134.55 (135.52)</td><td><0.001</td></tr>
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<td>14</td>
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<tr>
<td>Greene et al., (Greene, Emer P Doheny, et al. 2014) 2014(a)</td>
<td>N = 399 community dwelling volunteers aged > 60 years.

FFP;
30 F, 185 PF, 184 NF

Laboratory.</td>
<td>To investigate an automatic, non-expert quantitative assessment of the frailty state based on a simple protocol employing body-worn inertial sensors.

Participants performed a 3-m TUG test.</td>
<td>SHIMMER sensor worn on each shin.</td>
<td>Temporal-Spatial gait, Angular velocity & Turn parameters of 3-m TUG test

NOTE: results of sensor-derived data are not detailed in this article. Discussed in previous article in relation to falls (Greene et al. 2012; Greene et al. 2010)</td>
<td>*Authors report Inertial sensor-based method was more accurate in assessing frailty than max grip strength (MGS) or TUG time alone Mean accuracy 72.30% 95%CI. This increased to 75.20% when stratified by gender. *However when stratified by gender MGS and manual TUG time produced mean classification accuracies of 77.65 and 71.82% respectively</td>
<td>14</td>
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<tr>
<td>Greene et al., (Greene, Emer P. Doheny, et al. 2014) 2014(b)</td>
<td>N = 124 community dwelling volunteers aged > 65 years

FFP;
66 F, 58 NF

Laboratory</td>
<td>To develop classifier models to assess frailty (and falls risk) using sensor-derived features of TUG, Five Time Sit to Stand (FTSS) and Balance tests.

Participants performed 3 tests:
A 3-m TUG test.
FTSS in which they were instructed to stand up and sit down from a standardised chair as quickly as possible five times. Balance was assessed during 40-s of quiet standing, feet 30-cm apart under conditions of eyes open (EO) and eyes closed (EC).</td>
<td>SHIMMER sensor worn on each shin, right thigh, lumbar spine (L5) and sternum.

A pressure sensor platform was also used for balance data collection</td>
<td>Temporal-Spatial gait, Angular velocity & Turn parameters of 3-m TUG test
Time and acceleration parameters of FTSS
Postural Sway distance, velocity

NOTE: results of sensor-derived data are not detailed in this article. Discussed in previous article in relation to falls (Greene et al. 2012; Greene et al. 2010; Doheny et al. 2012; Doheny et al. 2013).</td>
<td>Combining sensor data from all three tests to a single classifier model, stratified by gender yielded Accuracy in discriminating between F and NF: Male 94%; Female 84% (95% CI)

Accuracy % of Sensor data from separate tests identifying frailty (CI 95%):
<table>
<tr><td></td><td>TUG</td><td>BAL</td><td>FTSS</td></tr>
<tr><td>Male</td><td>89</td><td>78.48</td><td>73.33</td></tr>
<tr><td>Female</td><td>72.3</td><td>68.46</td><td>80.11</td></tr>
</table>
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<td>12</td>
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</table>

Chen et al., (Chen et al. 2015) 2015	N = 1527 community dwelling volunteers aged > 65 years. FFP; 142 F, 670 PF, 715 NF Home	To define the low PA domain of the CHS (Cardiovascular Health Study) frailty phenotype. Participants wore an accelerometer for one week with a minimum of 600-minutes per day and 3 days wear-time	Active style Pro Body-location not specified	Low energy expenditure (defined as scoring in the lowest 20% of energy expenditure of PA per day) (kcal/kg)	Results demonstrate satisfactory internal construct validity of a frailty phenotype using accelerometer-based measurement of the low PA domain. Reported Low PA 19.5%; Accelerometer-based Low PA 19.1%	
Schwenk et al., (Schwenk et al. 2015b) 2015	N = 125 community dwelling or assisted living volunteers aged > 65 years. FFP; 21 F, 60 PF, 44 NF. Home.	To evaluate the ability of sensor-based home assessment of established outcomes to identify PF and F. To explore new objective parameters which might increase the accuracy of frailty assessments. Gait assessment was carried out under single and dual-task (counting backwards in 1's from 100)	LEGSys, BalanSens, PAMSys with sensors located at shanks, thighs and lumbar spine.	Gait speed (m/s) Stride time (s) Stride length (m) Double support (% of stride time) Gait variability (CV) of stride velocity (%) Sway ankle, hip (deg^2) COM in AP and ML direction (cm) PA (Daily duration of postural transitions and movements such as walking, standing, sitting, or lying) as % of 24-h	Gait parameters stride length and double support had highest validity to separate NF from PF and PF from F in age-adjusted model (AUC .857 & .841). **Stride length** (m) NF vs PF p = 0.005, Cohen's d = 1.07, PF vs F p = 0.015, d = 0.85, NF vs F p <0.001, d = d1.64 **Double Support** (%) NF vs PF p <0.001, d = 0.93, PF vs F p = 0.043, d = 0.70, NF vs F p <0.001, d = 1.56 PA parameters **Walking bout duration variability** was most sensitive for discriminating between frailty levels (AUC = 0.818). In PF screening **Single-task walking speed** had highest validity (AUC = 0.802) and **no. of steps** was most sensitive (AUC = 0.763) Balance parameters, **Hip sway** best discriminated between NF/PF (p=0.004, Cohen's d = 0.62) but not between PF/F (p = 0.999) or NF/F (p = 0.254)	15

<table>
<tr><td></td><td></td><td>conditions. Participants walked 4.57m over-ground in their home at self-selected speed. Balance was assessed during 15s quiet standing with feet together, eyes closed.
PA was measured over a 24-hour period in participants home or assisted living setting.</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Martinez-Ramirez et al., (Martínez-Ramírez et al. 2015) 2015</td><td>N = 718 community dwelling or assisted living volunteers (319 males, 399 females).

FFP;
65 F (age: 80±5.6 years),

327 PF (age: 76.5±5.6 years),

326 NF (age: 73.4±5.5 years).

Setting not specified.</td><td>To examine the acceleration signals obtained from a tri-axial inertial sensor and to extract parameters that will provide complementary information to identify frail populations.

Participants walked in a straight line at self-selected speed over a distance of 3m.</td><td>MTx XSENS worn on lumbar spine (L3).</td><td>Temporal-Spatial gait parameters: Gait velocity, Step Regularity, Stride Regularity, Symmetry, Step Time CoV</td><td>All parameters in vertical acceleration demonstrated significant differences between each frailty group (<0.05) In the AP component, significant difference in RMS (p<0.05) between PF/F and NF/F
In ML component, significant difference in symmetry parameter only, between NF/F only (p<0.05). The sensitivity, specificity, accuracy and precision for prediction of frailty are significantly higher using a model combining gait velocity and gait parameters of step regularity.
<table>
<tr><td></td><td>AUC Gait Velocity (GV)</td><td>AUC GV and Gait Parameters</td><td>P value</td></tr>
<tr><td>NF</td><td>0.782</td><td>0.863</td><td>0.004</td></tr>
<tr><td>PF</td><td>0.535</td><td>0.683</td><td>0.028</td></tr>
<tr><td>F</td><td>0.823</td><td>0.896</td><td><0.001</td></tr>
</table></td><td>15</td></tr>
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<tr>
<td>Toosizadeh, Mohler, Wendel et al.,(Toosizadeh, Mohler, Wendel, et al. 2015) 2015</td>
<td>N = 122 community dwelling volunteers aged > 65 years.

FFP;
19 F, 59 PF, 44 NF.

Setting not specified.</td>
<td>To use open-loop and closed-loop mechanisms to explore differences in postural balance mechanisms between NF, PF and F individuals.

Participants performed two 15s balance trials, standing, feet close together, not touching, arms folded across chest, under two conditions; eyes open (FTO) and eyes closed (FTC).</td>
<td>BalanSens located on lumbar spine and shin.</td>
<td>Postural sway
Hip and ankle joint sway AP and ML
OLCL parameters: Δt(s); slope (cm^2/s); sway (cm^2)</td>
<td>AP sway was higher in F group but with no significant difference between groups
No significant result observed in ML sway between groups
OLCL parameters: OL duration was approximately 33% (F) and 22% (PF) shorter compared with NF(Mean 1.9 +/-1.1).
Sway was 164% (F) and 66% (PF) higher compared with NF (Mean .03+/-.02cm^2/s)
Results were more pronounced during FTC condition.

Frailty prediction using Body Sway Vs OLCL parameters as independent variables:
Sensitivity: F 77/100% PF 56/74%
Specificity: F 94/83% PF 93/89%</td>
<td>16</td>
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<tr>
<td>Toosizadeh, Mohler, Najafi, (Toosizadeh, Mohler and Najafi 2015) 2015</td>
<td>N = 117 community dwelling volunteers aged > 65 years.

FFP;
16 F, 51 PF, 50 NF.

Home.</td>
<td>To objectively identify frailty using wireless sensors and an upper extremity flexion motion assessment routine that does not rely on gait.

Participants performed a 50s trial of elbow flexion in a seated position in a chair at home while wearing</td>
<td>BioSensics LLC on upper arm near biceps muscle and wrist.</td>
<td>Speed of elbow flexion (deg/s)
Flexibility (deg)
Power (deg^2/s^2
Rise-time (s/100)
Moment (Nm)
Jerkiness (%)
Speed-reduction (%)
Flexion no. (n)</td>
<td>All parameters extracted from elbow flexion task were significantly different between frailty groups (p<0.05).
Speed had the largest effect size between NF/PF (1.48) and NF/F (2.83). Power had the largest effect size between PF/F (1.82).

Mean (SD)
<table><tr><th>Parameter</th><th>NF</th><th>PF</th><th>F</th><th>Pairwise p value (ES)</th></tr><tr><td>Speed</td><td>1,117 (247)</td><td>792 (187)</td><td>461 (215)</td><td>NF/PF p<0.001 (1.48)
NF/F p<0.001(2.83)
PF/F p<0.001(1.64).</td></tr><tr><td>Flexibility</td><td>134 (22)</td><td>115 (24)</td><td>87 (28)</td><td>NF/PF
p 0.006 (0.83)
NF/F
p<0.001 (1.99)
PF/F p<0.001(1.07).</td></tr><tr><td>Power</td><td>205.1 (116.3)</td><td>79.3 (40.5)</td><td>23.5 (15.7)</td><td>NF/PF
p<0.001 (1.44)
NF/F</td></tr></table></td>
<td>16</td>
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<table>
<tr><td></td><td></td><td>the upper limb sensors. The 50s trial consisted of 20s of elbow flexion on both sides with 10s rest in-between.</td><td></td><td></td><td><table><tr><td></td><td></td><td></td><td></td><td>p<0.001 (2.19)
PF/F
p = 0.45 (1.82)</td></tr></table></td><td></td></tr>
<tr><td>Jansen, (Jansen et al. 2015) 2015</td><td>N = 84 community dwelling volunteers aged > 65 years.

ISAR-HP;
10 F, 74 NF.

Home.</td><td>To assess differences in indoor and outdoor PA in older adults using GPS and accelerometers between NF and F older adults.

Participants were instructed to wear the sensor during waking hours for seven consecutive days.</td><td>ActigraphGT3X+ worn on right side of waist.</td><td>PA Intensity (minutes per day) (classified in counts per minute (cpm). (Sedentary 0-50; Light PA 51-759; Moderate to Vigorous PA (MVPA) > 760). Metabolic Equivalent (MET) (minutes) Distance walked / cycled (m).</td><td>No significant differences between frailty groups are reported (p<0.05)<table><tr><td>Metric</td><td>F Vs NF p value</td></tr><tr><td>LPA (Weekly)</td><td>p 0.79</td></tr><tr><td>MVPA</td><td>p 0.181</td></tr><tr><td>MET minutes</td><td>p 0.22</td></tr><tr><td>Distance walked</td><td>p 0.336</td></tr><tr><td>Distance cycled</td><td>p 0.75</td></tr></table></td><td>20</td></tr>
</table>

<table>
<tr>
<td>Toosizadeh et al., (Toosizadeh et al. 2016) 2016</td>
<td>N = 101 hospital in-patients aged > 65 years.

TSFI (Rockwood); 49 F (age: 80±9 years), 52 NF (age: 78±10 years).

Hospital.</td>
<td>To validate the accuracy of Upper-Extremity-Frailty (UEF) assessment in distinguishing between F and NF participants

Participants performed a 20s trial of elbow flexion-extension as quickly as possible in supine position</td>
<td>BioSensics LLC on upper arm near biceps muscle and wrist.</td>
<td>Speed of elbow flexion (deg/s)
Flexibility (deg)
Power (deg^2/s^2)
Rise-time (s/100)
Moment (Nm)
Speed-variability (%)
Speed-reduction (%)
Flexion no. (n)</td>
<td>UEF Sensitivity 78%; Specificity 82% for predicting Frailty.
The highest effect sizes between F & NF were observed in Speed (p<0.0001, Cohen’s d = 1.50), Flexion n (p<0.0001, Cohen’s d = 1.18) Power and Moment (p<0.0001, Cohen’s d = 1.10).
Speed was 45% less among F group.</td>
<td>15</td>
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<tr>
<td>Millor et al., (Millor et al. 2017) 2017</td>
<td>N = 718 community dwelling volunteers (319 male, 399 female).

FFP;
31 F (age: 79±6 years),

206 PF (age: 73±5 years),

194 NF (age: 74±5 years)

Setting not specified.</td>
<td>To establish a set of objective and quantitative parameters of 30-s CST that can classify frailty status.

Participants performed as many CST repetitions as possible within 30-s, at self-selected speed, starting from seated position, with arms folded across chest, and one 3-m walking test in a straight line over-ground at self-selected speed.</td>
<td>MTx Orientation Tracker worn at the lumbar spine (L3).</td>
<td>No. of CST cycles (n)
Gait velocity (GV) (m/s)
Chair kinematics (CK) (range of AP orientation (deg), acceleration (m/s) and power (Nm)) in 3 directions (vertical, ML, AP) and in 3 phases (Impulse, Up, Down)</td>
<td>Sensitivity, specificity, accuracy and precision values were significantly higher for the model based on CK (e.g., range of AP orientation, acceleration and power) than gait velocity or no. of cycles.

AUC (95% CI)
<table><tr><td>Parameter</td><td>NF</td><td>PF</td><td>F</td></tr><tr><td>nCycles</td><td>0.65 (0.529-0.789)</td><td>0.53 (0.410-0.650)</td><td>0.657 (0.536-0.765)</td></tr><tr><td>GV</td><td>NF 0.65 (0.529-0.789)</td><td>0.763 (0.649-0.856)</td><td>0.516 (0.395-0.635)</td></tr><tr><td>CK</td><td>1.000 0.649-0.856)</td><td>0.938 (0.395-0.635)</td><td>0.936 (0.852-0.980).</td></tr></table>
Mean(SD) of top 3 important parameters measured: (p<0.05)
<table><tr><td>Parameter</td><td>NF</td><td>PF</td><td>F</td></tr><tr><td>Impulse AP Orientation range:</td><td>18.81 (9.60)</td><td>22.01 (9.73)</td><td>25.76 (12.00)</td></tr><tr><td>V Max power STS</td><td>88.37 (50.75)</td><td>65.40 (40.18)</td><td>38.13 (34.75)</td></tr><tr><td>Impulse V acceleration StSi</td><td>1.21 (0.37)</td><td>1.10 (0.39)</td><td>0.79 (0.30)</td></tr></table></td>
<td>14</td>
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<tr>
<td>Parvanneh et al., (Parvaneh et al. 2017) 2017</td>
<td>N = 120 community dwelling volunteers.

FFP;
76 F/PF (age: 80.7±8.68 years),

43 NF (74.23±6.15 years).

Home.</td>
<td>To monitor and assess postural transition differences among frailty levels.

Spontaneous daily PA were recorded for a period of 48 hours. The first 24h was used for the purpose of this study</td>
<td>PAMSys worn at the sternum in a shirt-embedded pocket.</td>
<td>Postural transitions: STS, St-Si, stand-to-walk, walk-to-stand, sit-to-walk, and walk-to-sit (further classified into 'cautious' or 'quick' sitting) (n),
Ratio of cautious sitting (%)</td>
<td>Between group comparisons (with adjustment for age) demonstrate statistical significance in
Total transition n (p = 0.032)
NF: n1,174 ±468; PF: 878±-333
St-walk n (p = 0.011)
NF: 475±208; PF: 332±148
Wlk-st n (p = 0.011)
NF: 453±202; PF: 314±141

The ratio of cautious sitting was significantly higher (6.2%) in the PF/F compared to the NF group (p = 0.025, Cohen’s d = 0.22</td>
<td>15</td>
</tr>
<tr>
<td>Huising-Scheetz et al., (Huisingh-Scheetz et al. 2018) 2018</td>
<td>N = 651 community dwelling volunteers (341 Female; 310 Male). Aged >62 years

Modified Frailty Phenotype

94 F
317 PF
240 NF</td>
<td>To determine how hourly activity level is related to clinical frailty criteria in older adults.

Participants were instructed to wear the sensor continuously for 72 consecutive hours</td>
<td>ActiWatch Spectrum worn on the non-dominant wrist</td>
<td>Mean hourly cpm</td>
<td>Mean hourly CPM was approximately 7% lower per frailty point
β -0.03 p≤0.001</td>
<td>20</td>
</tr>
<tr>
<td>Lee et al., (Lee et al. 2018) 2018</td>
<td>N = 100 hospital in-patients (age: 78.9±9.1 years)

TSFI (Rockwood);
49 F, 51 NF.

Hospital</td>
<td>To provide a physical frailty phenotype assessment tool using a single wrist-sensor.

Participants wore a sensor on the wrist and upper arm while</td>
<td>LEGSys worn at wrist and upper arm.</td>
<td>No. of cycles (n)
Mean, CV and % Decline (PD)of kinematic parameters of elbow Flexion / Extension:
Angular velocity range (deg/s)
Angle range (deg)
Power range (deg^2/sec^3)</td>
<td>Model developed from single (wrist) sensor identified 5 dominant features with 80.0% accuracy in identifying Frailty (95%CI: 79.7-80.3%):
Mean (SD)
<table>
<tr><th></th><th>NF</th><th>F</th><th>p value</th></tr>
<tr><td>Mean of angle range</td><td>106.67 (25.89)</td><td>81.35 (31.0)</td><td>p<0.001</td></tr>
<tr><td>PD of power range</td><td>-9.3 (26.95</td><td>-19.58 (24.01)</td><td>p0.043</td></tr>
<tr><td>CV of elbow extension time</td><td>0.09 (0.05)</td><td>0.17 (0.23)</td><td>p0.014</td></tr>
<tr><td>Mean of elbow flexion time</td><td>419.98 (129.98)</td><td>644.18 (357.60)</td><td>p<0.001</td></tr>
</table></td>
<td>14</td>
</tr>
</table>

<table>
<tr>
<td></td>
<td></td>
<td>performing elbow flexion and extension as many times as possible within a 20-s timeframe, while in supine position.</td>
<td></td>
<td>Rising time, falling time, rising and falling time (ms)
Flexion time, extension time (ms)
Flex/ext rate (n/min)</td>
<td>
<table>
<tr><td>CV of elbow flexion time</td><td>0.09 (0.05)</td><td>0.15 (0.15)</td><td>p0.005</td></tr>
</table>
</td>
<td></td>
</tr>
<tr>
<td>Razjouyan et al., (Razjouyan et al. 2018) 2018</td>
<td>N =153 community dwelling volunteers aged > 60 years.

FFP;
33 F,
78 PF, 42 NF.

Home.</td>
<td>To determine which sensor-derived parameters are capable of discriminating between the three frailty categories, to identify the most significant independent parameters to discriminate pre-frailty, and to build a composite model to discriminate the pre-frail stage from non-frail and frail stages.

Participants wore a pendant sensor continuously for 48hours while undertaking normal activity including sleep.</td>
<td>PAMSys worn at the sternum.</td>
<td>Total time (%&min)Walking, Sitting, Standing , Lying and Sedentary Time Bouts(s) of Walking, Sitting, Standing , Lying
Intensity: light /moderate-vigorous activity
Total steps(n)

Sleep parameters</td>
<td>Significantly different between groups were:

Mean (SD)
<table>
<tr><th>Parameter</th><th>NF</th><th>PF</th><th>F</th><th>P value (Cohen’s d) NV v PF</th><th>PF v F</th></tr>
<tr><td>Total % Walk</td><td>8.7 (3.9)</td><td>5.1 (3.3)</td><td>3.2 (3.2)</td><td>p0.000 (d1.02)</td><td>p0.012 (d0.57)</td></tr>
<tr><td>Longest unbroken walking bout(s):</td><td>351.3 (347.9)</td><td>187.9 (223.9)</td><td>110.3 (132.4)</td><td>p0.001 (d0.56)</td><td>p0.002 (d0.42)</td></tr>
<tr><td>Total n. of steps:(N/1000)</td><td>12.2 (6.1)</td><td>6.7 (4.2)</td><td>4.3 (4.3)</td><td>p0.000 (d1.04)</td><td>p0.018 (d0.57)</td></tr>
<tr><td>Longest unbroken stepping bout</td><td>694.3 (743.0)</td><td>322.9 (411.0)</td><td>162.5 (184.2)</td><td>p0.000 (d0.62</td><td>p0.006 (d0.57)</td></tr>
<tr><td>Total duration of sedentary behaviour(h)</td><td>9.6 (2.6)</td><td>11.7 (3.2)</td><td>13.2 (4.2)</td><td>p0.001 (d0.73)</td><td>p0.029 (d0.40)</td></tr>
<tr><td>Mod to vigorous activity (%)</td><td>6.0 (4.0)</td><td>2.2 (2.4)</td><td>1.2 (1.5)</td><td>p0.000 (d1.13)</td><td>p 0.066 (d0.50)</td></tr>
</table>
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<td>14</td>
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<table>
<tr>
<td>Castaneda-Gameros et al. 2018)</td>
<td>N = 60 community dwelling volunteers aged > 60 years.

FFP;
10 F, 23 PF, 27 NF.

Home.</td>
<td>To examine the association between PA and sedentary time (ST), frailty and factors influencing PA behaviours in migrant older women from ethnically diverse backgrounds.

Participants were instructed to wear the sensor for a period of 7 days, only removing for bathing, swimming and sleeping. To be included in the analysis participants had to wear the device for at least 3 days including one weekend day, and for at least 10-h/day of valid wear time.</td>
<td>Actigraph GT3X worn at the hip.</td>
<td>PA Intensity (min/day) (classified in counts per minute) (cpm) Low-Light PA (LLPA)(100-1040cpm) High-Light PA (HLPA) (1,041-1,951cpm) Moderate-Vigorous PA(MVPA) (>1,952cpm)

ST (<100 cpm) (min/day)</td>
<td>Only MVPA was significantly different between NF/PF and F groups (18.4 and 18.7 vs. 3.4 min/day)p=0.03
Mean (SD)
<table>
<tr><th>Parameter</th><th>NF</th><th>PF</th><th>F</th><th>p value</th></tr>
<tr><td>ST</td><td>523.7 (85.7)</td><td>533.1 (85.7)</td><td>576.7 (7.0)</td><td>p 0.48</td></tr>
<tr><td>LLPA</td><td>207.4 (57.8)</td><td>204.9 (66.7)</td><td>161.4 (68.7)</td><td>p 0.51</td></tr>
<tr><td>HLPA</td><td>27.1 (13.6)</td><td>29.8 (17.2</td><td>18.4 (23.0)</td><td>p 0.36</td></tr>
<tr><td>MVPA</td><td>18.4 (19.9)</td><td>18.7 (17.6)</td><td>3.4 (4.5)</td><td>p <0.01</td></tr>
</table>
MVPA F/NF p 0.02; F/PF p <0.01</td>
<td>16</td>
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<table>
<tr>
<td>Jansen et al., (Jansen et al. 2019) 2019</td>
<td>N = 112 community dwelling volunteers aged > 65 years.

FFP;
19 F, 53 PF, NF 40

Home.</td>
<td>To investigate whether the association between motor capacity and mobility performance is moderated by frailty status in older adults.

Participants wore the LEGSys sensors while performing a walk test under two conditions: at self-selected speed over a distance of 4.57m and as quickly as possible over a distance of 10m.

Participants wore the PAMSys sensor for a period of 48 hours while carrying out normal activities</td>
<td>PAMSys sensor embedded in a shirt. Location not specified.

LEGSys sensors worn at bilateral shins, thighs and lumbar spine (specific location not indicated).</td>
<td>Percentage of time walking or standing (%).
Average number of steps per walking bout (n).
Max number of steps in one walking bout (n).
Normal walking speed (NWS) (m/s).
Fast walking speed (FWS) (m/s).</td>
<td>Mean (SD)
<table><tr><th>Parameter</th><th>NF</th><th>PF</th><th>F</th><th>P value</th></tr><tr><td>% PA</td><td>25.0 (7.1)</td><td>18.9 (6.0)</td><td>16.4 (7.3)</td><td>< 0.001</td></tr><tr><td>Max steps in one bout</td><td>1668 (1724)</td><td>591 (556)</td><td>285 (387)</td><td>< 0.001</td></tr><tr><td>Average steps per bout</td><td>39 (24)</td><td>33 (15)</td><td>27 (12)</td><td>0.25</td></tr><tr><td>NWS</td><td>1.18 (0.15)</td><td>0.92 (0.22)</td><td>0.64 (0.25)</td><td>< 0.001</td></tr><tr><td>FWS</td><td>1.47 (0.22)</td><td>1.13 (0.27)</td><td>1.07 (0.12)</td><td><0.001</td></tr></table>
Using a moderation analysis to investigate how frailty changes the effect of motor capacity on mobility performance, association between motor capacity & mobility performance was found in PF and F groups only.</td>
<td>14</td>
</tr>
</table>

<table>
<tr>
<td>Zhou et al., 2019</td>
<td>N =61 community dwelling volunteers aged > 60 years.
N = 17 volunteers aged 20 -35 years.

FFP; 8 F, 29 PF, 24 NF.

Out-patients clinic.</td>
<td>To examine whether parameters from an instrumented trail-making task (iTMT) can distinguish different frailty stages and could describe different frailty phenotypes

The iTMT included standing in front of a standard computer in double-leg stance and performing a series of virtual trail-making tests by rotating the ankle joint to move a computer-cursor.
For gait speed participants were instructed to walk at habitual speed for 20m.</td>
<td>LEGSys worn on both shins</td>
<td>Gait Speed (m/s).
Sensor data (iTMT-derived parameters):
Time (s)
Velocity (unit/s)
Power (unit^2/sec^3)
Exhaustion (%) (% of decline in max ankle rotation velocity from Trials 1-5 and 11-15)
Variability (%) (CoV of ankle rotation velocity during the first 15 trials</td>
<td>Results indicate Gait Speed (p0.032), iTMT Velocity (p0.025) and Power (p0.040) can significantly distinguish between NF/F & PF/F groups (p<0.05).

<table>
<tr><th>Parameter</th><th>NF</th><th>F (PF and F)</th><th>p value (Cohen’s d)</th></tr>
<tr><td>Gait speed</td><td>1.06 (0.19)</td><td>0.94 (0.24)</td><td>p0.032 (0.56)</td></tr>
<tr><td>iTMT: Velocity</td><td>6.31 (0.98)</td><td>5.67 (1.09)</td><td>p0.025 (0.62)</td></tr>
<tr><td>Power</td><td>90.56 (26.73</td><td>73.70 (28.47)</td><td>p0.040 (0.61)</td></tr>
<tr><td>Exhaustion</td><td>8.23 (15.19</td><td>9.41 (10.58)</td><td>p0.698 (0.09)</td></tr>
<tr><td>Variability</td><td>20.92 (4.94)</td><td>23.05 (7.84)</td><td>p0.241 (0.33)</td></tr>
</table>

iTMT Velocity, Power, Exhaustion and Variability enable significant (p<0.05) discrimination between presence and absence of frailty phenotypes as determined by the FFC; slowness (d=1.40), weakness (d=1.38), exhaustion (d=0.98) and inactivity (d=0.90)</td>
<td>14</td>
</tr>
<tr>
<td>Mulasso et al., 2019</td>
<td>N = 25 community dwelling volunteers aged > 65 years.

Part B of TFI;</td>
<td>To investigate the relationships between the Mobility Index (MI) provided by the ADAMO System and a mobility</td>
<td>ADAMO System accelerometer @ wrist</td>
<td>Time spent in Low, Mod, Vigorous Activity (%)
Time to complete walk test(s)</td>
<td>4oo-m walk test correlates with physical frailty only. The MI is strongly associated with total frailty (Physical, Psychological & Social) Significant differences were observed between F and NF individuals for Low, Moderate and Vigorous activity.

Mean (SD)
<table>
<tr><td>Variable</td><td>NF</td><td>F</td><td>P value (ES)</td></tr>
<tr><td>Low activity</td><td>58.8 (6.6)</td><td>42.0 (8.3)</td><td>P < 0.001 (0.657)</td></tr>
<tr><td>Mod activity</td><td></td><td></td><td>P 0.008 (0.292)</td></tr>
</table></td>
<td>14</td>
</tr>
</table>

	14 F 11 NF Laboratory and Home	screening tool with frailty. To test the acceptance of the ADAMO System Carewatch for PA measurement (as part of project (SPRINTT) to validate and implement a practical and clinical prevention of frailty). Participants attended a test centre and were timed walking 400m (8 laps of a corridor). They then at home wore a wrist-watch continuously for 7 days.				25.5 (7.6)	33.8 (10.6		
					Vigorous activity	15.7 (7.2)	24.2 (10.8)	P 0.035 (0.195)	

<table>
<tr>
<td>Lepetit et al., 2019</td>
<td>N = 50 volunteers aged > 65 years. Dwelling not specified.

FI (Rockwood); 24 healthy young (HY) (age: 25±3 years),

11 F (age: 87±6 years), 39 NF (Healthy Senior) (age: 70±4 years).

Laboratory.</td>
<td>To design a diagnostic tool to detect functional deficit based on a single sensor during STS.

Participants were asked to perform STS at self-pace without UL assistance, 3 - 5 repetitions as physical ability allowed.</td>
<td>APDM worn at the chest.</td>
<td>STS parameters including:
Task duration (TD)(s)
Trunk: COM velocity (m/s)
Angular velocity (rad/s)
Inclination (Incl)
Acceleration (m/s2).
Kinetic energy (mEK)(J)</td>
<td>Frailty significantly influences STS (p<0.01). All mean-based parameters (mVG, mAcc, mAz, mAxy, mEK), max EK and maxVG decreased significantly for FS group compared with HY & HS (NF) groups
<table>
<tr><td>Parameter</td><td>NF</td><td>F</td><td>p value</td><td>AUC</td></tr>
<tr><td>mVG</td><td>0.390 (0.065)</td><td>0.242 (0.049)</td><td>P <0.01</td><td>0.97</td></tr>
<tr><td>mOmega:</td><td>0.637 (0.165);</td><td>0.43 (0.152</td><td>P <0.01</td><td>0.825</td></tr>
<tr><td>TD</td><td>1.92 (0.38);</td><td>4.22 (2.02)</td><td>p<0.01</td><td>0.923</td></tr>
<tr><td>mAcc</td><td>1.69 (0.41</td><td>0.91 (0.39)</td><td>p<0.01</td><td>0.911</td></tr>
<tr><td>mAz</td><td>1.16 (0.33</td><td>0.54 (0.27)</td><td>p <0.01</td><td>0.935</td></tr>
<tr><td>mAxy</td><td>1.03 (0.23);</td><td>0.63 (0.23)</td><td>p <0.01</td><td>0.886</td></tr>
<tr><td>mEK</td><td>2.97 (1.24</td><td>0.90 (0.51)</td><td>p <0.01</td><td>0.965</td></tr>
</table>
</td>
<td>15</td>
</tr>
<tr>
<td>Yuki et al., 2019</td>
<td>N = 401</td>
<td>To examine the association between frailty and PA</td>
<td></td>
<td>Steps (n)
LPA, MVPA (min)</td>
<td>Odds ratio for frailty:
<5000 steps 1.85 [95% CI),
MVPA for <7.5 minutes 1.80 (95% CI)
No significant association was observed between frailty and LPA</td>
<td></td>
</tr>
<tr>
<td>Ziller et al., (Ziller et al. 2020) 2020</td>
<td>N = 47 community dwelling volunteers aged > 65 years

FFP;
9 F, 15 PF, 23 NF

Home and Clinic</td>
<td>To analyse the variance in prevalence of frailty by using different models and methods for measuring the Low PA (LPA) criterion of the frailty assessment tools.

Participants were instructed to wear the sensor during</td>
<td>Actigraph worn at hip</td>
<td>Sedentary time (< 100 cpm) (hours/day).
MVPA (> 1952 cpm) OR
> 1041cpm) (min/week).
Daily steps (n/day)</td>
<td>Using accelerometer-based data for the PA criterion and Fried’s cut-off points, Prevalence of frailty calculated:
7F, 17 PF, 23 NF.</td>
<td>19</td>
</tr>
</table>

		waking hours for seven consecutive days. Wear time of four to seven days with at least six hours were included.				

<table>
<tr>
<td>Chen et al., 2020</td>
<td>N = 819 community dwelling volunteers aged > 65 years.

98 F
228 PF
493 NF

FRAIL J

Community Center</td>
<td>To investigate if sedentary behaviour, PA patterns and n steps are associated with frailty status and to determine optimal cut-off value of each to discriminate between F and NF.

Participants were instructed to wear the sensor for during waking hours for 7 consecutive days.
To be included in the analysis participants had to wear the device for at least 4 days and min 10-h per day</td>
<td>Active style Pro HJA- 350IT worn at the waist</td>
<td>Sedentary Time (≤ 1.5 METs)
LPA (1.5 – 3 METs)
MVPA ≥ (3 METs)
(min/day)
Steps (n)</td>
<td>Mean (SD)
<table>
<tr><th></th><th>NF</th><th>PF</th><th>F</th><th>P value</th></tr>
<tr><td>Total sedentary time</td><td>460.1 (113.0)</td><td>450.7 (104.4)</td><td>455.3 (118.7)</td><td>0.49</td></tr>
<tr><td>Total MVPA</td><td>54.5 (33.3)</td><td>52.8 (32.5)</td><td>40.5 (32.7)</td><td><0.001</td></tr>
<tr><td>*Bouted MVPA</td><td>22.5 (24.1)</td><td>21.2 (25.1)</td><td>12.6 (20.5)</td><td><0.001</td></tr>
<tr><td>Steps</td><td>5872.2 (2699.7)</td><td>5695.1 (2792.8)</td><td>4451.7 (3057)</td><td><0.001</td></tr>
</table>
*Bouted MVPA defined as ≥ 10 consecutive min, with an allowance for up to 2 min out of 10 to drop below the MVPA intensity threshold

Cut-off value to discriminate between F and NF were:
<table>
<tr><td>MVPA (min/day)</td><td>43.25</td></tr>
<tr><td>Bouted MVPA</td><td>9.13</td></tr>
<tr><td>Steps (n)1</td><td>3841</td></tr>
</table></td>
<td></td>
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</table>

<table>
<tr>
<td>Kikuchi et al., 2020</td>
<td>N = 511 community dwelling adults aged > 65 years.

J-CHS ; 13 F
234 PF
264 NF

Home</td>
<td>The present study aimed to examine associations of intensity-specific physical activity and bout-specific sedentary time with frailty status.

Participants were asked to wear a device for 7 consecutive days</td>
<td>Active style Pro HJA-750C worn at the hip</td>
<td>Bouts of ST (min/day)
Intensity of PA (METs) (ST ≤ 1.5 METs,
LPA 1.5 – 3 METs,
MVPA ≥ (Mins)3 METs)</td>
<td>MVPA and prolonged SB differed significantly between frailty levels

Mean (SD) p value
<table>
<tr><th>Parameter</th><th>NF</th><th>PF</th><th>F</th><th>NF v PF</th><th>PF v F</th><th>NF v F</th></tr>
<tr><td>Short-Bout of SB</td><td>273.1 (65.4)</td><td>261.2 (61.7)</td><td>231.0 (59.0)</td><td>0.287</td><td>0.0002</td><td>0.0001</td></tr>
<tr><td>Prolonged Bout of SB</td><td>167.3 (115.5)</td><td>186.0 (110.0)</td><td>289.9 (158.7)</td><td>0.0003</td><td><0.0001</td><td><0.0001</td></tr>
<tr><td>LPA</td><td>406.2 (97.4)</td><td>374.1 (101)</td><td>298.6 (157.9)</td><td>0.574</td><td>0.119</td><td>0.182</td></tr>
<tr><td>MVPA</td><td>58.6 (40.1)</td><td>47.4 (38.8)</td><td>14.9 (21.1)</td><td>0.0003</td><td><0.0001</td><td><0.0001</td></tr>
</table>
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<table>
<tr>
<td>Apsega (2020)</td>
<td>N = 133 community dwelling adults aged > 60 years.
86 female
46 male

FFP;
37 F
66 PF
30 NF

Not Specified</td>
<td>To examine the ability of wearable sensor-based assessments of gait to discriminate between frailty levels and to determine the cut-offs of the most sensitive gait parameters that separated the frailty levels.

Participants performed a 3-m TUG test</td>
<td>Shimmer sensors worn at bilateral thighs, shins and dorsum of feet.</td>
<td>Stance phase time (s)
Swing phase time (s)
Gait speed (cm/s)
Stride time, on right and left leg accordingly (s)
Double support time (ms)
Cadence (steps/min).</td>
<td>Parameters for discriminating three frailty levels:

<table>
<tr><th></th><th colspan="3">PF vs. NF</th><th colspan="3">Frail vs. NF</th></tr>
<tr><th></th><th>OR</th><th>95% CI</th><th>p Value</th><th>OR</th><th>95% CI</th><th>p Value</th></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>TUG time</td><td>2.36</td><td>1.68–3.31</td><td><0.0012</td><td>0 .67</td><td>1.89–3.78</td><td><0.001</td></tr>
<tr><td>Dynamic gait</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Index score</td><td>0.80</td><td>0.70–0.92</td><td>0.001</td><td>0.71</td><td>0.60–0.83</td><td><0.001</td></tr>
<tr><td>Gait speed</td><td>0.93</td><td>0.90–0.95</td><td><0.001</td><td>0.92</td><td>0.89–0.95</td><td><0.001</td></tr>
<tr><td>Stride time</td><td>1.006</td><td>1.003–1.009</td><td><0.001</td><td>1.006</td><td>1.003–1.009</td><td><0.001</td></tr>
<tr><td>Swing phase</td><td>1.007</td><td>1.001–1.013</td><td>0.028</td><td>1.008</td><td>1.001–1.015</td><td>0.024</td></tr>
<tr><td>Stance phase</td><td>1.009</td><td>1.005–1.013</td><td><0.001</td><td>1.008</td><td>1.004–1.012</td><td><0.001</td></tr>
<tr><td>Double support</td><td>1.02</td><td>1.01–1.03</td><td><0.001</td><td>1.01</td><td>1.01–1.02</td><td>0.002</td></tr>
<tr><td>Cadence</td><td>0.87</td><td>0.83–0.92</td><td><0.001</td><td>0.83</td><td>0.78–0.89</td><td><0.00</td></tr>
</table>

<table>
<tr><th colspan="3">Cut-off values of the most sensitive gait parameters that separated the frailty levels:</th></tr>
<tr><th></th><th>F Vs PF or NF</th><th>PF or F Vs NF</th></tr>
<tr><td>TUG Time</td><td>11.6</td><td>9.27</td></tr>
<tr><td>DGI</td><td>15.0</td><td>19.0</td></tr>
<tr><td>GS</td><td>0.60</td><td>0.82</td></tr>
<tr><td>Stride</td><td>1.27</td><td>1.19</td></tr>
<tr><td>Stance</td><td>0.80</td><td>0.68</td></tr>
<tr><td>Swing</td><td>0.48</td><td>0.48</td></tr>
<tr><td>DS</td><td>0.16</td><td>0.14</td></tr>
<tr><td>Cadence</td><td>99.54</td><td>101.22</td></tr>
</table>
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Appendix 3.5 AXIS Critical Appraisal Tool

Yes / No / Don't Know

Introduction

1 Were the aims/objectives of the study clear?

Methods

2 Was the study design appropriate for the stated aim(s)?

3 Was the sample size justified?

4 Was the target/reference population clearly defined? (Is it clear who the research was about?)

5 Was the sample frame taken from an appropriate population base so that it closely represented the target/reference population under investigation?

6 Was the selection process likely to select subjects/participants that were representative of the target/reference population under investigation?

7 Were measures undertaken to address and categorise non-responders?

8 Were the criterion measure and outcome variables measured appropriate to the aims of the study?

9 Were the *risk factor and outcome variables measured correctly using instruments/ measurements that had been trialled, piloted or published previously?

10 Is it clear what was used to determined statistical significance and/or precision estimates? (e.g., p values, CIs)

11 Were the methods (including statistical methods) sufficiently described to enable them to be repeated?

Results

12 Were the basic data adequately described?

13* Does the response rate raises concerns about non-response bias?

14 If appropriate, was information about non-responders described?

15 Were the results internally consistent?

16 Were the results for the analyses described in the methods, presented?

Discussion

17 Were the authors' discussions and conclusions justified by the results?

18 Were the limitations of the study discussed? Other

19 Were there any funding sources or conflicts of interest that may affect the authors' interpretation of the results?

20 Was ethical approval or consent of participants attained?

*Negative / unfavourable answer results in 'Y' .'. Yes = 0; No = 1

Appendix 4.1 Laboratory-Based Study Ethics Approval

DKIT
An Scoil Sláinte & Eolaíochta
School of Health and Science

7th January 2020

Ms. Grainne Vavasour,
NetwellCASALA Research Centre,
School of Health and Science,
Dundalk Institute of Technology,
Dundalk,
Co. Louth

Re: Comparing parameters of mobility obtained from body-worn sensors with clinical measurements

Dear Grainne,

The School Ethics Committee reviewed the original ethics application for the above study at its meeting dated the 17th October 2019 and the amended application at its meeting dated the 16th December 2019. I note the clarifications which you sent to me on the 6th January 2020. This application is now approved.

Wishing you the best of luck in your Research.

Yours Sincerely,

Edel Healy

Dr.Edel Healy
Chair of School of Health & Science Ethics Committee
cc. Dr. Oonagh Giggins, Netwell CASALA

Appendix 4.2 Laboratory-Based Study Recruitment Advertisement

WE ARE LOOKING FOR VOLUNTEERS

Calling all staff and students:
Are you aged 18 - 65, able to walk independently and willing to take part in our research?

We are carrying out a laboratory-based research study to test the reliability and accuracy of body-worn sensors in measuring physical activity.
Please contact me to express your interest and for any further information

grainne.vavasour@dkit.ie

Appendix 4.3 Laboratory-Based Study Participant Information Leaflet

Participant Information Leaflet

Study title: *Comparing parameters of mobility obtained from body-worn sensors with clinical measurements*

Researcher Name: Grainne Vavasour

Telephone number of Researcher: 087 2164685

Research Supervisor Name: Dr Oonagh Giggins

You are being invited to take part in a research study to be carried out at Dundalk Institute of Technology (DkIT).

Before you decide whether or not you wish to take part, you should read the information provided below carefully and, if you wish, discuss it with your family, friends or GP

Take time to ask questions – don't feel rushed and don't feel under pressure to make a quick decision.

You should clearly understand the risks and benefits of taking part in this study so that you can make a decision that is right for you. This process is known as 'Informed Consent'.

You don't have to take part in this study and a decision not to take part will not affect you in any way.

You can change your mind about taking part in the study any time you like. Even if the study has started, you can still opt out. You don't have to give us a reason. If you do opt out, rest assured it won't affect you in any way.

Why is this study being done?

This study is taking place to find out if measurements of mobility and physical activity obtained from body-worn sensors placed in different locations on the body are comparable in terms of accuracy to those obtained from clinical observation and from a validated inertial sensor and software system (Kinesis QTUG).

Who is organising and funding this study?

This study is part of a PhD thesis undertaken at DkIT, part funded by the HEA (Higher Education Authority)

Why am I being asked to take part?

You are being asked to take part in this study either because you are

18 - 65 years of age OR > 65 years of age

Healthy

Independently mobile

Physically capable of performing a series of mobility and physical activity tests

Have no cognitive or neurological deficits

Have no history in the past 12 months of orthopaedic trauma or surgery

How will the study be carried out?

Twenty healthy adult volunteers will be recruited and asked to perform a series of simple tests in an exercise laboratory setting in the PJ Carroll building, DkIT.

What will happen to me if I agree to take part?

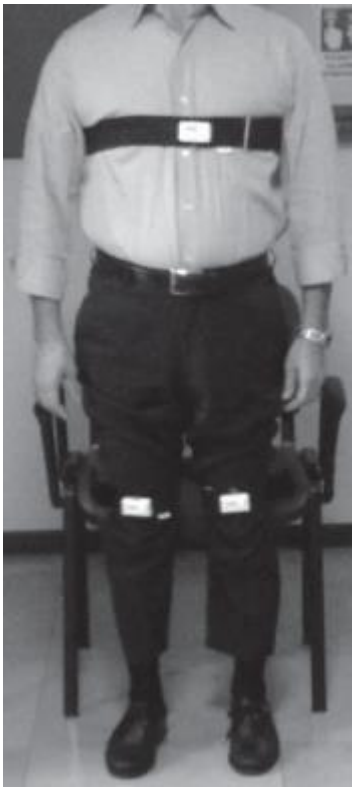
You will be asked to provide baseline participant profile information including demographic details, past medial history and current medications.

You will be asked to complete a Covid-19-specific questionnaire, have your temperature checked and your name and phone number recorded on a Contact Log. This Log will be stored securely by the researcher on campus at DkIT for 1 month from the date of your visit to fulfil a legal requirement of the Health and Safety Authority.

You will then be asked to wear a number of different sensors on the body for example on the legs, arms and trunk while performing a standard 'timed up and go' (TUG) test.

A TUG test measures in seconds, the time taken to stand up from a standard chair seat height 46cm (18in), walk a distance of 3m (10 feet), turn, walk back to the chair and sit down.

Resting pulse, pulse oximetry, height, weight and leg length will also be measured. A pulsometer worn on the middle finger will be used to measure pulse rate and oxygen saturation.



The TUG test will be carried out under different conditions

at normal pace

at normal pace while counting backwards from 100

at normal pace while carrying a glass of water

A further walking test will be performed at a predetermined slower than normal pace (<0.8m/s) on a treadmill for three minutes.

The testing will be carried out by a chartered physiotherapist. Non-identifiable video of each mobility test will be recorded for the purpose of retrospective manual counting of steps taken during each test. It will take 45 - 60 minutes. All communication and data obtained from the measurements will be confidential, recorded and discussed anonymously for the purpose of the study only.

What are the benefits?

There are no direct benefits to you. However, the data obtained from your participation in this study will assist with a subsequent study on wearable sensors and detection of frailty in older adults.

What are the risks?

There is minimal risk involved, no more than that experienced with activities of daily living.

As with any form of exercise, there is a minimal risk of injury associated with the performance of the exercises within the study e.g. a muscle strain, slip or trip. However, the exercises involved in the study are very simple i.e. walking 3 metres over ground and walking on a treadmill for 3 minutes. The study will be supervised by a chartered physiotherapist. The surface you will be walking on will be clean and dry, well lit and free from any obstacles or hazards.

The study will however take some of your time, approximately 45 – 60 minutes.

If you consider any of the physical activity to be too challenging for you then you should not take part in the study.

What if something goes wrong when I'm taking part in this study?

In the unlikely event of any emergency during the study, medical assistance will be called. If there are any incidental findings i.e. if we observe anything we think requires medical attention we will discuss with you and advise you to seek the appropriate medical advice e.g. your GP.

Will it cost me anything to take part?

There are no financial implications for participants.

Is the study confidential?

All information and results provided as a result of this study will be kept securely and confidentially at DkIT for the duration of the study and for a period of 7 years thereafter, in keeping with GDPR (General Data Protection Regulations, 2018) except Covid-19-specific information which will be destroyed after 1 month as per DkIT and Health and Safety Authority guidelines.

Your name and contact details will be stored separately from the information you provide.

At the start of the study, each participant will be given a 'participant ID', which will be stored securely and confidentially on a password-protected electronic file. Only the research team will have access to the file that matches your details with your id.

Communication will be confidential, between you and the researcher.

Results of the tests will be kept confidentially and used for the purposes of this study only. This includes writing a report for a doctoral thesis, details of which may be sent for publication in a scientific journal. You will not be identifiable in any reports, documentation or publication.

You are free to discuss the study with friends and family as you wish and on completion of the study you can be provided with your own results upon request.

Where can I get further information?

If you have any further questions about the study or you need any further information now or at any time in the future, please contact:

Grainne Vavasour grainne.vavasour@dkit.ie Phone: 087 2164685

Appendix 4.4 Laboratory-Based Study Consent Form

Validation study Participant Consent Form

Study title:

Comparing parameters of mobility obtained from body-worn inertial sensors with clinical measurements

I have read and understood the **Information Leaflet** about this research project. The information has been fully explained to me and I have been able to ask questions, all of which have been answered to my satisfaction.	**Yes** □	**No** □
I understand that I don't have to take part in this study and that I can opt out at any time. I understand that I don't have to give a reason for opting out and I understand that opting out won't affect me in any way	**Yes** □	**No** □
I have been assured that information about me will be kept private and confidential.	**Yes** □	**No** □
I have been given a copy of the Information Leaflet and this completed consent form for my records.	**Yes** □	**No** □
I have been advised on the need to fill out a Covid-19-specific self-declaration form prior to participation in the study	**Yes** □	**No** □
I give my permission for non-identifiable video recording of my participation in each mobility test for the purpose of retrospective manual counting of steps taken	**Yes** □	**No** □
Storage and future use of information: I give my permission for information collected about me to be stored or electronically processed for the purpose of research and to be used in related studies or other studies in the future but only if the research is approved by a Research Ethics Committee.	**Yes** □	**No** □
I understand details of my name and phone number will be recorded on a Contact Log and stored securely for 1 month from the date of my visit to the research centre for purposes of contact tracing in the event of a case of Covid-19, as a legal requirement, and will thereafter be destroyed	**Yes** □	**No** □

Participant Name (Block Capitals) Participant Signature Date

To be completed by the Researcher:

I, the undersigned, have taken the time to fully explain to the above participant the nature and purpose of this study in a way that they could understand. I have explained the risks involved as well as the possible benefits. I have invited them to ask questions on any aspect of the study that concerned them

Researcher Name (Block Capitals) Signature Date

Qualifications:

Appendix 4.5 COVID-19 Protocol and Questionnaire

Procedure for ensuring health and safety of participants and investigators in validation study:

Pre-study

The day prior to the validation study, participants will be screened over the phone for risk factors relating to Covid-19. See accompanying Visitor Covid-19 Questionnaire (Appendix A). Those deemed appropriate for inclusion will be invited to attend the study centre at a designated appointment time. To reduce face-to-face contact time demographic and subjective details will be obtained from each participant over the phone.

Day of Study

At a time no earlier than 5 minutes before allocated appointment, the participant will be met at a reception area at the entrance to the study centre by the principal investigator who will be wearing a surgical mask. The participant will be supervised with appropriate hand sanitising and given the Visitor Covid-19 Questionnaire to read in full, complete and sign. Following further hand sanitisation a surgical facemask will be provided with instruction on correct donning / doffing.

Both participant and investigator will proceed into the test / lab area maintaining social distance as required by NPHET guidelines.

The participant's temperature will be measured using a non-contact temperature probe (Manufacturer's details). If the temperature is above 37.5 degrees Celsius the Covid-19 Suspected Case Procedure will be implemented (Appendix B). If the body-temperature is below 37.5 C, the study will proceed:

Disposable, single-use personal protective facemask, apron and gloves will be worn by the investigator for obtaining each participant's measurements of weight, height and leg-length using wipe-able measurement tools (Manufacturers details of weighing scales, height and leg-length measurement-tools).

The participant will be instrumented with an inertial sensor at bilateral ankles, hip, L33, bilateral wrists (to include dominant and non-dominant upper limb) and sternum (Shimmer, Dublin, Ireland; Kinesis QTUG, Kinesis Health Technologies, Dublin, Ireland) using single-use elasticated material and/or tape.
An exercise will be performed by the participant under the direction of the investigator.

On completion of the exercise, when appropriate, sensors will be removed and cleaned according to manufacturer's guidelines:

- Wash hands properly before removing or handling the sensors
- Ensure a face mask and gloves are used in situations where it is difficult to practice social distancing or when handling the sensors after being worn
- Clean the outside of the sensor first and then use a common disinfectant to wipe down the sensor and clip surface and leads (if applicable).

The participant will be advised on and supervised with hand hygiene, escorted to the exit where instructions will be given on safe removal and disposal of facemask and further hand sanitising.

Sensors will be cleaned with a hypochlorite solution and left to air-dry. All surfaces will be cleaned and disinfected with 70% alcohol wipes. 90-minutes will be maintained between appointment times to facilitate social distancing, cleaning of equipment and surfaces and aeration of study-space.

Visitor / Contractor COVID-19 Questionnaire

Name:
Company:
Mobile No:
Visiting:
Date:

To ensure the Safety & Health of all people interacting with Dundalk Institute of Technology, visitors and contractors must complete this declaration form prior to entering any of the buildings on our campus and related sites. If you indicate to us that you have symptoms of COVID-19 OR you have been abroad in the last 14 days with exception to Northern Ireland you should not be on campus. Where this is the case, you are prohibited from entering this Campus/site and advised to seek professional medical help/assistance.

Please note The Visitor/Contractor COVID-19 Questionnaire will be kept for one month after the date of visit to meet the track and trace requirements, thereafter it will be securely shredded. It will be kept by the principal researcher in a secure location and only accessed by the relevant Head or Administrator. It may be shared with the COVID-19 Response Team or Government agency e.g. HSE in case of a suspected case of COVID-19 being discovered.

It is a legal obligation of the Institute to track visitors to the Campus and in the vital interests of our community and general public.

1. Have you visited any country outside Ireland excluding Northern Ireland Yes/No

2. Are you suffering any flu like symptoms/symptoms of Coronavirus COVID19 Yes/No

3. Are you experiencing any difficulty in breathing, shortness of breath? Yes/No

4. Are you experiencing any fever like/temperature symptoms? Yes/No

5. Have you consulted a Doctor or other medical practitioner in last 14 days? Yes/No

6. Are you feeling well health-wise? Yes/No

7. Are you a close contact of a person who is a confirmed or suspected case of COVID-19 in the past 14 days (i.e. less than 2 m for more than 15 minutes Accumulative in one day)? Yes/No

Note: When on campus/site, please adhere to our on-site standard processes/procedures regarding infection control, i.e. hand washing/hand sanitising and general coughing/sneezing etiquette.

Signature of Visitor: Date: _____

(Please circle your answers above)

COVID-19 Suspect Cases Procedure

What to do if participant becomes unwell and believe they have been exposed to COVID-19.

The prompt identification and isolation of potentially infectious individuals is a crucial step in protecting the participant and researcher. The following outlines the steps to deal with a suspected case that may arise during the course of the validation study.

Identify a designated isolation area in advance. This designated area and the route to the designated area should be accessible and as far as is reasonable and practicable should be accessible by people with disabilities. Ensure the designated area has the ability to isolate the person behind a closed door. Where a closed door is not possible, move to an area away from other persons. Provide as is reasonably practicable:

Ventilation i.e. via a window

Tissues, hand sanitiser, disinfectant and or wipes

PPE; gloves and mask

Clinical waste bags.

Designated isolation area: Living Lab area of the research lab in NetwellCASALA, PJ Carroll Building, DkIT.

If the participant has travelled alone in their own vehicle to the research centre, they should return to their car and return home, isolate and contact their GP for further advice. The unwell individual should be provided with a mask, to be worn at all times and continue to wear it until they arrive home.

If an individual cannot go home immediately:

Isolate the individual and accompany to the designated isolation area, keeping at least 2 metres away from the symptomatic person and also making sure that others maintain a distance of at least 2 metres from the symptomatic person at all times. The individual should avoid touching people, surfaces and objects while in isolation.

Assess whether the unwell individual can be directed to go home and call their doctor and continue self-isolation at home. If the individual does not have access to their own transport or are not fit to travel alone, arrange transport home with family or friend. Public transport of any kind should not be used.

Advice should be given to the person presenting with symptoms to cover their mouth and nose with the disposable tissue provided when they cough or sneeze and dispose of the tissue in the waste bag provided.

Facilitate the person with a means of making contact if they do not have access to their own mobile phone e.g. necessary supports for the individual to contact their doctor/HSE via telephone.

Arrange for appropriate cleaning of the isolation area and work areas involved

Carry out an assessment of the incident which will form part of determining follow-up actions and recovery.

Provide advice and assistance if contacted by the HSE.

Make note of the names and contact details (address, mobile number) of all people working in the same area as the unwell person, or who may have come into close contact with the unwell person.

Appendix 4.6 Case Report Form

Case Report Form

Title of Study: Comparing parameters of mobility obtained from body-worn sensors with clinical measurements

Principal Investigator: Grainne Vavasour

Supervisor: Dr. Oonagh Giggins

Site: NetwellCASALA Research Centre, PJ Carroll Building, DkIT, Dundalk, Co. Louth

Date of Study ☐☐☐☐ ☐☐ ☐☐ (YYYY_MM_DD)

Participant ID ☐☐_☐☐_☐☐ValSt_☐☐☐ (YY_MM_DD)

Gender M ☐F ☐

DOB (DDMMYY) ☐☐ ☐☐ ☐☐

Medical History:

_____

Current Medication:

_____

Covid-19 Questionnaire Completed		Y ☐ N ☐
Consent Form Signed		Y ☐ N ☐
Temperature (degrees Celsius)		☐☐☐.☐☐C
Weight (Kg)		☐☐☐. ☐☐kg
Height (Cm)		☐☐☐.☐☐cm
Leg Length (Cm) (Umbilicus to proximal medial malleolus		
	RIGHT	☐☐☐.☐☐cm
	LEFT	☐☐☐.☐☐cm
Pulse (BPM)		☐☐☐bpm
Oxygen Saturation (Sa02) (%)		☐☐☐%
Sensor Calibrated		Y ☐ N ☐
Shimmer Sensor Applied:		
5cm above lateral malleolus		Y ☐ N ☐
2cm lateral to ASIS		Y ☐ N ☐
L3 3		Y ☐ N ☐
2cm proximal to ulnar styloid:	RIGHT	Y ☐ N ☐
	LEFT	Y ☐ N ☐
Sternum; Upper 1/3		Y ☐ N ☐
Kinesis QTUG Sensor Applied (5cm above lateral malleolus, Anterior to Kinesis sensor)		
	RIGHT	Y ☐ N ☐
	LEFT	Y ☐ N ☐
Use of walking aid		Y ☐ N ☐
Chair Height (cm)		☐☐cm
TUG Test:		
Video		Y ☐ N ☐
No. of Steps taken		☐☐☐☐☐☐
Time taken (Minutes/Seconds.)		☐☐/☐☐.☐☐

On Completion:

Pulse ☐☐☐bpm

Sa02 ☐☐☐%

TUG-COGNITIVE Test:

Video Y ☐ N ☐

No. of Steps taken ☐☐☐☐☐☐

Time taken (Minutes/Seconds) ☐☐/☐☐.☐☐

On Completion:

Pulse ☐☐☐bpm

Sa02 ☐☐☐%

TUG-MANUAL Test:

Video Y ☐ N ☐

No. of Steps taken ☐☐☐☐☐☐

Time taken (Minutes/Seconds) ☐☐/☐☐.☐☐

On Completion:

Pulse ☐☐☐bpm

Sa02 ☐☐☐%

TREADMILL 3-m TEST:

Video Y ☐ N ☐

Pace (<0.8metre/second) (2.88km/h) ☐.☐☐km/hr

Pulse ☐☐☐bpm

Sa02 ☐☐☐%

Appendix 4.7 Data Dictionary

Data Dictionary for Laboratory-Based Study Comparing Step-count and Parameters of Gait from Wearable Sensors and Direct Observation during a Treadmill walk test and TUG tests under Different Conditions

Abbreviation	**Full name of variable**	**Definition of variable**	**Sources**	**Coding**
dd_mm_yyValSt_0##	Participant ID	dd_mm_yy = Date of initial assessment followed by assigned number	Assigned	
m f	Male / female	Gender of participant	CRF	M = 1 FM = 2
	age	Participant's age in years	CRF	
	Weight	Participant's in kilograms	CRF	
	Height	Participant's height in centimetres	CRF	
RtLL	Right Leg Length	Length of participant's right leg in cms	CRF	
LtLL	Left Leg length	Length of participant's left leg in cms	CRF	
	Age cohort	Age group of participant	Assigned	Under 65 = 2 Over 65 = 11
Countedsteps1stTUG	Counted steps from 1st TUG test	Number of steps counted during 1st TUG test	Under 65 years of age cohort: Direct observation. Over 65 years of age: Retrospective video observation	
SensorSteps1stTUG		Number of steps extracted from sensor during 1st TUG test		
Difference1stTUG		Difference between manually counted and sensor steps during 1st TUG test		
CountedStepsTUGCOG		Number of steps counted during TUG Cognitive test	Under 65 year of age cohort: Direct observation. Over 65 years of age:	

			Retrospective video observation	
SensorStepsTUGCOG		Number of steps extracted from sensor during TUG Cognitive test		
DifferenceTugCog		Difference between manually counted and sensor steps during TUG Cognitive test		
CountedStepsTUGMAN		Number of steps counted during TUG Manual test	Under 65 years of age cohort: Direct observation. Over 65 years of age: Retrospective video observation	
SensorStepsTUGMAN		Number of steps extracted from sensor during TUG Manual test		
DifferenceTugMan		Difference between manually counted and sensor steps during TUG Manual test		
CountedTreadmill		Number of steps counted during treadmill walk test		
AnkleShimmerTM		Number of steps extracted from ankle sensor during treadmill walk test		
WaistShimmerTM		Number of steps extracted from waist sensor during treadmill walk test		

Appendix 4.8 Data Management Plan

1.0 Data Collection, Documentation & Storage
All information and results provided as a result of this study will be kept securely and confidentially at DkIT for the duration of the study and a period of 7 years after, in keeping with GDPR (General Data Protection Regulations, 2018) with the exception of Covid-19-related documents.

1.1 Covid-19-Related Data
Paper-based Covid-19 Visitor Questionnaire and Contact Log documents will be stored securely in a locked filing cabinet in the principal researcher's office for a period of one month from the date of the participant's attendance at DkIT research centre.

Thereafter Covid-19 data will be shredded securely with a crosscut shredder. This is to comply with DkIT Return to Work Safely Protocol (DkIT COVID-19 Return to Work Operating Plan - OneDrive).

1.2 Paper-Based Data
All paper-based copies of information obtained throughout the study (with the exception of Covid-19-related documents) will be scanned onto the researcher's PC and stored safely in a password-protected electronic file. Passwords required will be shared with the researcher's supervisor in the event that the researcher is incapacitated .The original paper copies will be kept in a locked filing cabinet in the principal researcher's office in NetwellCASALA centre on campus with access restricted to researcher and supervisor.

1.3 Pseudonymisation
All data collected will be pseudonymised, stored securely on a password-protected electronic file on the researcher's PC and used for the purposes of this study only.

At the start of the study each participant will be given a 'participant ID' using the naming convention 'YY_MM_DD_ValStdy_00#. A digital master sheet containing participant details and participant ID will be generated. This master-sheet will be stored securely in a password-protected electronic file on the researcher's PC and used for administration purposes only. Only the participant ID will appear on study documentation from then onwards.

The master sheet will be destroyed on completion of the PhD study; therefore only anonymised copy of data will be archived.

Only the researcher and primary supervisor will have access to the file that matches each person to their participant ID.

1.4 Case Report Form (CRF)
A paper-based Case Report Form (CRF) (labelled 'Case Report Form [CRF] [Appendix 6]' in SOP) will be generated for each participant to record details of the Study Title, Principal Investigator, Research Centre, Date of Study (using naming convention ISO 8601 YYYY_MM_DD) and Participant identification number (Naming convention YY_MM_DDValStdy_00#). YY_MM_DD will refer to Date of Study and 00# to individual identification numbers 1-20.

1.4.1 Demographics & Medical History
Data on each participant's demographic, past medical history and current medication will be obtained by the principal investigator via phone conversations prior to participant's arrival to the research centre at DkIT. This data will be recorded in the CRF.

1.4.2 Clinical Data
Traditional clinical data measurements from the mobility tests obtained from manual timing in real time and retrospectively from video-recordings will be recorded in the CRF.

1.4.3 Sensor-Based Data
Sensor-data recorded from the QTUG and each shimmer device will be transferred via Bluetooth or USB-C connection to the researcher's password-protected PC after each participant's measurement session, labelled and stored using the participants ID code.

Validated algorithms will be used to extract metrics of mobility and physical activity from the raw sensor data.

1.5 Consent Forms
Participant-signed consent forms will be obtained, duplicated and a copy returned to each participant on the day of the mobility test. Retained copies will be stored securely in a locked container held by the researcher until processed on campus as above.

2.0 Data Collation
When data collection is complete, required data will be recorded in an excel spreadsheet. This will be recorded by the principal researcher using a double data entry and comparing spreadsheets for discrepancies. The reseracher's supervisor will verify a random sample.

The CRF will be scanned and stored securely in a password-protected electronic file in 'Digitised Hard Copies' folder as per section 4.0. The original paper copies will be kept in a locked filing cabinet in the principal researcher's office in NetwellCASALA centre on campus with access restricted to researcher and supervisor as per section 1.2.

3.0 Data Analysis
A comparative analysis will be performed between the sensor metrics to establish the correlation, if any, between the validated QTUG Kinesis, clinical measurements and the body-worn sensors. This will be carried out by two supervisors.

3.1 Data Sharing
Raw data from sensors will be shared with supervisors and subject to a Data Transfer Agreement, with UCD in the form of pseudonymised excel spreadsheets.

4.0 Storage & Back-up
A root folder will be created in C:\Users\vavasoug\Validation Study Documents on the researchers PC, which will nest folders for each aspect of Data Collection named accordingly i.e. 'Video-Recording', 'Shimmer Sensor Data', 'QTUG Data', 'Digitised Hard Copies'. Each participant's data will be stored in separate files within these folders, identifiable by individual participant ID.

All data will automatically upload to OneDrive as a backup.

5.0 Archiving and Destroying the Data
All data will be retained for the duration of the study and for seven years thereafter except the master sheet, which will be destroyed on completion of the PhD studies, in alignment with GDPR 2018.

All paper files will then be shredded securely with a crosscut shredder.

Electronic data will be destroyed by an appropriate IT staff member as per DkIT policy.

The Research Centre Manager and research supervisor will ensure all data has been destroyed.

18 May 2021 COVID-19 questionnaires shredded on campus in company of Suzanne Smith

Appendix 4.9 Data Protection Impact Assessment Approval

Loretto Gaughran | Grainne Vavasour; Oonagh Giggins | 16/10/2020

RE: DPIA & Appendices

You replied to this message on 16/10/2020 17:49.

Hi Grainne
I've had a chance to review your DPIA and associated documentation and I'm happy that you have comprehensively approached the risk assessment and documented any possible risks to the data collected.
Risks posed are noted as low risks in each case. I am happy that you have implemented the necessary security measures in noting who the data controllers will be, storing and accessing the data now and the in future including limited personnel access and use of encryption and also will be implementing the controls necessary to ensure the integrity and accuracy of the data which includes the minimal collection and specific use of the data.
I further note that the data will in the main, be housed as anonymous with an id allocated at the start of the study which is excellent. The information you will supply to the study participants is sufficient to inform them as to the reason for and nature of the study and you shall be obtaining explicit consent which is important when conducting such a programme and you also will inform them of their ability to opt out at any time which is important. You are also advising participants on the data collected via C-19 contact tracing effort and how it will be handled which is excellent. You've also noted a date for destruction of records which is great.

The only things I would suggest you add perhaps to your information leaflet or in some other visible way is a link to the data protection page on DkIT website or that of NetwellCASALA so that participants have full access to the suite of DP policies and procedures which also will give them access to their rights under DP in general. You might also summarise on your info leaflet the risks you have identified and how you will mitigate against them occurring during your assessment just for full transparency to the data subjects.
You have I think from reading your DPIA received already Research Ethics Committee approval so you might forward a summary of that on in due course just to complete my files. Other than that I am happy to sign off on your assessment and I wish you the very best with your research endeavours.

All the best
Take care
Loretto

Appendix 5.1 Home-Based Study Recruitment Advertisement

Appendix 5.2 Home-Based Study Participant Information Leaflet

Participant Information Leaflet

Study title:

Wearable Sensor-Based Assessment of Frailty

Researcher Name: Grainne Vavasour

Telephone number of Researcher: 087 2164685

Research Supervisor Name: Dr Oonagh Giggins

You are being invited to take part in a research study to be carried out on behalf of the School of Health and Science, NetwellCASALA, Dundalk Institute of Technology (DkIT).

Before you decide whether or not you wish to take part, you should read the information provided below carefully and, if you wish, discuss it with your family, friends or GP

Take time to ask questions – don't feel rushed and don't feel under pressure to make a quick decision.

You should clearly understand the risks and benefits of taking part in this study so that you can make a decision that is right for you. This process is known as 'Informed Consent'.

You don't have to take part in this study and a decision not to take part will not affect you in any way.

You can change your mind about taking part in the study any time you like. Even if the study has started, you can still opt out. You don't have to give us a reason. If you do opt out, rest assured it won't affect you in any way.

Why is this study being done?

This study is taking place to find out if measurements of mobility and physical activity obtained from body-worn sensors placed at different locations on the body can be used to identify levels of frailty.

Who is organising and funding this study?

This study is part of a PhD thesis undertaken at DkIT, part funded by the HEA (Higher Education Authority)

Why am I being asked to take part?

You are being asked to take part in this study either because you are

> 65 years of age

Healthy

Independently mobile

Physically capable of performing a series of mobility and physical activity tests

Have no cognitive or neurological deficits

Have no history in the past 6 months of orthopaedic lower limb trauma or surgery that will limit your ability to perform the activity tests

How will the study be carried out?

Between 50 – 60 older adults will visited in their homes by the primary researcher.

What will happen to me if I agree to take part?

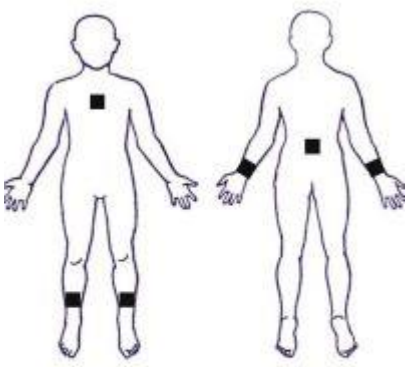
You will be asked to provide baseline participant profile information including demographic details, past medial history and current medications.

You will have your temperature checked and your name and phone number recorded on a Contact Log. This Log will be stored securely by the researcher on campus at DkIT for 1 month from the date of your assessment to fulfil a legal requirement of the Health and Safety Authority. You will then be asked to complete a Covid-19-specific questionnaire.

You will be asked to take part in a one-to-one training and education session on the application and use of a wearable sensor. You will be asked to complete two short questionnaires regarding your activity level and functional ability.

Your height and weight will be measured. A pulsometer worn on the middle finger will be used to measure pulse rate and oxygen level before the activities.

You will then be asked to wear a number of small sensors on the body for example on the legs, wrist and waist while performing some physical activity tests; Balance, walking and a standard ‘timed up and go’ (TUG) test.



A TUG test measures in seconds, the time taken to stand up from a standard chair seat height 46cm (18in), walk a distance of 3m (10 feet), turn, walk back to the chair and sit down.

The balance test require you to stand for 10-seconds with feet together, feet semi-tandem (the side of one heel touching the big toe of the opposite foot) and tandem (the tip of your big toe touching the back of the heel of your opposite foot).

The stand up / sit down task requires you to stand up and sit down five times.

The walk test requires you to walk 4m at your own pace.

The testing will be carried out by a chartered physiotherapist. The first part of the research will take 60 – 90 minutes. All communication and data obtained from the measurements will be confidential, recorded and discussed anonymously for the purpose of the study only.

On completion of the activities you will be asked to continue to wear the sensor on your wrist during waking hours for 48-hours, removing for bathing or showering. You will be required to fit the ankle sensors independently if able and carry out the TUG test on two separate occasions, 24 hours apart

over the subsequent 48 hours. You will have a step-by-step guide and information booklet to assist you with this.

The researcher will collect the sensors on the third day. On this visit you will be asked to complete a System Users Scale 10-point questionnaire and possibly take part in a non-identifiable audio-recorded interview to explore your experience using wearable sensors.

What are the benefits?

There are no direct benefits to you. However, the data obtained from your participation in this study will provide information that may be useful in developing tools for identifying those at risk of frailty.

What are the risks?

There is minimal risk involved, no more than that experienced with activities of daily living.

As with any form of exercise, there is a minimal risk of injury associated with the performance of the exercises within the study e.g. a muscle strain, slip or trip. However the exercises involved in the study are very simple i.e. walking 3 metres, standing with feet together in three different positions and standing up / sitting down five times. The first part of the study will be supervised by a chartered physiotherapist and performed in your own home.

The study will however take some of your time, approximately 60 – 90 minutes initially, followed by the unsupervised testing as described above over the next 48-hours and approximately 15 minutes when the researcher collects the sensors after the 48-hour period.

If you consider any of the physical activity to be too challenging for you or you are not comfortable with any aspect then you should not take part in the study.

What if something goes wrong when I'm taking part in this study?

In the unlikely event of any emergency during the study, medical assistance will be called. If there are any incidental findings i.e. if we observe anything we think requires medical attention we will discuss with you and advise you to seek the appropriate medical advice e.g. your GP.

Will it cost me anything to take part?

There are no financial implications for participants.

Is the study confidential?

All information and results provided as a result of this study will be kept securely and confidentially at DkIT for the duration of the study and for a period of 7 years thereafter, in keeping with GDPR (General Data Protection Regulations, 2018) except Covid-19-specific information which will be destroyed after 1 month as per DkIT and Health and Safety Authority guidelines.

Your name and contact details will be stored separately from the information you provide.

At the start of the study each participant will be given a 'participant ID', which will be stored securely and confidentially on a password-protected electronic file. Only the research team will have access to the file that matches your details with your id.

Communication will be confidential, between you and the researcher.

Results of the tests will be kept confidentially and used for the purposes of this study only. This includes writing a report for a doctoral thesis, details of which may be sent for publication in a scientific journal. Data may be shared with colleagues in another university for analysis using special processes. You will not be identifiable in any reports, documentation or publication.

You are free to discuss the study with friends and family as you wish and on completion of the study you can be provided with your own results upon request.

Where can I get further information?

If you have any further questions about the study or you need any further information now or at any time in the future, please contact:

Grainne Vavasour Phone: 087 2164685 email: grainne.vavasour@dkit.ie

Appendix 5.3 Home-Based Study Institutional Ethics Approval

DKIT
An Scoil Sláinte & Eolaíochta
School of Health and Science

31st May 2021

Ms. Grainne Vavasour,
NetwellCASALA Research Centre,
School of Health and Science,
Dundalk Institute of Technology,
Dundalk,
Co. Louth

Re: Wearable Sensor-Based Assessment of Frailty.

Dear Grainne,

The School Ethics Committee reviewed the original ethics application for the above study at its meeting dated the 18th May 2021 and the amendments which you sent to me on the 24th May. This application is now approved.

Wishing you the best of luck in your Research.

Yours Sincerely,

_____
Dr.Edel Healy
Chair of School of Health & Science Ethics Committee
cc. Dr. Oonagh Giggins, Netwell CASALA

Appendix 5.4 Home-Based Study HSE Ethics Approval

Feidhmeannacht na Seirbhíse Sláinte
Health Service Executive

Regional Manager Consumer Affairs
HSE Dublin North East

Bective Street, Kells
Co. Meath, A82 NX32

Tel: +353 (0) 469251264/
Fax: +353 (0) 469251774

Hampton Court, Cootehill Road
Cavan Town, H12 YY84

Tel: +353 (0) 49 4377343
Fax: +353 (0) 49 4377379
Email: consumeraffairs.heedne@hse.ie

Ms Grainne Vavasour
[redacted]

14/10/2021

Re/ Research Study Proposal:
"Wearable Senor-Based Assessment of Frailty"
REC Ref: REC/21/033

Dear Ms Vavasour

I refer to your email correspondence of the 9/9/21 in response to issues raised by the HSE North East Research Ethics Committee (REC) in connection with the above study. I wish to advise that I have had an opportunity to review same.

I can confirm that you have met all the conditions of the Committee.

Approval is now given to commence the above Study.

You should note that ethical approval will lapse if you do not adhere to the following conditions:

1. Submission of an Annual Progress Report (due annually from the date of this approval letter)
2. Report unexpected events or any event that may affect ethical acceptability of the study.
3. Submit any changes to study documentation (minor or major) to the North East REC for review and approval.
4. Notify North East REC of discontinuation of the study.
5. Submit a final Study Report/Study Synopsis when the study has been completed.

Due to Amendment to the Health Research Regulations which took effect from the 29th January 2021, a copy of the consent form completed by study participant must be provided to all Data Subject prior to commencement of the Health Research. This is a legal requirement now under Irish Data Protection Law.

This approval will be formally noted at the next REC meeting.

Yours sincerely,

Rosalie Smith Lynch
Chair, HSE North East Area
Research Ethics Committee

Copied to/ Fiona Brady, General Manager, Our Lady of Lourdes Hospital, Drogheda, Co. Louth
Aoife Bailey, Director of Nursing, Cottage Community Hospital, Scarlett Street, Drogheda, Co. Louth
Mary McCallan, Physiotherapy Manager, Physiotherapy Department, Our Lady of Lourdes Hospital, Drogheda, Co. Louth

HSE North East Area Research Ethics Committee
HSE Dublin North East, Bective Street, Kells, Co. Meath

List of site/s with favourable opinion/approval

Research Identification

Title of Research:	"Wearable Senor-Based Assessment of Frailty"

Approval to commence the study was given on 14/10/2021.

The study approval is extended to each of the site/s listed below.

Applicant	Site
Grainne Vavasour	Physiotherapy Department, Our Lady of Lourdes Hospital & Cottage Hospital

Signed: .....
Chair of Committee

Date: **14/10/2021**

Appendix 5.5 Home-Based Study Participant Consent Form

Home-Based study Participant Consent Form

Study title:

Wearable Sensor-Based Assessment of Frailty

*I have read and understood the **Information Leaflet** about this research project. The information has been fully explained to me and I have been able to ask questions, all of which have been answered to my satisfaction.*	***Yes***	***No***
I understand that I don't have to take part in this study and that I can opt out at any time. I understand that I don't have to give a reason for opting out and I understand that opting out won't affect me in any way.	***Yes***	***No***
I have been assured that information about me will be kept private and confidential.	***Yes***	***No***
I have been given a copy of the Information Leaflet and this completed consent form for my records.	***Yes***	***No***
I have been advised on the need to fill out a Covid-19-specific self-declaration form prior to participation in the study	***Yes***	***No***
I give my permission for non-identifiable video recording of my participation in each mobility test for the purpose of retrospective review.	***Yes***	***No***
I give my permission for non-identifiable audio recording of a post-intervention interview to explore my experience using wearable sensors	***Yes***	***No***
***Storage and future use of information:** I give my permission for information collected about me to be stored or electronically processed for the purpose of research and to be used in <u>related studies or other studies in the future</u> but only if the research is approved by a Research Ethics Committee. I understand data may be processed off-site, in another university because of special processing systems.*	***Yes***	***No***
I understand details of my name and phone number will be recorded on a Contact Log and stored securely for 1 month from the date of my involvement in this study for purposes of contact tracing in the event of a case of Covid-19, as a legal requirement, and will thereafter be destroyed.	***Yes***	***No***

| | |

Participant Name (Block Capitals) | Participant Signature | Date

To be completed by the Researcher:

I, the undersigned, have taken the time to fully explain to the above participant the nature and purpose of this study in a way that they could understand. I have explained the risks involved as well as the possible benefits. I have invited them to ask questions on any aspect of the study that concerned them. | |

Name (Block Capitals) Qualifications Signature | Date

Appendix 5.6 Home-Based Study COVID-19 Protocol

Procedure for ensuring health and safety of participants and investigators in validation study:

Pre-study

The day prior to the validation study, participants will be screened over the phone for risk factors relating to Covid-19. See accompanying Visitor Covid-19 Questionnaire (Appendix A). Those deemed appropriate for inclusion will be invited to mutually agree a suitable appointment time.

Day of Study

At a time no earlier than 5 minutes before allocated appointment, the researcher will present at the participant's home wearing a surgical facemask. The participant and researcher will perform hand-hygiene using appropriate hand sanitising agent. The participant's temperature will be measured using a non-contact temperature probe (Manufacturer's details). If the temperature is above 37.5 degrees Celsius the participant will be advised to self-isolate and seek medical advice. The study will be postponed and the researcher will leave the participant's home following appropriate hand hygiene. If the body-temperature is below 37.5 C, the study will proceed.

The participant will be given the Visitor Covid-19 Questionnaire to read in full, complete and sign followed by further hand sanitisation. Social distance will be maintained as required by NPHET guidelines.

Disposable, single-use personal protective facemask, apron and gloves will be worn by the researcher for obtaining each participant's measurements of weight, height and leg-length using wipe-able measurement tools (Manufacturers details of weighing scales, height and leg-length measurement-tools).

The participant will be instrumented with an inertial sensor at bilateral ankles, waist, chest and bilateral wrists (to include dominant and non-dominant upper limb) (Shimmer, Dublin, Ireland; Kinesis QTUG, Kinesis Health Technologies, Dublin, Ireland) using single-use elasticated material and/or tape.

A battery of tests and questionnaires will be performed by the participant under the direction of the researcher.

On completion of the exercise, when appropriate, sensors will be removed and cleaned according to manufacturer's guidelines:

Wash hands properly before removing or handling the sensors

Ensure a face mask and gloves are used in situations where it is difficult to practice social distancing or when handling the sensors after being worn

Clean the outside of the sensor first and then use a common disinfectant to wipe down the sensor and clip surface and leads (if applicable).

The participant will be advised on and supervised with hand hygiene. Sensors will be cleaned with a hypochlorite solution and stored in manufacturer's case. All surfaces will be cleaned and disinfected with 70% alcohol wipes. The researcher will leave the home

Visitor / Contractor COVID-19 Questionnaire

COVID-19 Questionnaire

Name:
Phone No:

Date:

To ensure the Safety & Health of all people interacting with Dundalk Institute of Technology, participants must complete this declaration form prior to taking part in a study. If you indicate to us that you have symptoms of COVID-19 OR you have been abroad in the last 14 days we are prohibited from entering your home and you are advised to seek professional medical advice.

Please note the COVID-19 Questionnaire will be kept for one month after the date of visit to meet the track and trace requirements, thereafter it will be securely shredded. It will be kept by the principal researcher in a secure location and only accessed by the relevant Head or Administrator. It may be shared with the COVID-19 Response Team or Government agency e.g. HSE in case of a suspected case of COVID-19 being discovered.

It is a legal obligation of the Institute to track contacts and in the vital interests of our community and general public.

PLEASE **CIRCLE** YOUR ANSWERS

1. Have you visited any country outside Ireland excluding Northern Ireland

Yes / No

2. Are you suffering any flu like symptoms/symptoms of Coronavirus (COVID-19)

Yes / No

3. Are you experiencing any difficulty in breathing, shortness of breath?

Yes / No

4. Are you experiencing any fever like/temperature symptoms?

Yes / No

5. Have you consulted a Doctor or other medical practitioner in last 14 days?

Yes / No (If yes, please give brief details: _____

6. Are you feeling well health-wise?

Yes / No

7. Are you a close contact of a person who is a confirmed or suspected case of COVID-19 in the past 14 days (i.e. less than 2 m for more than 15 minutes Accumulative in one day)?

Yes / No

Signature of Participant: _____

Name (BLOCK CAPITALS) _____

Date: _____

Appendix 5.7 Fried's Frailty Phenotype Frailty Assessment tool (FFP)

Participant ID _____

Date _____

Administered by _____

Criteria	Options	Weight	score
Unintentional weight loss (>4.5kg / 10lbs in previous year)	No Yes BMI < 18.5kg/m^2	0 1 1	
Physical Energy / Endurance: Q1. Do you feel full of energy? Q2. During the last 4 weeks, how often have you rested in bed during the day?	 Yes / No Every day / Every Week / Once / Never	0 = 'Yes' & 'Every day/week' 0 = 'No' & 'Once/Never' 1 = 'No' & 'Every day / week'	
Low physical activity: Frequency of mild / mod/ high energetic PA	≥3 times per week 1-2 times per week 1-3 times per month Hardly ever Never	1 = Hardly ever / Never for high AND for mod energetic PA	
Weakness: Handgrip strength in kg. dominant hand, average of 3 measures	Lowest 20% (by sex, BMI)	Men BMI — Grip Strength ≤24 — ≤29 24.1 – 26 — ≤ 30 – 28 — ≤30 >28 — ≤32 Women ≤23 — ≤17 23.1 – 26 — ≤17 26.1 – 29 — ≤18 >29 — ≤21	
Slow walking speed: Time to complete "timed up and go test" (TUG)	Frailty cut point: TUG time ≥19 seconds	0 = ≤ 18.9 seconds 1 = ≥19 seconds	
			TOTAL SCORE

Frail: ≥3 criteria present

Pre-Frail:1 or 2 criteria present

Robust: 0 criteria present

https://www.cgakit.com/fr-1-frailty-phenotype

Appendix 5.8 Frail Elderly Functional Assessment Questionnaire (FEFAQ)

Participant ID # _____ Date: _____

1. Are you able to walk? __ a. Yes, without help __ b. Yes, with a cane or walker c. Yes, with the help of another person __d. Not at all

2. Can you transfer out of bed? a. Yes, alone without a transfer board or other assistive device __ b. Yes, with the help of a transfer board or other device __ c. Yes, with the help of one or more than one person __ d. Yes, with the help of both another person and some assistive device e. Not at all

3. Are you able to turn over on your side in bed? __ a. Yes, without help __ b. Yes, with assistive device(s) __ c. Yes, with some help from another person d. No, must be turned

4. Are you able to wash dishes? __a. Yes __b. No

5. Are you able to prepare your own hot dinner? __a. Yes __ b. No, but am able to heat up already prepared meals __ c. No, but am able to make a peanut butter and jelly sandwich __ d. Not at all

6. Are you able to manage money (paying bills, keep check- book, etc.)? __a. Yes __ b. Partially, but not major bills and balancing a check- book __ c. Sign checks but unable to handle even minor trans- actions __d. No

7. Are you able to use the telephone? __ a. Yes, including dialling and answering the phone __ b. Yes, but unable to dial __ c. Yes, but am not able to dial or pick up receiver __d. No

8. Are you able to eat by mouth, including feeding yourself? __ a. Yes, without help __ b. Yes, with assistive device(s) __ c. No, but can eat if fed d. No, but can give own tube feeding __ e. No, must be tube fed

9. Are you able to dress yourself in pants, shirt or blouse, slip on shoes, and socks if clothes are placed out? __ a. Yes, without help of either a person or assistive device __ b. Yes, with assistive device(s) __ c. Partially, but some help is required from another / person __ d. No, completely dependent on another person

APPENDIX 1: FEFA QUESTIONNAIRE (Cont'd)

10. Are you able to dress yourself in a robe and slippers if both are placed out? __ a. Yes, without help of either a person or assistive device __ b. Yes, with assistive device(s) __c. Partially, but some help is required from another person __d. No, completely dependent on another person

11. Are you able to bathe in a tub or shower yourself? __ a. Yes, without help __ b. Yes, with assistive device(s), e.g., tub chair or grab bar __ c. Partially, but some help is required from another person __ d. Partially, but some help is required from another person and assistive device(s) __ e. No, completely dependent on another person

12. If the answer to #11 was 'e' (completely dependent on another person), are you able to sponge bathe yourself? __ a. Yes, without help __ b. Partially, but some help is required from another person __ c. No, completely dependent on another person __ d. Not applicable (#11 was a, b, c, or d)

13. Are you able to use the toilet, including getting to the bathroom? __ a. Yes, without help __ b. Yes, with assistive device(s) __ c. Yes, with some help from another person __ d. Yes, with help from another person and assistive device(s) __ e. No, unable to use toilet in the bathroom

If you answered #13 as 'a' (yes, without help) skip to #15.

14. If you answered #13 above as 'e' (unable to use toilet in the bathroom) are you able to use a bedside commode? __ a. Yes, without help __ b. Yes, with assistive device(s) __ c. Yes, with some help from another person d. Yes, with help from another person and assistive device(s) __ e. No, unable to use bedside commode __ f. Not applicable (#13 was a, b, c, or d)

If you answered #14 as 'a' (yes, without help) skip to #16

15. If you answered #14 above as 'e', unable to use bedside commode, are you able to use a bedpan/urinal? __ a. Yes, without help __ b. Yes, with help __ c. No, am unable to recognize bladder fullness or bowel movement d. No, have an ostomy (who cares for the site and empties the bag?)

__ e. Not applicable (#13 or #14 was a, b, c, or d)

16. Are you able to sit up? __ a. Yes, without help __ b. Yes, with assistive device(s) __ c. Yes, but some help is required from another person __d. No

17. Are you able to grasp a cup or a cloth with your hands? __a.Yes, either hand __b.Yes, but only with one hand __c. No

18. Are you able to reach out past your nose? __a. Yes, with arm fully extended at shoulder level __b. Yes, but cannot fully extend at shoulder level __c. No

19. Are you usually able to take your own medications every day? __a. Yes, without help __b. Yes, if medication doses are set out by another person __c. No, must have medication administered by another person __ d. No, do not take medication on a daily basis

FEFA Questionnaire Scoring Instructions

1. a) 0; b) l; c) 2; d) 3

2. a) 0-d) 3

3. a) 0-d) 3

4. a) 0-b) 1

5. a) 0-d) 3

6. a) 0-d) 3

7. a) 0-d) 3

8. a) 0-e) 4

9. a) 0-d) 3

10. a) 0-d) 3

11. a) 0-e)4

12. a) 0-c) 2; d) 0

13. a) 0-d) 3; e) 0

14. a) 0-e) 4; f) 0

15. a) 0-d) 3; e) 0; if answer is d and patient cares for and empties ostomy without help score as 0

16. a) 0-d) 3

17. a) 0-c) 2

18. a) 0-c) 2

19. a) 0-c) 2; d) 0

Total 0 to 55 (low scores infer better function).

Reference:

Gloth, F.M., Scheve, A.A., Shah, S., Ashton, R. and McKinney, R. (1999). The frail elderly functional assessment questionnaire: Its responsiveness and validity in alternative settings. *Archives of Physical Medicine and Rehabilitation*, 80(12), pp.1572–1576.

Appendix 5.9 Short Physical Performance Battery of tests (SPPB)

All of the tests should be performed in the same order as they are presented in this protocol. Instructions to the participants are shown in bold italic and should be given exactly as they are written in this script.

1. **BALANCE TESTS** The participant must be able to stand unassisted without the use of a cane or walker. You may help the participant to get up.

Now let's begin the evaluation.

I would now like you to try to move your body in different movements. I will first describe and show each movement to you. Then I'd like you to try to do it. If you cannot do a particular movement, or if you feel it would be unsafe to try to do it, tell me and we'll move on to the next one.

Let me emphasize that I do not want you to try to do any exercise that you feel might be unsafe.

Do you have any questions before we begin?

A. Side-by-Side Stand

1. Now I will show you the first movement.

2. (Demonstrate) I want you to try to stand with your feet together, side-by-side, for about 10 seconds.

3. You may use your arms, bend your knees, or move your body to maintain your balance, but try not to move your feet. Try to hold this position until I tell you to stop.

4. Stand next to the participant to help him/her into the side-by-side position.

5. Supply just enough support to the participant's arm to prevent loss of balance.

6. When the participant has his/her feet together, ask "Are you ready?"

7. Then let go and begin timing as you say, "Ready, begin."

8. Stop the stopwatch and say "Stop" after 10 seconds or when the participant steps out of position or grabs your arm.

9. If participant is unable to hold the position for 10 seconds, record result and go to the gait speed test.

B. Semi-Tandem Stand

1. Now I will show you the second movement.

2. (Demonstrate) Now I want you to try to stand with the side of the heel of one foot touching the big toe of the other foot for about 10 seconds. You may put either foot in front, whichever is more comfortable for you.

3. You may use your arms, bend your knees, or move your body to maintain your balance, but try not to move your feet. Try to hold this position until I tell you to stop.

4. Stand next to the participant to help him/her into the semi-tandem position

5. Supply just enough support to the participant's arm to prevent loss of balance.

6. When the participant has his/her feet together, ask "Are you ready?"

7. Then let go and begin timing as you say "Ready, begin."

8. Stop the stopwatch and say "Stop" after 10 seconds or when the participant steps out of position or grabs your arm.

9. If participant is unable to hold the position for 10 seconds, record result and go to the gait speed test.

C. Tandem Stand

1. Now I will show you the third movement.

2. (Demonstrate) Now I want you to try to stand with the heel of one foot in front of and touching the toes of the other foot for about 10 seconds. You may put either foot in front, whichever is more comfortable for you.

3. You may use your arms, bend your knees, or move your body to maintain your balance, but try not to move your feet. Try to hold this position until I tell you to stop.

4. Stand next to the participant to help him/her into the tandem position.

5. Supply just enough support to the participant's arm to prevent loss of balance.

6. When the participant has his/her feet together, ask "Are you ready?"

7. Then let go and begin timing as you say, "Ready, begin."

8. Stop the stopwatch and say "Stop" after 10 seconds or when the participant steps out of position or grabs your arm.

SCORING:

A. Side-by-side-stand

Held for 10 sec ❒ 1 point

Not held for 10 sec ❒ 0 points

Tried but unable ❒ 1 point

Not attempted ❒ 0 points

If participant did not attempt test or failed, circle why:

1 Participant could not hold position unassisted

2 Not attempted, you (researcher) felt unsafe

3 Not attempted, participant felt unsafe

4 Participant unable to understand Number of seconds held if instructions

5 less than 10 sec: ___sec

6 Participant refused

7 Other (specify)

If 0 points, end Balance Tests

B. Semi-Tandem Stand

Held for 10 sec ❒ 1 point

Not held for 10 sec ❒ 0 points

Not attempted ❒ 0 points (circle reason)

If participant did not attempt test or failed, circle why:

1 Participant could not hold position unassisted

2 Not attempted, you (researcher) felt unsafe

3 Not attempted, participant felt unsafe

4 Participant unable to understand Number of seconds held if instructions

5 less than 10 sec: ___sec

6 Participant refused

7 Other (specify)

Number of seconds held if less than 10 sec: ___ sec

If 0 points, end Balance Tests

C. Tandem Stand

Held for 10 sec ❒ 2 points

Held for 3 to 9.99 sec ❒ 1 point

Held for < than 3 sec ❒ 0 points

Not attempted ❒ 0 points (circle reason)

If participant did not attempt test or failed, circle why:

1 Participant could not hold position unassisted

2 Not attempted, you (researcher) felt unsafe

3 Not attempted, participant felt unsafe

4 Participant unable to understand Number of seconds held if instructions

5 less than 10 sec: ___ sec

6 Participant refused

7 Other (specify)

Number of seconds held if less than 10 sec: ___ sec

D. Total Balance Tests score (sum points)

Comments:

Gait Speed Test

Now I am going to observe how you normally walk. If you use a cane or other walking aid and you feel you need it to walk a short distance, then you may use it.

A. First Gait Speed Test

1. This is our walking course. I want you to walk to the other end of the course at your usual speed, just as if you were walking down the street to go to the store.

2. Demonstrate the walk for the participant.

3. Walk all the way past the other end of the tape before you stop. I will walk with you. Do you feel this would be safe?

4. Have the participant stand with both feet touching the starting line.

5. When I want you to start, I will say: “Ready, begin.” When the participant acknowledges this instruction say: “Ready, begin.”

6. Press the start/stop button to start the stopwatch as the participant begins walking.

7. Walk behind and to the side of the participant.

8. Stop timing when one of the participant’s feet is completely across the end line.

B. Second Gait Speed Test

1. Now I want you to repeat the walk. Remember to walk at your usual pace, and go all the way past the other end of the course.

2. Have the participant stand with both feet touching the starting line.

3. When I want you to start, I will say: “Ready, begin.” When the participant acknowledges this instruction say: “Ready, begin.”

4. Press the start/stop button to start the stopwatch as the participant begins walking.

5. Walk behind and to the side of the participant.

6. Stop timing when one of the participant’s feet is completely across the end line.

Study ID Date Tester Initials

GAIT SPEED TEST SCORING:

Length of walk test course: Four meters ❒ Three meters ❒

A. Time for First Gait Speed Test (sec)

1. Time for 3 or 4 meters. ___sec

2. If participant did not attempt test or failed, circle why:

Tried but unable 1

Participant could not walk unassisted 2

Not attempted, you felt unsafe 3

Not attempted, participant felt unsafe 4

Participant unable to understand instructions 5

Other (Specify) 6

Participant refused

3. Aids for first walk……None ❒ Cane ❒ Other ❒

Comments:

Complete score sheet and go to chair stand test

B. Time for Second Gait Speed Test (sec)

1. Time for 3 or 4 meters. ___sec

2. If participant did not attempt test or failed, circle why:

Tried but unable 1

Participant could not walk unassisted 2

Not attempted, you felt unsafe 3

Not attempted, participant felt unsafe 4

Participant unable to understand instructions5

Other (Specify) 6 Participant refused 7

3. Aids for second walk…… None ❒ Cane ❒ Other ❒

What is the time for the faster of the two walks?

Record the shorter of the two times. ___sec

[If only 1 walk done, record that time].___ sec

If the participant was unable to do the walk: ❒ 0 points

For 4-Meter Walk:	For 3-Meter Walk
If time is more than 8.70 sec: ❒ 1 point	If time is more than 6.52 sec: ❒ 1 point
If time is 6.21 to 8.70 sec: ❒ 2 points	If time is 4.66 to 6.52 sec: ❒ 2 points
If time is 4.82 to 6.20 sec: ❒ 3 points	If time is 3.62 to 4.65 sec: ❒ 3 points
If time is less than 4.82 sec: ❒ 4 points	If time is less than 3.62 sec: ❒ 4 points

3. CHAIR STAND TEST

Single Chair Stand

1. Let's do the last movement test. Do you think it would be safe for you to try to stand up from a chair without using your arms?

2. The next test measures the strength in your legs.

3. (Demonstrate and explain the procedure.) First, fold your arms across your chest and sit so that your feet are on the floor; then stand up keeping your arms folded across your chest.

4. Please stand up keeping your arms folded across your chest. (Record result).

5. If participant cannot rise without using arms, say "Okay, try to stand up using your arms." This is the end of their test. Record result and go to the scoring page.

Repeated Chair Stands

1. Do you think it would be safe for you to try to stand up from a chair five times without using your arms?

2. (Demonstrate and explain the procedure): Please stand up straight as QUICKLY as you can five times, without stopping in between. After standing up each time, sit down and then stand up again. Keep your arms folded across your chest. I'll be timing you with a stopwatch.

3. When the participant is properly seated, say: "Ready? Stand" and begin timing.

4. Count out loud as the participant arises each time, up to five times.

5. Stop if participant becomes tired or short of breath during repeated chair stands.

6. Stop the stopwatch when he/she has straightened up completely for the fifth time.

7. Also stop:

• If participant uses his/her arms

• After 1 minute, if participant has not completed rises

• At your discretion, if concerned for participant's safety

8. If the participant stops and appears to be fatigued before completing the five stands, confirm this by asking "Can you continue?"

9. If participant says "Yes," continue timing. If participant says "No," stop and reset the stopwatch.

SCORING

Single Chair Stand Test

A. Safe to stand without help YES ❒ NO ❒

B. Results:

Participant stood without using arms ❒ → Go to Repeated Chair Stand Test

Participant used arms to stand ❒ → End test; score as 0 points

Test not completed ❒ → End test; score as 0 points

C. If participant did not attempt test or failed, circle why:

Tried but unable 1

Participant could not stand unassisted 2

Not attempted, you felt unsafe 3

Not attempted, participant felt unsafe 4

Participant unable to understand instructions 5

Other (Specify) 6

Participant refused 7

Repeated Chair Stand Test

A. Safe to stand five times YES ❒ NO ❒

B. If five stands done successfully, record time in seconds.

Time to complete five stands ___. sec

C. If participant did not attempt test or failed, circle why:

Tried but unable 1

Participant could not stand unassisted 2

Not attempted, you felt unsafe 3

Not attempted, participant felt unsafe 4

Participant unable to understand instructions 5

Other (Specify) 6

Participant refused 7

Scoring the Repeated Chair Test

Participant unable to complete 5 chair stands or completes stands in >60 sec: ❒ 0 points

If chair stand time is 16.70 sec or more: ❒ 1 points

If chair stand time is 13.70 to 16.69 sec: ❒ 2 points

If chair stand time is 11.20 to 13.69 sec: ❒ 3 points

If chair stand time is 11.19 sec or less: ❒ 4 points

Scoring for Complete Short Physical Performance Battery

Test Scores Total Balance Test score _____ points

Gait Speed Test score _____ points

Chair Stand Test score _____ points

Total Score _____ points (sum of points above)

Appendix 5.10 Case Report Form

Case Report Form

Title of Study: Wearable Sensor-Based Assessment of Frailty

Principal Investigator: Grainne Vavasour

Supervisor: Dr. Oonagh Giggins

Site: NetwellCASALA Research Centre, PJ Carroll Building, DkIT, Dundalk, Co. Louth

Date of Study	☐☐ ☐☐ ☐☐☐☐ (DD_MM_YYYY)
Participant ID (DD _MM_ YY)(HomeBasedStudy)	☐☐_☐☐_☐☐HBS☐☐☐ participant number
Gender	M ☐ F ☐
DOB (DD MM YY)	☐☐ ☐☐ ☐☐
Temperature (degrees Celsius)	☐☐☐.☐☐C
Covid-19 Questionnaire Completed	Y ☐ N ☐
Consent Form Signed	Y ☐ N ☐

Medical History:

_____

Current Medication:

_____

Weight (Kg) ☐☐☐☐☐kg

Height (Cm) ☐☐☐☐☐cm

Pulse (BPM) ☐☐☐bpm

Oxygen Saturation (Sa02) (%) ☐☐☐%

Grip strength (Average of n1,2,3) ☐☐☐☐Kg

Grip Strength 1 (Kg)	
Grip Strength 2	
Grip Strength 3	

FFP Completed. Score /5 Y ☐ N ☐. ☐

FEFAQ Completed. Score /55 Y ☐ N ☐. ☐☐

Shimmer Sensor Configured. Y ☐ N ☐.

Time of 'Tape&Shake' ☐☐.☐☐

Shimmer Sensor Applied:

Above LSp 5,

(immediately proximal to and in line with iliac crest) Y ☐ N ☐

2cm proximal to ulnar styloid: Right Y ☐ N ☐

(Shimmer logo facing out, port caudal) Left Y ☐ N ☐

Floor surface Type: Carpet / Wood / Tile / Lino

SPPB Start Time ☐☐.☐☐

SPPB Score /12 ☐☐

QTUG and Activity Tracker Training Y ☐ N ☐

Kinesis QTUG Sensor Applied: RIGHT Y ☐ N ☐

Bilateral Lower Limb

(midway between ankle and knee, over calf muscle) LEFT Y ☐ N ☐

Use of walking aid Y ☐ N ☐

Chair Height (cm) ☐☐cm

TUG Test: Start time ☐☐.☐☐

Time taken (Seconds) ☐☐.☐☐

Time Shimmer3 sensors switched off (removed) ☐☐.☐☐

Wrist Activity Tracker Non-Dominant Wrist Y ☐ N ☐

Information Booklet Provided Y ☐ N ☐

@48 hours later:

Activity Tracker Collected Y ☐ N ☐

Kinesis QTUG Collected Y ☐ N ☐

Unsupervised QTUG I (Assistance?) Y ☐ N ☐ (Y ☐ N ☐)

Unsupervised QTUG II (Assistance?) Y ☐ N ☐ (Y ☐ N ☐)

SUS Y ☐ N ☐

Interview Y ☐ N ☐

Participant Instruction Leaflet

for QTUG test

A QTUG test is a quantified 'Timed Up and Go' test. It measures in seconds, the time taken to stand up from a standard chair, walk a distance of 3m (10 feet), turn, walk back to the chair and sit down.

You will be guided through this test with me the researcher and asked to repeat it on your own, unsupervised on the next two days if possible.

Contact Details for researcher:
Grainne Vavasour
Phone 087 2164685
Email grainne.vavasour@dkit.ie

Participant Details

ID

Age

Height

Weight

To be completed by participant

	Completed? (Y/N) Date/time	**Assistance Required? (Y / N)**
Unsupervised test no.1		
Unsupervised test no.2		

This booklet is to support and guide you through the walking test I would like you to perform on your own on the two days after my visit to you (one test on each day). It is the same test as you performed with me on the first visit involving the chair and the leg sensors.

The booklet is divided into four sections

Tablet, Sensors and Charging equipment layout

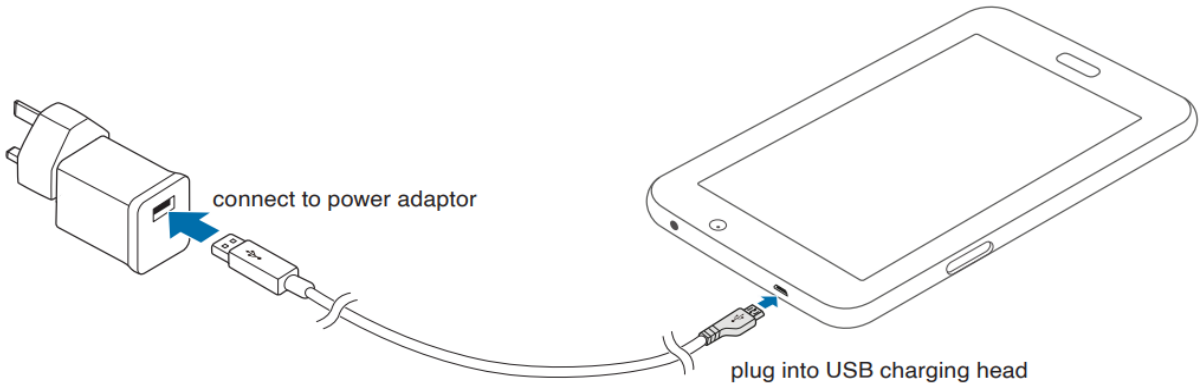
How to carry out the test

How to attach the sensors

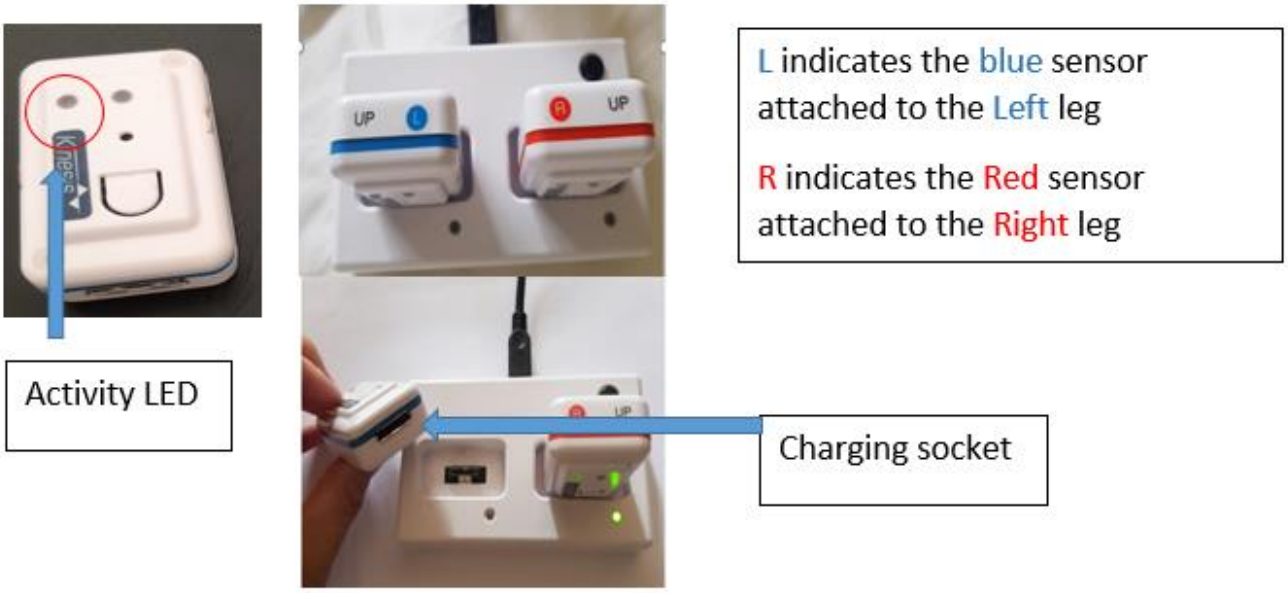
Tips / Trouble shooting

Section 1. Tablet Layout

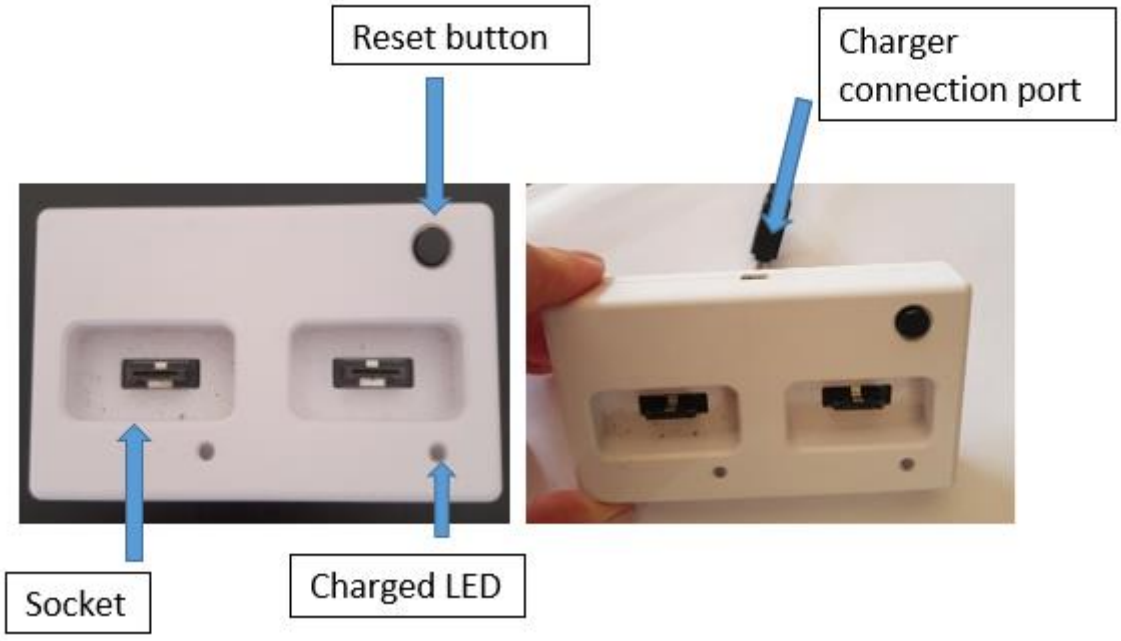
Tablet Charger



Sensor Layout



Sensor Charging-Dock Layout

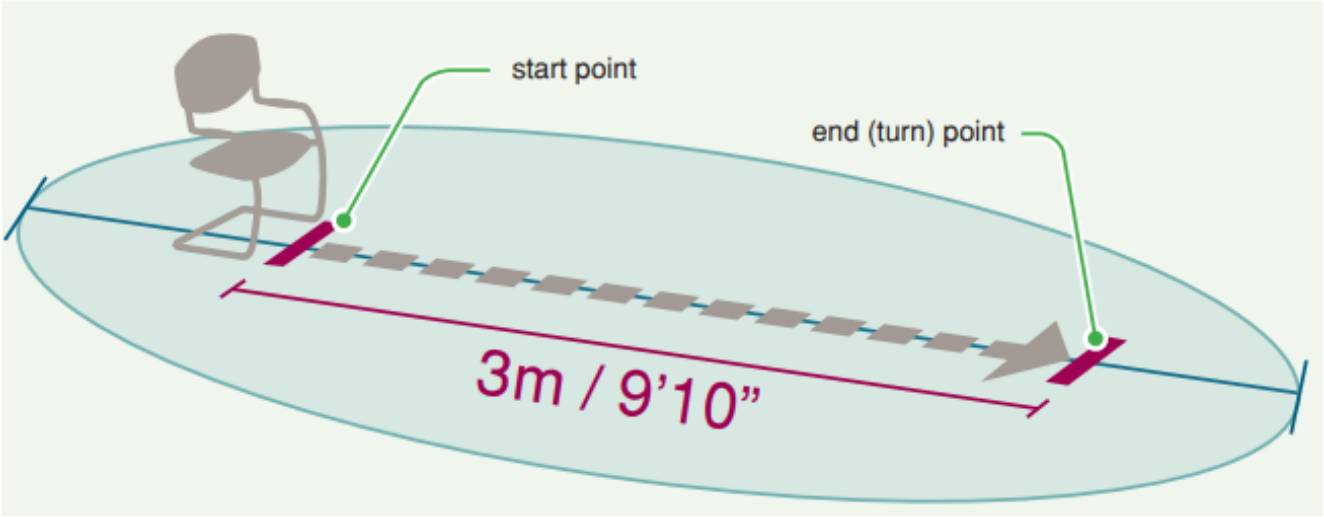


Section 2. To Carry Out The Test:

<u>Step 1:</u>

First, setup the area needed for the test the same way it was during the 1st test with the researcher using the three pieces of tape we left positioned on your floor. Place the front

legs of the chair behind the tape marked ‘Chair’ and when sitting your feet will rest behind the tape marked ‘Feet’. The turn point is identified by the tape marked ‘Turn’.



Step 2: Turn on the Sensors:

The **sensors must be turned on before the tablet**.

If the tablet is turned on first the test will not work.

Plug in the Charging Dock

Place the Blue sensor on the Left hand side and the Red sensor on the Right hand side

Check that the sensors are charged. **The LED on the *Charging Dock* indicates if the sensors are charged** (see image below)**.** Orange = NOT charged. Green = charged.

Check that the sensors are ready for use. **The LED on the sensor indicates that the sensors are ready for use.** Orange = NOT ready. Green = ready

If the sensors are charged and ready for use, but the LED on the sensor is not green, **press the ‘Reset’ button on the charging dock and hold for 5 seconds** (see image below). When you release the reset button the **Activity LED on each sensor** will turn orange. Wait a few moments until they turn green. This sensor LED indicates the sensors are ready for use (It Does ***Not*** Mean The Sensors Are Charged). In the unlikley event the charging dock LED is orange, see Tip #4 below.

Remove the Sensors from the Charging Dock. The light on the sensors will remain green

Sensors ‘READY’ indicator Reset Button

Sensors ‘CHARGED’ indicator

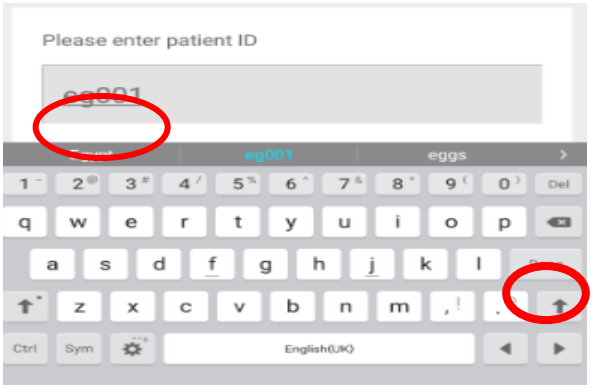
Step 3: Turn on the Tablet and Open the QTUG App

a)

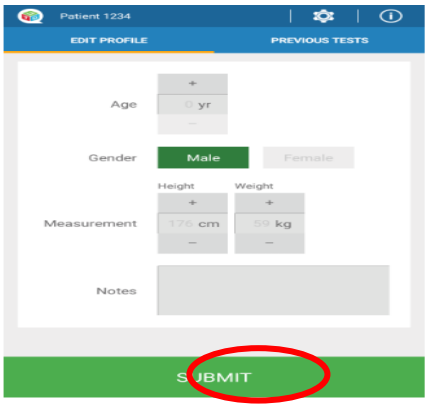
To turn on the tablet press and hold the **Power button** for 3 seconds. Wait approximately 20 seconds until the Settings and QTUG icons appear on screen

Select the QTUG icon. This is the QTUG App

c) Enter 'ID' as provided on the first page of this participant information leaflet and press 'DONE'



d) Enter Age, Gender, Height and Weight (provided on the first page of this participant information leaflet) and press 'SUBMIT'



Do Not Press 'START' yet

Place the tablet down while you attach the Sensors

Step 4: Attach the sensors

To attach the sensors, wrap the straps securely around your legs at the fattest part of your calf, between knee and ankle under clothes if possible but over trousers / tights is fine if more convenient.

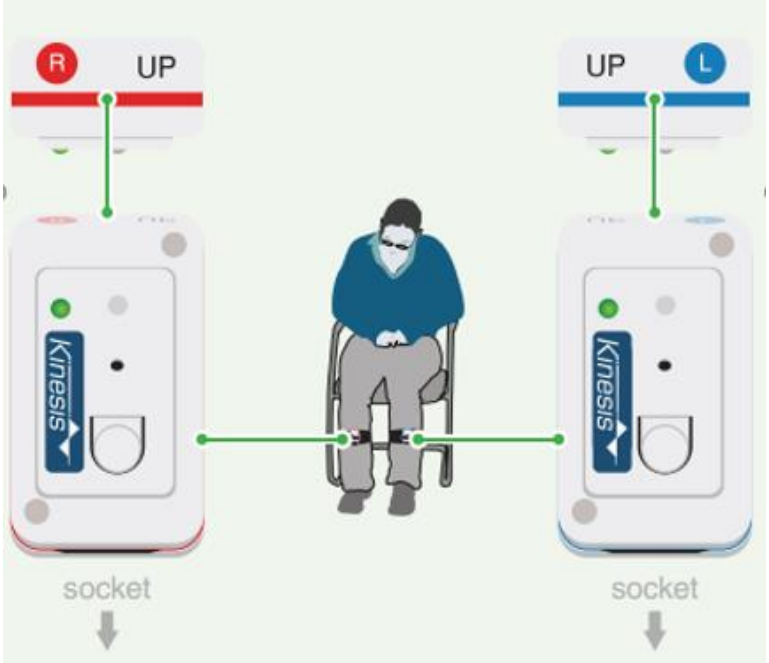
The image below shows how the sensors should be placed on the legs. Place the sensors in the elastic strap with:

Socket facing down

Kinesis logo facing out

Red sensor on the Right leg

Blue sensor on the Left leg

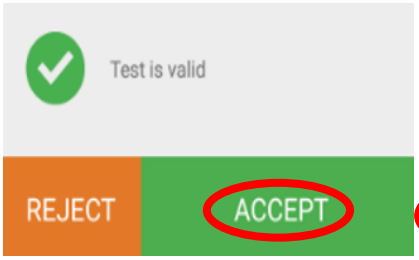


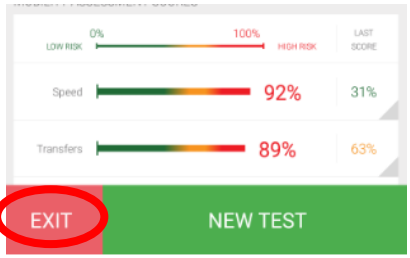
Step 5 – The Test

You are now ready to begin the test: **Have the Tablet on a table or chair beside you**

In the seated position, press the 'START' button on the QTUG app on the tablet. Leave the tablet on the table or chair beside you. Immediately stand up, walk as quickly and safely to the designated turning point, walk around the turning point marked on the floor and **return to a seated position** on the chair you stood up from before you press 'STOP'. Immediately on sitting press the 'STOP' button.

Wait a few moments while the test is validated. If the message on the tablet reads ‘Test is valid’ press the ‘ACCEPT’ button, then press ‘EXIT’ and then press the Home button.





Power off the Tablet by pressing the power button and selecting ‘Power off’

Replace the sensors back into the charging dock. Press and hold the reset button on the charging dock for 3 seconds to switch off the sensors. You can now unplug the charging dock.

Please repeat this procedure again after 24-hours if convenient to do so. Thank you

Section 4. TIPS / Troubleshooting

The sensors must be turned on **before** the tablet. If the tablet is turned on first the test will not work as the sensors will not be recognised.

Below are some tips on what to try if you have any technical difficulties with the equipment.

#1. Issue - ***Sensor*** *light not on*

Fix - Place sensors in charging dock. Press reset button on charging dock for 5 seconds. The **sensor** LED will turn orange and when the sensor is ready its LED will turn green.

#2. Issue - *Is sensor charged?*

To check this, place the sensor on the charging dock. If the LED on the **charging dock** is green, the sensor is charged. If the LED on the **charging dock** is orange, the sensor needs to be charged.

(When the sensors are docked the light on the charging dock will be either orange or green. When the sensors are undocked there will be no light on the charging dock)

#3. Issue – *Light on the charging dock is orange*

Fix - In the unlikely event that the light on the charging dock is Orange, turn off the sensors by pressing and holding the Reset button on the charging dock for 5 seconds. The LED on the **sensor** will turn off. Leave to charge for 6 hours. Turn off the tablet also.

After 6 hours start again at step 1 'To carry out the test'

#4. Issue: *How to charge sensor*

Fix: Ensure the charging dock is plugged in. Place the sensors in the charging dock. **Turn off sensors while charging** by holding the Reset button on the charging dock for 5 seconds. The LED on the sensor will be off (no colour). Turn off the tablet also.

#5. Issue: *Sensors won't connect or message saying 'Please power on both sensors and retry'*

Fix: Do not clear this message. Place the sensors in the Sensor Dock and press the Reset button **Once** on the Sensor Dock, wait a minute until the LED on the ***sensors*** turn green. Reposition the sensors on your legs as before and press Retest.

#6. Issue: *Sensors are still not recognised; message reads 'Please power on both sensors and retry'*

Press Home button to return to home screen,

Select Settings 

Select Bluetooth 

Tap the green button once  until it turns grey (Off)

Tap again once and it will turn to green

Press the home button, Select QTUG and repeat the procedure.

Contact me on 087 2164685 if you need support and I can either come visit you or talk you through the procedure over the phone.

Thank you,

Grainne

Appendix 5.12 Smartwatch Evaluation Framework

Activity Tracker Device Score (Connelly et al. 2021)

Rating Scale:

1: Very Difficult/Very Poor; 2: Difficult/Poor; 3: Neither Easy or Difficult/Poor or Good;

4: Easy/Good; 5: Very Easy/Very Good

Yes/No (Y/N): 1:Y; 0:N

#	Evaluation Criteria	Ratings					
		Notes	Apple	Fitbit Inspire 2	Garmin Vivioactive 45	Samsung Galaxy Active	Withings Scan watch
1	**Ease of setting up** How easy or difficult was it to get started with the device? Includes items such as pairing with mobile device, account setup, and finding the app from the app store.		5	4	2	4	4
2	**Ease of use for device controls** How easy or difficult is it to control the device (buttons, touchscreens)? Includes the comfort of using the controls, ease of accessing different screens using control buttons, and ease of navigating on the wearable device.		5	2	2	4	4
3	**Wearable display viewability** How easy or difficult is it to read the screen? Includes the comfort of using the controls, ease of accessing different screens using control buttons, and ease of navigating on the wearable device.		4	2	2	5	4
4	**Wearable display interpretability** How is the cognitive load of interpreting the wearable display? Includes ease of access of different functions and data on the wearable device, as well as the granularity of the data displayed.		4	3	4	5	4
5	**Ease of use for mobile app** How is the cognitive load of accessing and interpreting the data on the paired mobile app? Includes ease of accessing the different data on the paired mobile app, as well as the granularity of the data displayed.		4	5	3	4	5

6	**How is wearing the device for extended** amounts of time? Factors considered include size of the device, size of display, comfort while wearing the device.		4	4	4	4	3
7	**Device water resistance** 1: Not waterproof or resistant 3: Water resistant/splash proof 5: Waterproof/submersible (could swim with it on)		5	5	5	5	5
8	**Wearable device battery** 1: ≤2 days; 2: 2 days – 1 week; 3: 1 week – 1 month; 4: 1 month – 6 months; 5: ≥ 6 months		1	3	2	1	3
9	**Device effect on mobile battery** Was there a noticeable drain on your smartphone's battery life? can be hard to detect but some devices are very obviously a drain.		2	4	4	2	5
10	**Syncing performance** How easy is syncing the device? Includes how consistent auto syncing is, ease of manually syncing and max duration of not syncing.		5	5	5	5	5
11	**Device aesthetics** How does the device look? Includes overall look and feel of device.		4	4	3	4	3
12	**Device customization** What customization options are available? Includes belt clips/straps and colour options and different band materials.	NR					
13	**Parameter measures** Does the device measure the most common parameters and are they relatively accurate? Include Steps, Sleep, Elevation, Intensity, Activity Recognition, Heart rate, Oxygen Level and Calories.		Y/N 1	Y/N 1	Y/N 1	Y/N 1	Y/N 1
14	**Motivational features** Does the device or app include any motivational features? Includes app badges and motivational notifications.	NR					
15	**Notifications** Does the device support smartphone notifications?	NR					
16	**Clock**		Y/N	Y/N	Y/N	Y/N	Y/N

	Does the device have a clock display?		1	1	1	1	1
17	**Availability of personal data inputs/reminders** Does the device or app have personal data inputs or reminders users can set? Includes weight input and food intake tracking.	NR					
18	**Connectivity to other apps** Does the device support connectivity to other 3rd party apps?	NR					
TOTAL SCORE			45	43	38	45	47

Abbreviations: Not tested as deemed not relevant (NR).

Appendix 5.13 System Usability Score (SUS)

Participant ID: _____Date: _____

For each of the following statements, please mark circle the number that best describes your reactions to the Kinesis QTUG

Rating Scale: 1: Strongly Disagree; 5: Strongly Agree

1. I think that I would like to use Kinesis QTUG frequently. 1 2 3 4 5

2. I found Kinesis QTUG unnecessarily complex. 1 2 3 4 5

3. I thought Kinesis QTUG was easy to use. 1 2 3 4 5

4. I think that I would need the support of a technical person to be able to use Kinesis QTUG. 1 2 3 4 5

5. I found the various functions in Kinesis QTUG were well integrated. 1 2 3 4 5

6. I thought there was too much inconsistency in Kinesis QTUG. 1 2 3 4 5

7. I would imagine that most people would learn to use Kinesis QTUG very quickly. 1 2 3 4 5

8. I found Kinesis QTUG very cumbersome (awkward) to use. 1 2 3 4 5

9. I felt very confident using Kinesis QTUG. 1 2 3 4 5

10. I needed to learn a lot of things before I could get going with Kinesis QTUG. 1 2 3 4 5

Scoring:

For each of the odd numbered questions, subtract 1 from the score.

For each of the even numbered questions, subtract their value from 5.

Take these new values which you have found, and add up the total score. Then multiply this by 2.5.

The result of all these tricky calculations is that you now have your score out of 100. This is NOT a percentage, but it is a clear way of seeing your score.

Appendix 5.14 Home-Based Study Interview Questions and Protocol

Interview protocol

Researcher: "Thank you for agreeing to an interview regarding the use of the sensor system and the watch you have used over the past 48-hours, and for allowing me to audio record the interview. Your experience, thoughts and opinions will help us understand how older adults engage with technology and help with further research involving older adults and the use of technology. You will not be in any way identifiable in any write-up of the information obtained from this interview.

I will tell you when I am turning on the audio recorder. You can decline to answer any question or ask to stop the recording at any time, by either saying so or indicating with a hand gesture".

Set up voice recorder on college phone, which has no SIM card in situ.

"We will begin. May I switch on the recorder now"?

Researcher records: Participant id _____ on date_____ at time_____

Previous experience with technology

Can you tell me if you use any technology usually, before taking part in this study?

Prompt: Mobile phone? Smartphone / tablet device/ PC / computer / laptop?

What do you use this for?

Prompt: Phone-calls / text messages /Google / games / health tracker / other?

How often do you use them?

Prompt: weekly /daily?

Have you ever used an activity tracker? Do you monitor your steps for example?

Experience with Technology during study

How did you find using the sensor system for this study?

Prompt: What were the challenges?

Were the instructions given to you on how to operate the sensor system useful?

Did the instruction booklet provided assist you in using the system and performing the walk test?

Did you feel confident in how to use the system after the training / education session?

Could you remember how to use the system or did you rely on the instruction booklet?

Could you perform the test successfully each time?

Did you need assistance?

Do you think the information on the system would be useful or beneficial? In what way might it be useful?

Do you think you would be interested in using this system regularly?

Do you think you would be interested in using this system regularly if you knew there was a HCP monitoring the results?

How do you think you would use this information? What do you think would be the benefits?

ScanwatchHow did you find wearing the watch? Did you use any of the functions available eg the heart rate / oxygen level / ECG functions?

If yes, did you find it interesting?

Do you think it is something that you would use in the future?

If you didn't use any of the functions, what was the reason?

Do you feel any more confident with using technology as a result of your participation in this study?

Did the use of the technology influence your activity?

Did taking part in this study, using the sensor system or the wrist-watch change how you thought about your level of activity?

Were you more aware of your level of activity as result of taking part in this study?

Do you think using a piece of technology would influence your level of activity in the future?

Do you think you would invest in an activity tracker in the future or would you investigate the functions on your phone?

Conclusion

Have you any suggestions in relation to the study?

What have you like most about taking part in the study?

What have you liked least?

Thank you for your time and for the information you have shared

Switch off audio recorder

Appendix 5.15 Data Dictionary

Data Dictionary for Home-Based Study

Abbreviation	**Full name of variable**	**Definition of variable**	**Sources**	**Coding**
DD_MM_YY(HBS)_0##	Participant ID	DD_MM_YY = Date of initial assessment followed by assigned number	Assigned	
HBS	Home Based Study	Name of study	CRF	
M F	Male / female	Gender of participant	CRF	M = 1 FM = 2
DOB	Date of Birth	Participant's date of birth	CRF	
	Weight	Participant's in kilograms	CRF	
	Height	Participant's height in centimetres	CRF	
FFP	Fried's Frailty Phenotype	Frailty Status Assessment	CRF	
FEFAQ	Frail Elderly Functional Assessment Questionnaire	Score achieved	CRF	
LSp5	5th Lumbar vertebrae	Site of shimmer sensor placement		
SPPB	Short Physical Performance Battery of tests	Score achieved		
QTUG	Quantified Timed Up and Go test	Frailty Risk Score		
SUS	System Usability Score	Score achieved		
N_steps	Number of steps	Number of steps recorded during 48 hours of study	ScanWatch	
N_bouts	Number of bouts of activity	Number of bouts of activity recorded during 48 hours of study		

MAX SEDt	Maximum Sedentary Time	Time spent in longest duration of inactivity		
MIN SEDt	Minimum Sedentary Time	Time spent in shortest duration of inactivity		
#_48hrsData_8_8	Participant identification number _ 8am_8pm for duration of data collection	File name for each participant's file of ScanWatch data extracted for analysis		
SW	ScanWatch	Smartwatch used in study for data collection		

Appendix 5.16 Data Management Plan

1.0 Data Collection, Documentation & Storage

All information and results provided as a result of this study will be temporarily kept securely and confidentially on the researcher's password-protected PC at the researcher's home office due to work from home restrictions and subsequently at DkIT for a period of 7 years after completion in keeping with GDPR (General Data Protection Regulations, 2018) with the exception of COVID-19-related documents.

1.1 Covid-19-Related Data

Paper-based Covid-19 Visitor Questionnaire and Contact Log documents will be kept for a period of one month to comply with DkIT Return to Work Safely Protocol (DkIT COVID-19 Return to Work Operating Plan - OneDrive).

This data will be temporarily stored securely in the principal researcher's home office due to work from home restrictions and periodically transferred to a locked filing cabinet in the researcher's office on campus, with access restricted to the researcher and principal supervisor.

Thereafter COVID-19 data will be shredded securely with a cross-cut shredder at NetwellCASALA, DkIT.

1.2 Paper-Based Data

All paper-based copies of information obtained throughout the study (with the exception of Covid-19-related documents) will be stored securely in the researcher's home office until scanned onto the researcher's PC and stored safely in a password-protected electronic file. Passwords required will be shared with the researcher's supervisor in the event that the researcher is incapacitated .The original paper copies will then be kept in a locked filing cabinet in the principal researcher's office in NetwellCASALA centre on campus with access restricted to researcher and supervisor.

1.3 Pseudonymisation

All data collected will be pseudonymised, stored securely on a password-protected electronic file on the researcher's PC and used for the purposes of this study only.

At the start of the study each participant will be given a 'participant ID' using the naming convention 'DD_MM_YY_HBS_## (Day_Month_Year_HomeBasedStudy_Participant-specific number). A digital master sheet containing participant details and participant ID will be generated. This master-sheet will be stored securely in a password-protected electronic file on the researcher's PC and used for administration purposes only. Only the participant ID will appear on study documentation from then onwards.

The master sheet will be destroyed on completion of the PhD study, therefore only anonymised copy of data will be archived.

Only the researcher and primary supervisor will have access to the file that matches each person to their participant ID.

1.4 Case Report Form (CRF)

A paper-based Case Report Form (CRF) (labelled 'Case Report Form [CRF]) will be generated for each participant to record details of the Study Title, Principal Investigator, Research Centre, Date of Study (using naming convention DD_MM_YYYY) and Participant identification number (Naming convention DD_MM_YY_HBS##).

1.4.1 Demographics & Medical History

Data on each participant's demographic, past medical history and current medication will be obtained by the principal investigator on the day of participant's home-visit. This data will be recorded in the CRF.

1.4.2 Clinical Data

Clinical data measurements from the questionnaires and mobility tests obtained will be recorded on

the appropriate document in real time. The scores will be calculated and recorded on the CRF by the principal researcher at a later date.

1.4.3 Sensor-Based Data

Sensor-data recorded from each Shimmer device will be transferred via Bluetooth or USB-C connection to the researcher's password-protected PC after each participant's measurement session, labelled and stored using the participant's ID code.
Validated algorithms will be used to extract metrics of mobility and physical activity from the raw sensor data.
Sensor-data recorded from the Kinesis QTUG is automatically stored on the Galaxy Tablet via Bluetooth and labelled using the participant's ID code. On completion of the repeated tests after 48-hours, this data will be transferred from the tablet to the researcher's password-protected PC, labelled and stored using the participant's ID code. All data will be then removed from the tablet.

1.5 Consent Forms

Participant-signed consent forms will be obtained, duplicated and a copy returned to each participant by email or post (Participant's preference). Retained copies will be stored securely in a locked container held by the researcher until processed on campus as above.

2.0 Data Collation

When data collection is complete, required data will be recorded in an excel spreadsheet. This will be recorded by the principal researcher using a double data entry (one researcher inputting data into two separate spreadsheets) and comparing spreadsheets for discrepancies. The reseracher's supervisor will verify a random sample. The CRF will be scanned and stored securely in a password-protected electronic file in 'Digitised Hard Copies_HomeBasedStudy' folder as per section 4.0. The original paper copies will be temporarily stored securely in the researcher's home office until transferred to NetwellCASALA where they will be kept in a locked filing cabinet in the principal researcher's office, with access restricted to researcher and supervisor as per section 1.2.

3.0 Data Analysis

A comparative analysis will be performed between the sensor metrics to establish the correlation between data from each sensor with frailty phenotypes as measured using Fried's Frailty Phenotype Assessment Tool.

3.1 Data Sharing

Pseudonymised data will be shared with supervisors for analysis via a DkIT OneDrive account with access restricted to supervisors for data-analysis. An external supervisor will receive pseudonymised sensor-derived data via a password-protected OneDrive link. Password required to access data files will be communicated over the phone.

4.0 Storage & Back-up

A root folder will be created in C:\Users\vavasoug\HomeBased Study Documents on the researchers PC, which will nest folders for each aspect of Data Collection named accordingly i.e. 'Shimmer Sensor Data', 'QTUG Data', 'Digitised Hard Copies'. Each participant's data will be stored in separate files within these folders, identifiable by individual participant ID.
All data will automatically upload to OneDrive as a backup.

5.0 Archiving and Destroying the Data

All data will be retained for the duration of the study and for seven years thereafter except the master sheet which will be destroyed on completion of the PhD studies, in alignment with GDPR 2018.
All paper files will then be shredded securely with a cross-cut shredder. Electronic data will be destroyed by an appropriate IT staff member as per DkIT policy. The Research Centre Manager and research supervisor will ensure all data has been destroyed.

Appendix 5.17 Data Protection Impact Assessment Approval

Gerald O'Driscoll <Gerald.ODriscoll@dkit.ie>
Thu 22/07/2021 12:34
To: Grainne Vavasour <Grainne.Vavasour@dkit.ie>
Grainne,

This DPIA is ok to proceed with and I will log it here.

Regards

Ger

Can Older Adults Capture an objective Frailty Risk Score Unsupervised, in Their Own Home?

Grainne Vavasour* Oonagh M. Giggins, Member, IEEE, Julie Doyle, Daniel Kelly.

Abstract— The syndrome of frailty is one of the greatest challenges facing an ageing population, placing older adults at risk of falls, delirium, hospitalization, and mortality. This study compared an objective measure of frailty risk obtained by older adults unsupervised in their own homes with that obtained from a researcher-applied test using a validated wearable sensor system. Up to 60% of participants successfully obtained a frailty risk score independently. Results indicate a strong positive correlation between the frailty scores.

Clinical Relevance— **The results are of great importance to an ageing population as providing a means for older adults to independently capture an objective measure of frailty can promote awareness, facilitate early intervention and potentially mitigate the adverse health outcomes associated with frailty.**

I. INTRODUCTION

Frailty is associated with but is not an inevitable part of ageing. It is recognized as a precursor for disability and a predictor of adverse health outcomes. Screening to facilitate early identification of frailty could reduce the risks associated with its development. Traditional frailty assessment tools are time-consuming and cumbersome to implement and involve an element of subjective self-report [1]. Facilitating older adults to independently and objectively identify frailty risk could reduce the risk of disability and functional decline.

II. METHODS

Participants (n=52) recruited from local community groups were visited in their homes where they performed a supervised Timed Up and Go (TUG) test while instrumented with the Kinesis QTUG Mobility and Falls Assessment system. One 9DoF inertial sensor was positioned at each ankle. Participants were instructed in the application and use of the QTUG system and requested to perform the TUG test unsupervised once daily over the subsequent two days. Participants were stratified into non-frail (NF), pre-frail (FP) and frail (F) according to Fried's Frailty Phenotype assessment tool (FFP). Data analysis was performed using Microsoft Excel-16 and SPSS-26 (IBM). The relation between the frailty estimates was analysed using Spearman's rank correlation coefficient (r_s). A p value of $< .05$ was considered statistically significant.

This work was co-funded through the Higher Education Authority Landscape Funding and Dundalk Institute of Technology and the ECME project which has been funded by the EU's INTERREG VA programme, managed by the Special EU Programmes Body (SEUPB). G. Vavasour, O.M. Giggins, and J. Doyle are with NetwellCASALA, Dundalk Institute of Technology. Co. Louth A91 K584 *(corresponding author phone: +353 42 9370200; e-mail: vavasoug@dkit.ie). D. Kelly is with Ulster University, DerryLondonderry. BT48 7JL

III. RESULTS

Descriptive statistics of age and frailty risk estimates for each frailty group are presented in Table 1. There was a strong positive correlation between the supervised and independently captured frailty estimate percentages (r_s = .942 for Supervised/Day 1, .874 for Supervised/Day 2, and 0.938 for Day1/Day2) (p<.01). The mean absolute error (MAE) is deemed acceptable at 9.03, 10.25 and 7.80[2].

Table 1. Comparing frailty estimates between supervised and independent QTUG tests within stratified frailty groups

Frailty Group	Age Mean (SD)	Supervised Frailty Estimate% Mean (SD)	Independent Frailty Estimate% Day 1 Mean (SD)	Independent Frailty Estimate% Day 2 Mean (SD)
NF	71.7 (6.8)	28.1 (21.1)	32.55 (28.65)	33.70 (19.38)
n		14	11	10
PF	78.52 (7.7)	57.16 (32.98)	48.44 (30.59)	49.80 (32.04)
n		31	16	15
F	85.33 (7.14)	95.17 (8.0)	96 (6.92)	93.50 (2.12)
n		6	3	2

IV. DISCUSSION & CONCLUSION

This study examined the correlation between objective frailty risk scores obtained by a researcher and those obtained by older adults independently, unsupervised in their own home. The Kinesis QTUG is designed to be implemented by a clinician however, almost 60% of participants performed the test unsupervised with low differences in findings. Results demonstrate a strong relationship with acceptable accuracy between both the supervised and unsupervised tests and between the two unsupervised tests performed. To the author's knowledge this has not been examined previously. The results contribute positively toward future effective, independent frailty screening by older adults, in free-living conditions.

[1] B. J. Buta *et al.*, "Frailty assessment instruments: Systematic characterization of the uses and contexts of highly-cited instruments," *Ageing Research Reviews*, vol. 26. pp. 53–61, 2016.

[2] J. Brownlee, "Regression Metrics for Machine Learning." 2021. [Online]. Available: ttps://machinelearningmastery.com/regression-metrics-for-machine-learning/. [Accessed: 14-Mar-2022].