Targeted Use of Technology to Assist With Fall Risk Classification in Older Adults

by

Drew Commandeur
BSc (Honours), University of Victoria, 2013

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY

in the School of Exercise Science, Physical and Health Education

Supervisory Committee

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Abstract

Falling is a significant risk for older adults in Canada. Suffering a fall can result in injury and reduced quality of life which may include loss of autonomy. Additionally, injuries and rehabilitation from falls are a significant resource burden on the healthcare system. With the increasing proportion of older adults in Canada, there will be an increase in incidence of falls. Early identification of fall-risk is an essential step for the prevention of falls, and will provide the opportunity for fall-prevention interventions for at-risk older adults. This research is comprised of four projects that investigate and enhance current methods of fall risk detection which has potential to improve the quality of life of older adults.

The first study was a scoping review that identified tools for self-assessment of fall-risk. Seven distinct fall-risk self-assessments were identified; of which most were survey based. The most effective self-assessment tools were those that included physical assessments, with interactive technology-based assessments showing exceptional promise in preliminary studies. While self-assessment is an important first-line defense for fall-risk identification and monitoring, more sensitive measures that require administration by trained professionals are likely required for accurate prediction of fall risk.

The second project concurrently investigated a battery of clinical, physiological, and biomechanical assessments, to determine which measures, alone or in combination, best retrospectively classified fall risk. Ten clinical balance and mobility tests, comprising 40 unique measures, 5 physiological assessments, and 45 gait measures were included. From this extensive battery, only 5 measures were required to classify fallers with 92% sensitivity and consisted only of gait measures.

A practical clinical fall risk detection tool must be both time efficient and accurate. Thus it is essential to determine the minimum amount of reliable data that is required to maintain accuracy. To this end, based on the value of walking gait assessment for fall risk detection, it is essential to determine the minimum number of strides required to accurately classify fallers. To determine the number of strides required to identify fallers, subsets of a large sample of gait data measured with a GAITRite™ pressure sensing walkway were created and compared for internal consistency and variance between the reduced and complete data sets. For measures of mean values for dual-task and difference scores of walking gait it was determined that a minimum of 10 strides are required, while for measures of variability between 30-50 strides, are required. It is encouraged to acquire as much gait data as possible, however, reasonable limits may be set to reduce the strain on older adults. This will allow for studies to include additional measures, such as clinical tests which prolong the experiment duration, to produce a clinically viable tool.

Emerging technologies allow research to remain at the cutting edge and provide opportunities to expand into new markets. The use of Microsoft Kinect V2 for measurement of walking gait will allow for long term monitoring of fall status in the homes of older adults. To this end, we developed a walking stride detection algorithm that can be utilized for measurement of gait. The proven measurement accuracy of the Microsoft Kinect depth sensing capability coupled with an accurate and reliable stride detection algorithm provides the opportunity for affordable and portable gait analysis. This algorithm can be utilized with any 3D depth sensing technology, and future investigations will assess the accuracy across devices and clinical populations.

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LIST OF ABBREVIATIONS

5x STS – Five Times Sit-to-Stand

30s STS – 30 second Sit-to-Stand

ABC – Activities Specific Balance Scale

ADL – Activities of Daily Living

ANOVA – Analysis of Variance

BBS – Berg Balance Scale

BOSVD – Base of Support Variability Difference

BSE – Balance Self Efficacy

CADV – Cadence Variability

CB&M – Community Balance and Mobility Scale

CTSIB – Clinical Test of Sensory Interaction and Balance

DS – Difference Score

DSTD – Double Support Time Difference

DSTV - Double Support Time Variability

DSTVD – Double Support Time Variability Difference

DT – Dual-task

EFRT – Elliot Falls Risk Test

FAB – Fullerton Advanced Balance Scale

FES – Falls Efficacy Scale

FES – I – Falls Efficacy Scale International

FES –S – Falls Efficacy Scale Swedish

FRAT – Fall Risk Assessment Tool

FRT – Functional Reach Test

IADL – Instrumental Activities of Daily Living

IC – Internal Consistency

ICC – Intraclass Correlation

M - Mean

MCI – Mild Cognitive Impairment

MK – Microsoft Kinect

MMSE – Mini Mental State Exam

PAR-Q – Physical Activity Readiness Questionnaire

PCA – Principal Component Analysis

PPA – Physiological Profile Assessment

SAFE – Survey of Activities and Fear of Falling in the Elderly scale

SCD – Swing % of Cycle Difference

SD – Standard Deviation

Sen – Sensitivity

S%C – Swing % of Cycle

S%CV – Swing % of Cycle Variability

S%CVD - Swing % of Cycle Variability Difference

Spe - Specificity

SPPB – Short Physical Performance Battery

SL – Stride Length

SLD – Stride Length Difference

SLV – Stride Length Variability

SLVD – Stride Length Variability Difference

SSTV – Single Support Time Variability

ST – Single-task

STANTV – Stance Time Variability

STANTVD - Stance Time Variability Difference

STD –Stride Time Difference

STV – Stride Time Velocity

STVD - Stride Time Velocity Difference

SV – Stride Velocity

SVD – Stride Velocity Difference

SVV – Stride Velocity Variability

SVVD – Stride Velocity Variability Difference

SWD –Stride Width Difference

SWVD – Stride Width Variability Difference

TUG – Timed Up and Go

V - Velocity

VD – Velocity Difference

Acknowledgments

I would like to express my deepest gratitude to my doctoral supervisors, Marc Klimstra and Sandra Hundza. Both of you have helped guide my academic career, and I certainly wouldn't be here without the guidance and support you have given me. Marc, you have helped me to develop as a student, researcher, and teacher. You have been an amazing role model and advocate for me, and have created opportunities for me that I can't thank you enough for. Your constant support and dedication to my success have helped me achieve more than I could have dreamed of, and you have taught me to always strive to be the best I can at everything I do. Sandra, you have always believed in my abilities and have gone out of your way to ensure that I have had opportunities to succeed, and provided me endless support when I most needed it. You have helped guide my career and have helped keep me grounded in my research. I would like to thank you both so much for everything you have provided me, and I hope I will be able to repay the kindness and support you have shown me.

Thank you Stuart MacDonald for being part of my committee, for the opportunity to collaborate with you and your lab, and for always being there when I had nagging statistics quandaries to explore.

The Motion and Mobility Rehabilitation Laboratory provided a place for me to meet some truly incredible people, and allowed me to pursue my interest in research and technology. I would like to thank the wonderful research assistants who have been instrumental in my success, I never could have done it without your countless hours of hard work. Matt, I am so glad that I met you, your inquisitive mind is an inspiration and you have become a great friend. I don't know that I would have made it out of this with my sanity if you didn't help me distract myself by working in the shop, I know we said we would get the table finished one day, but maybe that's how it was always intended to be.

My research would not have been possible without the commitment of all of my participants who stuck it out with me for three long years.

This research was supported by the generous financial support received from Mitacs Accelerate PhD fellowship program through the investment of Jintronix, and The Canadian Frailty Network, as well as the support of the NSERC.

I would like to thank my family most of all. Hailey, I would not be here without your love, support, and encouragement. I can't thank you enough for always having faith in me and encouraging me to pursue my dreams. You have always been there for me and have provided me with the motivation to stick with it, no matter how difficult things got. And finally, Mom and Dad, thank you for always believing in me and supporting me no matter what I chose to do, your love and support has helped me become the person I am today.

Dedication

This work is dedicated to my family. You have been my constant source of love and support and have helped me achieve more than I ever thought possible. I could not have done any of this without you.

Chapter 1: Introduction

The following Chapter (1) will present a brief synopsis of relevant content to support the value of the projects in Chapters 2-4 and will help to outline the need for early identification of fall risk. This information will include the prevalence of falling in Canadian older adults, the economic and social burden of falling, mechanisms of increased fall risk and techniques for assessing fall risk.

1.1 Prevalence of Falls in Canada

Aging is a natural process that is accompanied by physical and cognitive decline (Atkinson et al., 2007). Older adults (65+ years) have an increased risk of falling which is related to their declining physical and cognitive abilities (Rubenstein, 2006). Presently, it is estimated that between 20% and 30% of Canadian seniors experience a fall each year. Further investigation shows that the incidence of injuries due to falls has increased by 43% between 2003 and 2010, and the incidence of deaths due to falls increased by 65% from 2003-2008 (Public Health Agency of Canada, 2014). These staggering numbers are of great significance when considering the rapidly growing number of older adults in Canada which is expected to increase from 16% to over 25% of the population over the next 20 years (Statistics Canada, 2015). Seniors frequently experience falls which may or may not result in injuries. Falls are commonly understood to be an unintentional falling to the ground, however, this intuitive definition is not sufficient for understanding fall risk; an operational definition of falling is required. Seniors, health care providers, and researchers were found to provide different definitions of what constitutes a fall, with both seniors and health care providers focusing on the negative outcome (injuries) and researchers focusing on the events leading up to the fall and the actual fall itself (Zecevic, Salmoni, Speechley, & Vandervoort, 2006). The World Health Organization suggests a

common definition of a fall as “inadvertently coming to rest on the ground, floor, or other lower level, excluding intentional change in position to rest in furniture, wall or other objects” (World Health Organization, 2007). In addition to this, we would add that environmental influences such as slippery surfaces or tripping hazards which may reasonably be expected to result in a fall in healthy young adults should be excluded when considering falls experienced by older adults for research purposes.

1.2 Economic and Social Burden of Falls in Canada

Falling is the leading cause of death, hospitalizations, permanent partial disability, and permanent total disability in Canada, and is the second leading cause of emergency room visits. In 2010, falls were the leading health care cost, accounting for $8.7 billion, and more than twice that of the next leading cause, transport incidents ($4.3 billion) (Parachute, 2015). The current expense, combined with the projected increase in the proportion of older adults highlights the urgent need for early fall risk identification and subsequent intervention. While the economic cost to Canada is enormous, social implications for the senior involved and their family can be devastating. The Canadian healthcare system provides support for seniors who fall, however, recovery from injury is only one of many challenges seniors face. After sustaining a fall, many older adults are no longer able to provide self-care, experience reduced quality of life and may be admitted into a short or long-term care facility (Hartholt et al., 2011). Experiencing repetitive falls has been shown to have a dose-response relationship with the ability to perform basic activities of daily living and accelerated functional decline coupled with social withdrawal that are not seen with a single injurious or non-injurious fall (Tinetti & Williams, 1998).

1.3 Increased Fall Risk in Older Adults

Aging results in musculoskeletal and neurological changes that increase the risk of falling. While it has been well established that the best predictor of future falls is a previous injurious fall, this is not a useful metric for identification of individuals who are at the greatest risk of falling before they have a fall (Jørgensen et al., 2017; Mulasso, Roppolo, Gobbens, & Rabaglietti, 2017). Age-associated changes in strength and balance, osteoarthritis, and visual impairment contribute to increasing the risk of falling (Berry & Miller, 2008; Smee, Berry, Anson, & Waddington, 2017). Gender also plays a significant role in fall risk. Elderly women have an increased relative risk of falling compared to men and are more likely to sustain serious injuries than their male counterparts (Campbell, Spears, & Borrie, 1990; Liu-Ambrose, Ashe, Graf, Beattie, & Khan, 2008). Injurious falls that result in hospitalization lead to an immediate decrease quality of life while non-injurious falls may lead to fear of falling which contributes to decreased quality of life over time (Hartholt et al., 2011). In order to assess the risk of falling in older adults, assessment protocols have been designed which either measure individual fall risk factors or apply a multivariate approach to characterise the associated measures of fall risk. Each of these assessments seeks to measure an intrinsic risk factor, or a combination of risk factors including but not limited to: Vision, physical performance, gait and gait variability, static and dynamic balance, vestibular function, proprioception, and cognition (World Health Organization, 2007).

1.4 Methods of fall risk assessment

Early detection of fall risk and timely preventative interventions is essential to reduce the incidence of falls in older adults. There are several approaches to consider which will determine who the target end-user of the assessment tool will be. Most fall risk assessment tools can be broken down

into four categories: Self-assessment tools, clinical assessments, physiological assessments, and gait assessments.

Self-assessment tools

Self-assessment tools are intended to be used by older adults without the aid of a health care professional or caregiver. The goal of these self-assessment tools is to use survey-based tools and/or physical assessments to predict fall risk in older adults. Several survey tools have been utilized as self-assessment tools including the Activities-Specific Balance Confidence scale (ABC), Falls Efficacy Scale (FES), and the Elliot Falls Risk Test (EFRT) (Elliot, Jamieson, Donnelly, & Malone, 2004; Powell & Myers, 1995; Yardley et al., 2005). Others have used simple physical self-assessments of gait (Bongers, Schoon, Graauwmans, Schers, et al., 2015) and technology (Yamada, Aoyama, Nakamura, et al., 2011) to predict fall risk in older adults. A scoping review of fall risk self-assessment tools is presented in Chapter 2.

Traditional Clinical Assessments

Clinicians use targeted assessments specifically developed to identify salient characteristics associated with fall risk. These assessments can include anything from simple reaching tasks which assess the individual's ability to maintain static balance while reaching for an object, such as the Functional Reach Test (FRT) (Duncan, Weiner, Chandler, & Studenski, 1990), to complex assessments of gait and balance, such as the Community Mobility and Balance scale (CB&M) (Balasubramanian, 2015).

Many tests seek to measure static balance as a potential fall risk indicator. This is an intuitive measure with high face validity as a loss of balance could result in a fall. Common tests of balance

include the Fullerton Advance Balance Scale (FAB) (Rose, Lucchese, & Wiersma, 2006), Berg Balance Scale (BBS) (Berg, Wood-Dauphinee, Williams, & Maki, 1992), and the Clinical Test of Sensory Interaction and Balance (CTSIB) (Shumway-cook, Horak, & Horak, 1986).

Simple tests of muscular strength and endurance, as well as gait speed, are also frequently used to identify fallers; comprehensive test batteries including balance, gait speed, and endurance are also used to discriminate fallers from non-fallers (Lusardi et al., 2017). The Five-times Sit-to-Stand (5x STS) (Teo, Mong, & Ng, 2013), Five-Step Test (5-Step) (Murphy, Olson, Protas, & Overby, 2003), and 30-second Sit-to-Stand (30s STS) (Jones et al., 1999) are all representative of simple muscular strength and endurance tests which have been successfully used to identify older adult fallers. The Timed Up-and-Go is (TUG) is one of the most commonly used gait speed assessment tools due to its ability to discriminate fallers and its ease of use (Podsiadlo & Richardson, 1991). Comprehensive tests such as the Short Physical Performance Battery (SPPB) utilize tests of many fall risk indicators such as gait speed, balance, and muscular strength and endurance (Guralnik et al., 1994). Reliability, validity, sensitivity, and specificity for these clinical tests are presented in Table 1.1.

Table 1.1

Reliability, Validity, Sensitivity, and Specificity of Traditional Clinical Fall Risk Assessments

Test	Reliability	Validity	Sensitivity	Specificity
BBS	Interrater reliability was 0.88 (Bogle-Thorbahn & Newton, 1996) Interrater reliability ICC 0.945 (Major, Fatone, & Roth, 2013)	internal consistency alpha 0.827 (Major, Fatone, & Roth, 2013)	53% (Bogle-Thorbahn & Newton, 1996)	96% (Bogle-Thorbahn & Newton, 1996)
CTSIB	Test Re-test r= 0.75 (Anacker & DiFabio, 1992)	Concurrent Validity Longer stand duration was associated with higher task	Age 65+ 63% , > 81+ 80% (Di Fabio & Anacker 1996)	Age 65+ 77%, 81+ 83% (Di Fabio & Anacker, 1996)

		completion scores and shorter stance duration indicated a decrement in balance function. Subjects who had an abnormal CTSIB pattern were 8.67 times more likely of falling (Di Fabio & Anacker, 1996)		
FAB	test-retest reliability 0.96, interrater reliability 0.94-0.97, intrarater reliability 0.97-1.00 (Rose et al., 2006)	Spearman rank correlation r= 0.75 (Rose et al., 2006)	A cut-off score of 25 out of 40 = 74.6% (Hernandez & Rose, 2008)	A cut-off score of 25 out of 40 = 52.6% (Hernandez & Rose, 2008)
FRT	test-retest ICC=0.98, interrater r=0.92 (Murphy et al., 2003)	FRT correlates with centre of pressure excursion r=0.71 (Weiner, Duncan, Chandler, & Studenski, 1992)	73% (Murphy et al., 2003)	was 88% (Murphy et al., 2003)
TUG	Interrater ICC = 0.98 (Shumway-Cook, Brauer, & Woollacott, 2000)	Spearman rank correlation, r=.71-.90) (Sebastião, Sandroff, Learmonth, & Motl, 2016)	87% (Shumway-Cook, Brauer, Woollacott, et al., 2000)	87% (Shumway-Cook, Brauer, & Woollacott, 2000)
SPPB	Test-retest ICC 0.89 (Freire, Guerra, Alvarado, Guralnik, & Zunzunegui, 2012)	scoring 7 or less on the SPPB, 20%–60% of them completed the 400 m walk. scoring 8 or more than 80% completed the 400 m walk at baseline. (Vasunilashorn et al., 2009)	SPPB score of 9 or less = 54%, 10 or less = 69%. (Vasunilashorn et al., 2009)	SPPB score of 9 or less = 92%. 10 = 84%. (Vasunilashorn et al., 2009)

Instrumented Clinical Assessments

While many clinical assessments were originally designed to allow for simple and subjective administration by clinicians, the need for improved accuracy and objective measurement has resulted in the development of instrumented clinical tests. For example, in its initial form, the CTSIB included subjective measures of balance as well as a timed test until falling, to a maximum of 30s. More recent

studies have utilized a force plate to improve the measurement accuracy of centre of mass displacement (Pandian, Ukamath, Jetley, & Ramaprabhu, 2011). Other examples of instrumented measurement include an instrumented Timed up and Go assessment (Vervoort, Vuillerme, Kosse, Hortobágyi, & Lamoth, 2016; Weiss et al., 2011), instrumented functional reach test (Behrman, Light, & Flynn, 2002) and instrumented Berg balance test (Craig, Bruetsch, Lynch, Horak, & Huisinga, 2017). While some of these instrumented tests currently require expensive research-grade technology the increase in commercially available motion capture and wearable technology can provide an affordable and easy to use instrumentation solution. For example devices such as Inertial Measurement Units (IMU's) (within mobile phones or independent devices) (Howcroft, Kofman, Lemaire, & McIlroy, 2016; Howcroft, Kofman, Lemaire, O'Sullivan, & Baddour, 2013) the Microsoft Kinect and the Wii Balance board have provided accessible technology to augment clinical tests and improve their measurement accuracy (Franco, Jacobs, Inzerillo, & Kluzik, 2012; Pluchino, 2010; Zerpa, Lees, Patel, & Pryzsucha, 2015). However, use of these technologies for clinical tests requires great attention to the technical development and validation of their use to ensure informed clinical decision-making.

Physiological assessments

Physiological assessments seek to evaluate fall risk by correlating performance related decline in physical capacity to fall risk. These include tests of visual acuity, pulmonary function, muscle strength and endurance, and proprioception. One measure which both intuitively and experimentally relates to increased fall risk is visual acuity. Vision impairment leads to vestibular disruption and postural instability which contributes to increased fall risk, however, contrary to common testing techniques which only assess visual acuity, contrast sensitivity and depth perception have been identified as the most important visual components of fall risk (Lord, 2006). Pulmonary function has

also shown promise for discerning fallers as it may relate to reduced functional capacity and is more evident in frail individuals at the greatest risk of injurious falls (Koski, Laippala, & Kivela, 1996). Loss of muscle strength, and poor grip strength, in elderly women specifically, has been identified as an important fall risk indicator (Campbell, Borrie, & Spears, 1989; Campbell et al., 1990). The most comprehensive assessment of physical capacity for fall risk is the Physiological Profile Assessment (PPA) (Lord, Menz, & Tiedemann, 2003). This test includes measures of visual acuity, contrast sensitivity, vestibular function, tactile sensitivity, proprioception, muscle strength, reaction time, and balance. This vast assortment of assessments accurately characterizes the multifactorial nature of fall risk.

Gait assessments

Changes in walking gait, such as increased variability, decreased velocity, and impaired dual-task performance, have been related to increased fall risk in older adults (Montero-Odasso, Muir, & Speechley, 2012; Verghese, Holtzer, Lipton, & Wang, 2009). While many gait metrics have been identified as potential fall risk indicators, dual-task walking conditions have been suggested by many as more sensitive measures for fall risk identification than single-task paradigms (Beauchet et al., 2008; Montero-Odasso, Muir, et al., 2012; Muhaidat, Kerr, Evans, Pilling, & Skelton, 2014; Walshe, Patterson, Commins, & Roche, 2015). Dual-task walking is comprised of performing a walking task while simultaneously performing a second task. It is common that the second tasks are cognitively demanding such as counting backward by serial sevens (Beauchet et al., 2008) or spelling backward (Hollman et al., 2010). The intent of the dual-task is to increase the cognitive demand which seems to elicit modifications to the task of walking (Montero-Odasso, Verghese, Beauchet, & Hausdorff, 2012). This supports the potential that increased cognitive demand may impair mobility performance of

individuals at risk of falls. Difference scores (DS), which are the difference between single and dual-task performance, for mean step width, step time, and step length were associated with either an increased risk of falling or a protective strategy to avoid falling (Nordin, Moe-Nilssen, Ramnemark, & Lundin-Olsson, 2010). Others have observed a similar decrease in dual-task gait walking speed and subsequent increases in stride time variability (Lamoth, Deutekom, van Campen, de Vries, & Pijnappels, 2009).

While there is strong evidence that dual-task paradigms show promise as indicators of fall risk, others have found conflicting results showing no additional sensitivity over single-task walking. Taylor, Delbaere, Mikolaizak, Lord, & Close, (2013) found that mean gait velocity, stride length, double support time, and stride width, as well as variability for swing time and stride length were different for older adults with multiple falls than non-fallers but that dual-task conditions did not significantly improve the ability to discriminate fallers. Similarly, a review by Menant, Schoene, Sarofim, & Lord, (2014) found that single and dual-task conditions were comparable for identifying fall risk in older adults, including those with mild cognitive impairment (MCI).

These discrepancies in the ability of single and dual-task walking to identify fall risk may be related to the means by which dual-task performance is assessed. Comparing faller and non-faller group means for performance of a dual-task paradigm does not take into account individual difference in one's ability to perform the task independently as a single-task. In order to account for this, difference scores which compare the difference between single and dual-task performance within an individual can be used and have the potential to be more sensitive indicators of fall risk. This technique is utilized in the research presented in Chapter 3. Other potential issues with most studies measuring walking gait are measurement validity, accuracy, and ensuring sufficient quantity of gait data are collected to ensure reliability (Hollman et al., 2010).

1.5 Standardization of measurement in gait assessment

Gait assessments have shown great promise as early indicators of fall risk in older adults (Hausdorff, Rios, & Edelberg, 2001). To ensure that reliable measures of gait parameters are being collected by all researchers, minimum standards for data collection practices should be established. Work by Hollman et al. (2010) has sought to determine the minimum number of strides required for accurate and reliable gait measurement and determined that as many as 370 strides may be required for assessment of gait variability, e.g. stride time variability, while fewer strides were required for measures of average gait parameters, e.g. stride length. Other researchers have suggested that far fewer strides are required, however, none of these studies have included a complete and comprehensive analysis of gait variables, and there have been no direct comparisons between older adult fallers and non-fallers (Almarwani, Perera, VanSwearingen, Sparto, & Brach, 2016; N. König, Singh, Von Beckerath, Janke, & Taylor, 2014). Thus the minimum standards for accurate and reliable gait assessment are yet to be clearly defined in the extant gait assessment literature. Determining the minimum standards for gait assessment is of critical importance to help ensure that assessments are accurate and reliable while being kept to the minimum duration to account for the effects of fatigue and discomfort associated with prolonged gait assessments in older adults populations (Mody et al., 2008). Further in order for gait assessments to have clinical utility their duration needs to be limited.

1.6 Affordable devices for measurement of walking gait

With the advent of cost-effective and portable motion capture devices such as depth sensing single camera 3D motion capture devices, e.g. Microsoft Kinect V2, there is potential for application of these devices as an alternative to expensive motion capture equipment which could be utilized in

laboratory, clinic, pharmacy, and home settings (Sun & Sosnoff, 2018). The Kinect has been shown to accurately and reliably detect gait parameters in healthy subjects (Cippitelli, Gasparrini, Spinsante, & Gambi, 2015; Mentiplay et al., 2015; Pfister, West, Bronner, & Noah, 2014) and in fallers (Sun & Sosnoff, 2018). In order to utilize the Microsoft Kinect or similar devices, accurate walking stride detection algorithms must be developed which are robust to gait characteristics of all populations, including older adult fallers. The advantage of these systems over traditional clinical and research equipment, such as the GAITRite™ pressure mat and optoelectronic 3D motion capture systems, is the cost savings. Microsoft Kinect cameras can be purchased for approximately $100-200 while traditional measurement systems may range from $20,000 (GAITRite™) to hundreds of thousands of dollars (Vicon 3D™). The affordable and accurate measurements provided by the Kinect, and similar devices, allows for the application of these devices in various settings including long-term in-home monitoring of fall risk (Stone & Skubic, 2011).

1.7 Outline and specific objectives of this dissertation

This goal of this dissertation is to discuss the currently available tools for self-assessment of fall risk in older adults (Chapter 2), utilize comprehensive clinical and biomechanical assessments to develop a composite fall classification tool (Chapter 3), determine minimum standards for measurement of walking gait (Chapter 4), and develop a stride detection algorithm for use with single camera 3D depth sensing technologies (Chapter 5).

Chapter 2

Chapter 2 is a scoping review of fall risk self-assessment tools for older adults. The goal of this review was to identify the currently available assessments and determine both the relative abilities to

discriminate fallers and the need for further systematic or meta-reviews to assess the quantity and quality of available literature. In this review I found that there are a limited number of distinct fall-risk self-assessment tools (seven) available for older adults and the inclusion of clinically administered tests alongside self-assessment is recommended.

Chapter 3

The study presented in this chapter aimed to determine the optimal components of a composite measure, of clinical tests and gait measures, that can be easily administered in a clinical setting and retrospectively classify fallers and non-fallers with the highest sensitivity and specificity. To date, no study has concurrently evaluated the relative contributions of measures of clinical mobility and balance, postural sway, physiological indicators and gait (dual-task and single-task and difference scores between them) to differentiate fallers from non-fallers. I found that five gait measures were sufficient for classifying fallers from non-fallers with 92.3% sensitivity (correctly classified fallers) and 66.7% specificity (correctly classified non-fallers) with a total model classification of 82.9%. The five gait measures were all difference scores between single-task and dual-task (cognitively loaded) walking trials, highlighting the important interplay between cognition, gait and fall risk.

Chapter 4

In this study I investigated the minimum number of strides required to accurately measure dual-task and difference score gait metrics for a comprehensive set of gait measures using the GAITRite™ pressure sensing mat. This work builds upon current guidelines (Hollman et al., 2010; N. König, Singh, et al., 2014) which have been suggested for a very limited number of gait metrics. We found that for all metrics except CADV the minimum number of strides required to accurately

quantify dual-task gait metrics was 30 strides for non-fallers and fallers. Additionally, for mean gait metrics only 10 strides were required to result in highly reliable measurements while measures of variability required at least 30 strides. Further, we found that few variables were able to discriminate fallers from non-fallers regardless of the stride count and more strides were needed for specific metrics to detect group differences. The following discussion will present contemporary findings related to current stride count recommendations and the use of dual-task gait metrics to discriminate older adult fallers from non-fallers.

Chapter 5

Chapter 5 presents a technical "white paper" which details the development of a walking stride detection algorithm using the depth sensing capability of the Microsoft Kinect. This algorithm will be further developed to ensure accurate detection of stride characteristics in various populations, including healthy young adults, healthy older adults, older adult fallers, as well as other clinical populations. The applications of this algorithm could include measurement of temporospatial gait metrics in clinical, research, and in-home settings, and ultimately could be incorporated into a comprehensive fall risk identification and monitoring tool.

1.8 Publications

Portions of this dissertation are in the process of publication. Chapter 2 is intended for submission to the *Canadian Journal on Aging* (Commandeur, Wilson, Roy, Verma, Maximos, Leyenaar, & Mróz, 2018). Chapter 3 has been published in *Gait & Posture*. Chapter 4 is intended for submission to *Gait & Posture* (Commandeur et al., 2018). And Chapter 5 is part of a patent application with Jintronix which is currently in the process of revision.

Chapter 2: Self-assessment of fall-risk

2.1 Intro

Aging results in physiological changes that affect balance, walking and cognition, which can increase fall-risk in older adults (Mbourou, Lajoie, & Teasdale, 2003). Falling is a considerable health risk for older adults in Canada and is a major cause of disability and death. A Canadian study indicated that between 20% to 30% of Canadians over 65 years old fall each year (Public Health Agency of Canada, 2014). In the community, 20% of older adults reported a fall, with half of the falls happening at home and 12% in the broad community (e.g. public area, street, and highway, service area), and 17% in residential institutions (Canadian Institute for Health Information, 2016). Falls remain the leading cause of injury-related hospitalization among older Canadians (Scott, Wagar, & Elliot, 2011) and are the direct cause of 95% of all hip fractures (Scott, Wagar, Sum, Metcalfe, & Wagar, 2010). Over one-third of older adults hospitalized following a fall, the incident is discharged to long-term care, which represents almost twice the proportion of those who lived in that setting before the incident (Scott et al., 2011).

With the demographic shift towards an older Canadian population, it is increasingly important to update our knowledge regarding falls in order to reduce the risk of falling as well as injuries and loss of quality of life accompanying them. Indeed, on July 1st, 2015, there were officially more Canadians aged 65 and older (16.1% of the population) than children under 15 (Statistics Canada, 2015) and it is estimated that more than 25% will be age 65 years or older by 2036. With this growing elderly population, a correspondingly increased number of Canadians will be at risk of falling, which could be considerably reduced by properly assessing fall-risk factors and taking steps to mitigate them.

The consequences of falls, which can not only lead to injuries but also cause disability and death, affect the injured individuals as well as their family, friends, care providers and the entire healthcare system. In 2004, the health-care costs associated with falls among older Canadians were estimated at over $2 billion CAD, while the total economic burden of falls is estimated at $6 billion annually (Smartrisk, 2009). Understanding risk factors for falling older adults is crucial to reduce the aforementioned unintentional injuries. Numerous factors have been found to increase the risk of falling among older adults, and at-risk individuals might be subject to multiple risk factors based on their life circumstances, health status, and behaviours, economic situation, social support, and the built environment (Chippendale, 2015; Chippendale & Boltz, 2015). The Public Health Agency of Canada categorized those factors as biological/intrinsic, behavioural, social/economics and environmental (Public Health Agency of Canada, 2014b).

Based on the impact of those risks factors, The Public Health Agency of Canada undertook a literature review to identify best practices in fall prevention (Public Health Agency of Canada, 2014b). Their investigation led to the conclusion that multifactorial risk assessment of falls administered by clinicians or health professionals should be combined with a multifactorial intervention targeting risk factors identified during the assessment. Following their recommendations, which are based on the American Geriatrics Society and British Geriatrics Society (Panel on Prevention of Falls in Older Persons, American Geriatrics Society, & British Geriatrics Society, 2011), primary health care providers should ask all older adults at least once a year about the occurrence of falls and difficulties with gait or balance. Thus, older adults who have fallen in the past, have difficulty with gait or balance, or have been subject to two or more falls in the previous 12 months would then be eligible for a comprehensive risk assessment. Older adults who are not eligible for the risk assessment program, or

who are not followed by primary health care providers must independently adopt fall prevention strategies and identify their personal risk factors for falling through the use of instruments that measure the self-reported, or self-assessed, level of fall-risk.

Research on best practices in fall prevention among older adults has flourished over the last decade and many instruments to assess falls risk have been developed for clinicians to administer in clinical settings, (e.g. Timed Up & Go (TUG) (Shumway-Cook, Brauer, & Woollacott, 2000) and Fall Risk Assessment Tool (FRAT) (MacAvoy, Skinner, & Hines, 1996)), however, there have been few instruments developed for self-assessment of fall-risk. To date, there has not been a rigorous review and comparison of the available fall risk self-assessment tools to determine their reported efficacy. Therefore, the purpose of this scoping review was to assess the current state of available self-report instruments for assessing fall-risk in older community-dwelling adults and to identify any gaps in the existing evidence-base that could inform the need for future research.

2.2 Methods

Identifying Relevant Studies

Two researchers conducted comprehensive literature searches in multiple electronic databases (AgeLine, CINAHL, and PubMed) in May 2016. Four main concepts were searched (see Table 2.1 below) using major headings, or the thesaurus tool, and free vocabulary for each database. The search strategy was not limited by study design and date; however, the scope was limited to peer-reviewed academic literature published in English or French languages.

Table 2.1

Search Terms Used to Search Academic Literature in Electronic Databases

Concept (AND)	Free and Controlled Vocabulary (OR)
Older adults	elder*, senior, aging, ageing, "old age", older *, old*, aged, "frail elderly", "aged, 80 and over", "old old"
Community-dwelling	community, "community living", "community dwelling", "independent living"
Fall-risk	fall*, "fall risk*", "accidental fall*", "fall factor*", "fall prevention"
Self-report	"self assessment", "self report", "self management", "self appraisal", "self evaluation", "self rating", "risk assessment", "risk evaluation", "risk estimation, "self diagnosis", "outcome assessment", "measurement issues and assessments", assessment, "noninstitutionalized populations"

Note: Search terms with asterisks (*) were used to retrieve variations of the root word.

Study Selection

Following the initial literature search, abstracts were screened for eligibility (see Table 3) by two reviewers and any discrepancies related to inclusion for full-text review were decided by a third reviewer. The articles included after abstract screening were then reviewed in full by two reviewers using a custom screening tool (*see* Table 2.2) and again any discrepancies were resolved by a third reviewer.

Table 2.2

Identification Tool for Title and Abstract Screening

Title and Abstract Screening Tool	
Reviewer name:	Date:
Article ID & Citation:	
Country:	
Identification Questions	

Does the title/abstract indicate community-dwelling older adults (65 years old or more)?	Yes = 1 / No = 0 / Unsure = 2
Does the title/abstract indicate fall risk assessment measures?	Yes = 1 / No = 0 / Unsure = 2
Does the title/abstract indicate some form of data (process or outcome?)	Yes = 1 / No = 0 / Unsure = 2

Inclusion/Exclusion Criteria

	Include	Exclude
Who	Includes adults 65 years and older Community-dwelling - Range must be 60 and above	● Adults younger than 65 years ● Youth or children ● Living in long-term residential care ● Living with cognitive impairment and disability (i.e., chronic conditions)
What	-Self-assessment (self-report) measure of fall risk	-Clinical fall-risk assessment - TUG, BERG, FRAT etc.
Outcome	Level of Fall Risk (i.e., report measures fall-risk) ● Self -monitored technology ● Tool that has set questions (example FES, ABC)	● Only report prediction of fall-risk ● No interviews/ semi- structured interview ● Asking about the number of falls or fall history ● Self-reported medical history and other information that does not involve an assessment tool
Type of study design	All	
Article Type	<u>Include</u> -peer-reviewed journal articles - English/French	<u>Exclude</u> -non-peer reviewed; conference proceedings; dissertations; abstracts only; grey literature
Overall Decision	**INCLUDE for full-text review**: **yes/no/ unsure**	

Data Extraction

Two reviewers independently extracted relevant information from each of the included studies utilizing the standardized charting form (see Table 2.3). Any discrepancies were resolved by the reviewers, or a third reviewer if necessary.

Table 2.3

Example of Standardized Charting Form

Citation Reference Number	1
Citation (Author, Date, Journal)	example
Origin/ Country	Canada
Authors clinical credentials	eg. 3 MD, 2 RN, 1 PT, & 1 OT
Assessment Tool	
self-assment tool used	FES, ABC, interview, technology etc
Definition of fall	as stated in article
Stated reason for tool use	validity study, intervention, analysis of population etc
Study Objective/ Research Question	what is the research question being asked
Research Design	RCT, case-control, cohort, cross-sectional, quasi-experimental, descriptive, from MMAT
Duration / Sampling Frequency	duration of trial or observation
Sample Size/ Intervention #, Control #	Total sample size, completed, and drop-out/subsequently excluded, cases/controls
Study population (Age, Location, etc)	Minimum age, age range, median age, and recruitment process
Sex Details	50% male and 50% female
Assesment Details (Intervention, Tool)	Describe how was the self-assessment tool administered or employed. eg. test training/instructed, observed for compliance, any follow-up
Type of assessment	physical assessment vs questionnaire or other
Number of questions/components	
Duration of assessment (minutes)	
Baseline measurements	what physical assessment or questionnaire was used to inform outcomes
Other considerations/needs/assessment limitations	need for equipment, need for informal caregiver
Outcome Measures	was a tool an outcome measure or what was their outcome measure - as stated
Limitations	stated in paper or otherwise observed
Key findings that relate to the scoping review questions	how well does it answer our research question how well does the tool work
General comments	Overall strengths or weaknesses of paper, Controversies, Disagreements with other authors
Implications for Furture Research/Practice	as stated in article
Effect size	If stated

Note. Article information was independently charted by two reviewers for all included articles. The table includes sample information that would be included in the data-charting form.

2.3 Results

The comprehensive literature search yielded 1,683 articles; with 1204 articles remaining after duplicates were removed (Figure 2.1). Following title and abstract reviews, 41 articles were selected for full-text assessment and 12 articles were selected for inclusion in this review.

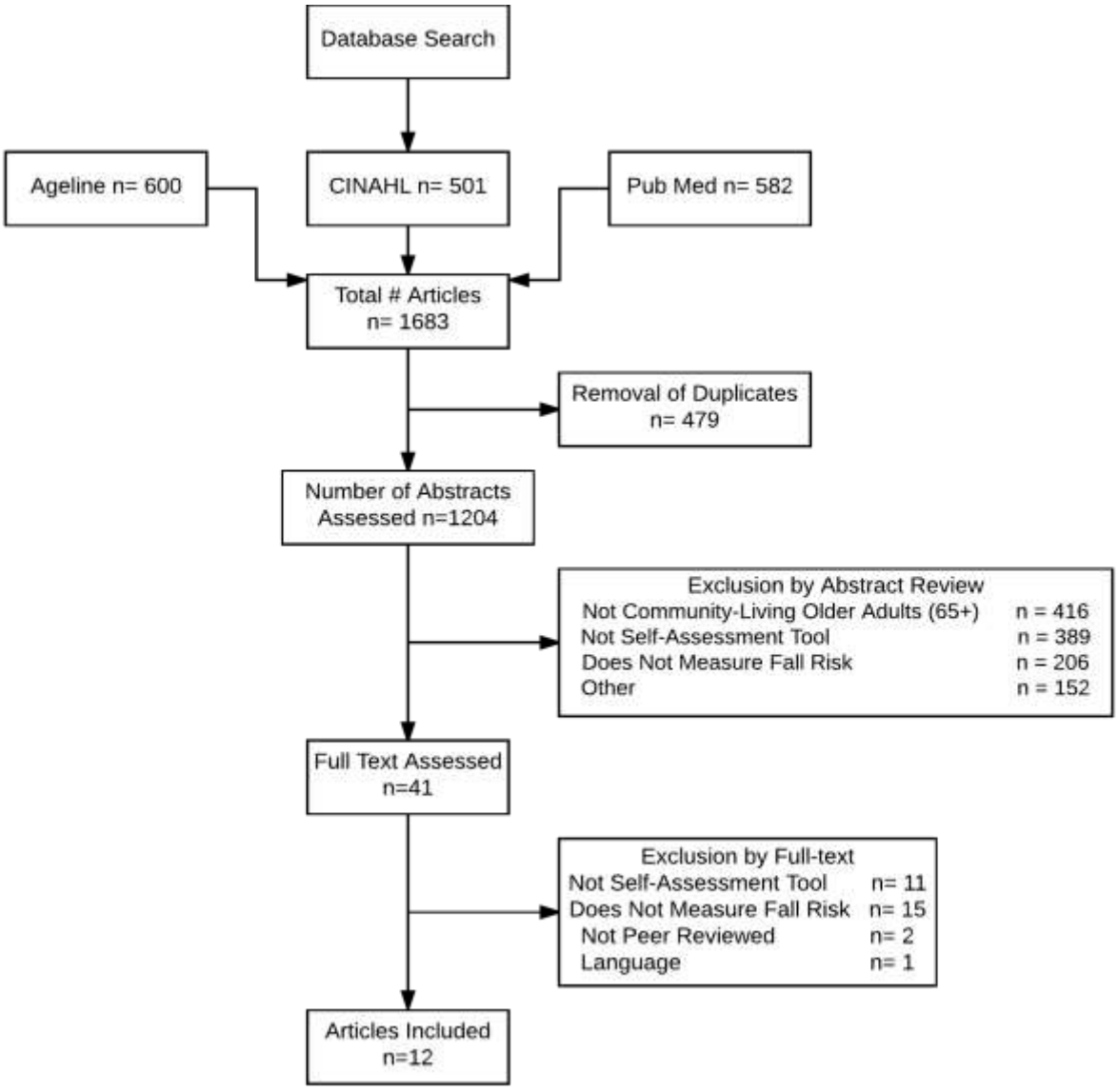

Figure 2.1. *Flow diagram of article selection process*

Study Design

Five of the included studies were cross-sectional design, five were prospective, one study included both prospective and cross-sectional cohorts, and one was descriptive (see Table 2.4 for summary). Sample sizes ranged from 45 to 1378 (average 234 +/- 345) participants with a mean age ranging from 68-82 years old. In five of the studies, there was a large proportion of females represented (>60%) compared to males. Four had neutral gender inclusion (40-59%), and three studies did not report gender.

Self-Assessment Instruments

This review identified 12 studies which included seven unique survey instruments and three physical assessments that have been used for self-assessment of fall risk in community-dwelling older adults. See Table 2.4 for a summary of on the details of each measure including relevant reported statistics. While there were seven surveys identified, the most frequently utilized assessments were the Activities-specific Balance Confidence Scale (ABC) which was used in three studies (Hotchkiss et al., 2004; Schott, 2012; Smee, Berry, Anson, & Waddington, 2015) and the Falls Efficacy Scale (FES) which was used in four studies (Camargos, Dias, Dias, & Freire, 2010; Hellström et al., 2013; Hotchkiss et al., 2004; Smee et al., 2015). Some of the studies used modified versions of the FES and ABC, including different languages as well as shortened versions of the test. One study used the Elliot Falls Risk Tool (EFRT) (Elliott, Jamieson, Donnelly, & Malone, 2004), one study used the Balance Self-Efficacy Scale (BSE) (Gunter et al., 2003), one used the Survey of Activities and Fear of Falling in the Elderly scale (SAFE) (Hotchkiss et al., 2004). Two studies included homemade fall risk assessments (Marks & Katz, 2009; Okochi et al., 2006). The physical assessments included a Nintendo

Wii Fit program (Yamada, Aoyama, Nakamura, et al., 2011), the iStoppFalls Fall Risk Assessment video game (Marston et al. 2015), and a test of gait speed, step length, and lower body endurance (Bongers, Schoon, Graauwmans, Hoogsteen-Ossewaarde, et al., 2015).

Reliability, Validity, Sensitivity, and Specificity

Reliability measures were provided for most of the studies and typically showed high internal consistency (IC) (validity) and high test-retest or inter-rater reliability as represented by intraclass correlations (ICC) (see Table 2.4). Few studies reported the sensitivity or specificity for classification of fall risk. The Nintendo Wii Fit program %) (Yamada, Aoyama, Nakamura, et al., 2011) showed the highest sensitivity and specificity (Sen=86%, Spe=86), followed by the BSE (Gunter et al., 2003) which demonstrated high sensitivity but poor specificity (Sen=82.7%, Spe=38.5), the ABC (Smee et al., 2015) had moderate sensitivity and better specificity (Sen=78%, Spe=85%), the Working Group of Fall Prevention Questionnaire (Okochi et al., 2006) had moderate sensitivity and specificity (Sen=68%, Spe=70%), and the FES (Camargos et al., 2010) showed poor sensitivity and specificity (Sen=47%, Spe=66%), however, after removal of outliers this was greatly improved (Sen=100%, Spe=87%). It is important to note that for both ABC and FES only one study for each reported sensitivity and specificity. See Table 1 for all reported and missing values.

Table 2.4

Characteristics of Self-Report Fall-risk Instruments for Community-Dwelling Older Adults

Reference	Assessment Type	Study Design	Self-Assessment Tool	Number of Questions	Time Required	Sample Size	Mean Age	Sex	Reliability/Validity	Sensitivity (%)	Specificity (%)	Cut-off
Camargos, et al. 2010	Survey	Cross-Sectional	Falls Efficacy Scale-I (FES-I) (Brazil)	16	NR	58	73.44 +/- 5.51	78% F	IC = 0.93	47 100 (after removal of outliers)	66 87 (after removal of outliers)	31
Elliot, et al. 2004	Survey	Expert panel (development), Prospective cohort (validation)	Elliot Falls Risk Tool	20	NR	52	81 +/- 5	80% F	Test-retest r= 0.91	NR	NR	NR
Gunter, et al. 2003	Survey	Prospective cohort	Balance Self-Efficacy Scale (BSE)	18	NR	142	79.8 +/- 5.4	80% F	Kappa = 0.22	82.7	38.5	NR
Hellström, et al. 2013	Survey	Cross-Sectional	FES (Sweden)	13	NR	378	81.7 +/- 4.84	55% F	ICC = 0.97	NR	NR	49
Hotchkiss, et al. 2004	Survey	Cross-Sectional	ABC, FES , Survey of Activities and Fear of Falling in the Elderly (SAFE)	ABC = 16, FES = 10, SAFE = 11)	30 min	118	75.8	NR	α: ABC = 0.96 FES= 0.90 SAFE = 0.91	ABC= 1% var FES= 4% Var SAFE= 5% Var	NR	NR
Marks & Katz, 2009	Survey	Cross-Sectional	Homemade falls risk self-assessment tool kit (Environmental Hazards and Health[EHH] and Global Health [GH])	42 questions and timed 20-foot walk	NR	61	75+/- 3.5	57% F	Validity r: Q2 = .116; Q4 = .378	EHH = ~55; GH = ~60	NR	NR

Reference	Assessment Type	Study Design	Self-Assessment Tool	Number of Questions	Time Required	Sample Size	Mean Age	Sex	Reliability/Validity	Sensitivity (%)	Specificity (%)	Cut-off
Schott, N. 2014	Survey	Cross-Sectional and Prospective Cohort	ABC-D6 and ABC-D16	6 and 16 questions	NR	384	71.1 +/-9.7	57% F	α: ABC-D16 = .97, ABC-D6 = .95; ICC = .81 - .99	78	85	NR
Smee, et al. 2015	Survey	Cross-Sectional	FES-1 and ABC	FES-I = 16 ABC = 16	NR	245	68.12, 6.21	70% F	FES-I & ABC scale r = -.7(male), -.65(female)	NR	NR	NR
Okochi, et al. 2006	Survey	Prospective Cohort	Working Group of Fall Prevention Questionnaire	22, then shortened to 5	NR	1378	75.8, 6.8	NR	ROC Curve Area = 0.74	68	70	6
Bongers, et al. 2015	Physical Assessment	Prospective Cohort	Maximal Step Length (MSL), Gait Speed (GS), Chair Test (CT)	3 physical assessments	NR	49	75.8, 3.96	43% F	MSL: ICC 0.95 GS: ICC 0.89 CT: ICC 0.71	MSL 77.6 GS 44.9 CT 38.8	NR	NR
Marston, et al. 2015	Physical Assessment	Descriptive	iStoppFalls Fall Risk Assessment (Video game)	10 components	NR	160	NR	NR	NR	NR	NR	NR
Yamada, et al. 2011	Physical Assessment	Prospective	Nintendo Wii Fit program - Basic Step and Ski Slalom	2 Games	NR	45	81.3± 7.4	100 % F	BS ICC = 0.79 SS ICC = 0.61	BS = 86	BS = 86	111

Note. NR=not reported

2.4 Narrative Review

Studies that included FES and or ABC Survey Instruments

Camargos et al., 2010

This Brazilian study sought to validate the Falls Efficacy Scale – International (FES-I) in a sample of 163 community-dwelling Brazilian older adults. The study was a cross-sectional design with an initial test administered to 163 participants and a follow-up completed by 58 participants. This study found that the FES-I can be used to assess fall risk in a community-dwelling elderly Brazilian population and that a score of 23 or higher indicated that the respondent suffered from sporadic falls while a score of 31 or more indicated recurrent falls. A limitation of the study is that a convenience sample was used as participants were recruited from health centres, outpatient clinics, research projects, and from physical activity projects, additionally, there was no definition of sporadic or recurrent falls. Additionally, the sample was gender biased towards female participants (77.9%). A limitation of the instrument itself is that it relies on self-reported measures.

Hellström, et al. 2013

The purpose of this Swedish article was to identify fall risk factors in community-dwelling older adults and investigate what characterized non-fallers and fallers. This was a cross-sectional design, which utilized the Falls Efficacy Scale (Swedish) FES (S). Of the 525 solicited individuals, 378 responded to the questionnaire (55% female and 45% male). Help with activities of daily living (ADLs), diabetes, hypnotics and FES (S) instrumental activities of daily living (IADL) were predictive of at least one fall incidence in the last 6 months, with scoring on the FES (S) IADL being the strongest predictor. Fear of falling was not a significant predictor of

falls in this study. The main limiting factors of this investigation were the potential for underestimation due to self-report and the lack of a causal relationship between risk factors and falls due to the cross-sectional design.

Hotchkiss, et al. 2004

This US study compared the ABC, FES, and the Survey of Activities and Fear of Falling in the Elderly (SAFE) to determine their convergent validity and see which one best-identified frequency of falls, the level of activity restriction, and frequency of leaving the home. This cross-sectional study included 118 participants recruited from senior centers, senior housing centers, and private housing. The investigators found that the ABC and FES measure similar constructs (high convergent validity), however, none of the 3 instruments were able to correctly and independently identify the frequency of falls, the level of activity restriction, or frequency of leaving the home. The authors suggest that a multivariate approach to predicting falls risk would be more effective than assessing fear of falling. One factor to consider with their methods is that participants filled out surveys in a community setting with little privacy, which may have resulted in peer influenced responses. Additionally, some participants required further explanation of questions in order to complete the surveys.

Schott, N. 2014

This prospective cohort study in Germany examined the reliability, construct validity, and correlation between German versions of the ABC-D16 and ABC-D6 scores. Both questionnaires were administered at baseline and then again 10 days later. Several physical assessments, as well as self-reported falls history, were collected at baseline. The two scores

were highly comparable with respect to test-retest reliability and discriminative power (**Table 2.4**). This suggests that the shorter ABC-D6 is a valid alternative to the 16-item questionnaire for falls risk self-assessment among community-dwelling older adults.

Smee, D.J., et al. 2015

This cross-sectional study in Australia examined the correlation between two fall risk self-assessment instruments, the FES-I and ABC. Both questionnaires were administered to participants who also completed a number of standardized health and function questionnaires as well as reported the number of falls in the previous 12 months. The study found that ABC and FES-I are strongly correlated (Table 2.4). Substantial differences were observed in how males and females self-assess their risk of falling and what characteristics they contribute to explaining these self-assessments. FES-I correlates better with body composition measures than fall risk and may thus be more appropriate in a clinical environment. This study highlights the importance of considering sex differences in future falls self-assessment research.

Studies with Unique Survey Instruments

Elliot, et al. 2004

This article details the development of the Elliot Falls Risk Tool (EFRT) which is an early self-assessment questionnaire for seniors. The authors developed this instrument because at the time they could find no suitable self-assessment instruments available after performing a literature search. The study consisted of an expert panel to develop the instrument and a prospective cohort study to validate the EFRT. Fifty-two participants (Age 81 +/- 5 years) completed baseline measures which included the Mini-Mental State Exam (MMSE), Berg

Balance Scale (BBS), and Timed Up and Go (TUG) in addition to the EFRT. These established objective measures of fall risk were compared to the constructs assessed by the EFRT to determine the validity of the self-assessment tool. While the EFRT showed high retest reliability (Pearson Correlation 0.91) after 14 days, there was no significant correlation between the EFRT and fall risk. Scores on the EFRT trended towards positive correlation with each of the other established objective measures, and participants reporting falls scored higher on the EFRT. The authors determined that the EFRT on its own is not suitable for self-assessment of fall risk. Limitations of the study include a gender bias (80% F, 20% M) and recruitment a larger sample to allow for improved predictive validity.

Gunter, et al. 2003

This US study used the Balance Self-Efficacy Scale (BSE) to investigate the relationship between changes in balance self-efficacy and specific balance and mobility risk factors for falls, falling laterally rather than anterior or posteriorly, over the course of 1 year. The study involved 198 community-dwelling older adults recruited from the Oregon Falls surveillance study in the Bone Research Laboratory at Oregon State University. Baseline and follow-up assessments were performed at 3-month intervals and included 169 of the original participants with 142 participants completing all assessments (Fallers n=67, Non-fallers n=75). This prospective cohort study tracked baseline measures of mobility, strength, balance tests, balance self-efficacy, medication history, and physical activity along with the 18 question BSE survey and compared them after the 1yr follow-up. The assessments of balance and mobility were the get-up-and-go test, sway during tandem stance, and tandem walk. The BSE test was able to identify fallers from non-fallers and showed no significant changes from baseline to the 1yr follow-up, indicating

reliable measures were obtained. Based on these findings the authors suggest that it may be more useful for screening individuals at risk of injurious falls than either the ABC or FES questionnaires.

Marks, B.L. and Katz, L.M. 2009

This US cross-sectional study examined a homemade falls self-assessment toolkit, which included several standardized questionnaires and physical assessments, including a timed 20-foot walk. The questionnaire involved 42 questions and the overall assessments required approximately 35 minutes to perform. The total falls risk score was related to the actual number of falls reported and was 50 - 60% sensitive in detecting past fallers. The major limitations of this study are that it is time-intensive and portions of the physical assessment require assistance to be performed correctly.

Okochi, J. et al. 2006

This prospective cohort study in Japan developed and validated a shortened version of the 22-item questionnaire that was developed by the Working Group on Falls Prevention to predict future falls risk. Participants completed the questionnaire at baseline and were followed for 6 months to assess falls. The authors were able to identify 5-items of the self-assessment, which could be used to predict falls. A binary fall risk cut-off score on the 5-item tool was established. The sensitivity and specificity were 68% and 70%, respectively, for fall risk at the selected cut-off point. Participants who screened as positive had a 27.9% rate of falls in the next 6 months, compared with 7.2% among participants who screened negative. This is a brief screening instrument designed and validated for use in routine health check-ups.

Studies with Physical Assessments

Bongers, et al. 2015

This prospective cohort study in the Netherlands examined the reliability, safety, and feasibility of 3 physical assessments (maximal step length, gait speed, and chair test (5x sit-to-stand)) for falls risk self-assessment. The researcher explained and practiced the potential self-tests with the subjects and their informal caregivers. Participants had a trial period of 4 weeks to practice performing the self-test, which they were asked to perform once weekly at home. After 4 weeks, the researcher visited the subjects and asked them to execute the self-test. All errors and unsafe maneuvers were recorded. The maximal step length test had good sensitivity and specificity, and the least errors made by the participants indicating it as the only feasible test of the three. It had the highest reliability (Table 2.4) and had the highest percentage of correct measurements (77.6%). The major limitations of this study were that the study sample had good mobility overall and the study was not able to determine how well maximal step length predicts falls risk, thus further research is needed about predictive ability and generalizability.

Marston, H.R. et al. 2015

This paper describes the design of a randomized controlled trial, expected to enroll 160 healthy community-dwelling older adults. Individuals respond to the Fall Risk Assessment to identify their fall risk factors. Then, they use the technological devices to complete an exercises program including balance and strength exercises. Following completion, they were provided feedback on their performance/results and educational information. Additionally, they can share their results on a social media platform. While no data was presented in this study, publications

were released by the group after the initial search date of this review that detail their qualitative (Ogonowski, et al. 2016) and quantitative findings (Vaziri, et al. 2016).

Yamada, M., et al. 2011

This cross-sectional Japanese study with 45 participants, examined whether 2 games in the Nintendo Wii Fit Program, Basic Step and Ski Slalom, could be useful for falls risk assessment Participants were taught to play the Wii games by a research assistant and then performed 2 trials of each game separated one-hour apart. Physical performance measures and self-reported history of falls were assessed at baseline. The Basic Step, but not the Ski Slalom, was found to have adequate test-retest reliability (Table 2.4). A score of 111 points on the Basic Step was determined to be the fall-related cut-off point using discriminant analysis, by which 88.6% of the cases were correctly classified. The major limitations of this study were that participants were entirely female, excluded if they had significant comorbidities, and they were likely highly motivated and interested in health issues, which may limit generalizability. Access to a Wii fit instrument is required and could limit the accessibility of this instrument, however, the Basic Step has promise in falls risk self-assessment.

2.5 Discussion

Currently, there are a limited number of distinct fall-risk self-assessment tools available for older adults. This review identified 12 studies which included seven unique survey tools and three physical assessment instruments intended for personal use by community-dwelling older adults. Several of the studies were validations of instruments (e.g. or i.e. FES and ABC) already

used in different settings (Gunter et al., 2003), in different configurations (Hotchkiss et al., 2004; Schott, 2012; Smee et al., 2015), or in different languages (Camargos et al., 2010; Hellström et al., 2013). Also, novel survey-based assessments were developed in three studies (Elliott et al., 2004; Marks & Katz, 2009; Okochi et al., 2006). Physical assessments were all uniquely designed and included measures of gait and lower body endurance (Bongers, Schoon, Graauwmans, Hoogsteen-Ossewaarde, et al., 2015), strength and balance (Yamada, Aoyama, Nakamura, et al., 2011), and one study which combined physical assessments with fall-risk surveys (Marston et al., 2015). Many of the studies included other well-established physical and survey-based assessments developed for clinical use; however, only tests which can be self-administered by community-dwelling older adults have been included.

One of the primary concerns when assessing the utility of fall-risk self-assessment instruments is the ability to accurately identify those at risk of falling. None of the novel survey-based instruments provided an improvement over the two most commonly used self-assessments (FES and ABC), however, they generally performed at a similar level. The physical assessments (Bongers, Schoon, Graauwmans, Hoogsteen-Ossewaarde, et al., 2015; Marston et al., 2015; Yamada, Aoyama, Okamoto, et al., 2011) were about as effective at classifying fallers compared to the FES and ABC scale. A number of studies reported that a survey-based assessment is not adequate on its own to predict fall-risk, however, they might be acceptable for monitoring risk in individuals with a previous fall history.

Findings from this review identified a lack of longitudinal studies to demonstrate the reliability of assessment instruments within the same sample over a sufficient time span (at least one year). Six of the studies included were cross-sectional and included samples with a gender bias, thus limiting their external validity to similar populations. It does not appear that a

systematic review of fall-risk self-assessment instruments for community-dwelling older adults is currently necessary based on the limited number of novel assessment instruments, their inability to improve on already established measures, and the overabundance of cross-sectional studies. Given the rapid development of technology, it is expected that many technology-based assessments will be developed in the near future and a follow-up to this scoping review should be conducted at a later date to assess the volume and predictive validity of these instruments.

Conclusion and Future Research

There are several fall-risk self-assessment instruments available for community-dwelling older adults, with the majority of studies utilizing either the FES or ABC instrument to positive effect. Assessments utilizing technology are becoming more popular and may provide an opportunity to engage in both fall-risk identification and fall-risk management concurrently via in-home monitoring devices (Rantz et al., 2015). Future research should incorporate both physical assessments and survey instruments to improve fall-risk classification, and when possible should consider leveraging technological advances to improve the accuracy of measurements. Additionally, studies need to be conducted with longitudinal designs to assess the reliability and validity of the assessment instruments over time within the same sample group.

Chapter 3 Biomechanical and Clinical Measures for Classification of Fall Risk

3.1 Introduction

Falls are frequent occurrences in community-dwelling older adults, with up to 30% of Canadians over the age of 65 experiencing one or more falls each year (Public Health Agency of Canada, 2014b). Falls are the leading cause of fatal and nonfatal injuries among adults aged ≥65 years (Stevens, J, & KAP, 2008). These debilitating and potentially life-threatening injuries have long term consequences to physical, psychological, and economic well-being (Rubenstein & Josephson, 2002). Early and accurate identification of at-risk individuals is essential in providing effective interventions to decrease the likelihood of falling and subsequent injury (Scott, Votova, Scanlan, & Close, 2007). For this reason, many researchers and clinicians have examined the use of screening tools appropriate for clinical settings based on known risk factors in an attempt to identify future "fallers". Initially these tools included history of falling, simple tests of muscular strength and endurance (Jones et al., 1999; Shumway-Cook, Brauer, & Woollacott, 2000), postural sway (Boulgarides, Mcginty, Willett, & Barnes, 2003), and clinical tests of balance and mobility (Rose et al., 2006). Although a history of falls remains the most accurate predictor of future falls (Gerdhem, Ringsberg, Kesson, & Obrant, 2005), it is not useful in models striving for early detection and prevention of first time falls.

Recently, gait measures have been considered potentially predictive of fall risk and may be more sensitive than clinical tests (N. König, Taylor, Armbrecht, Dietzel, & Singh, 2014a). Differences have been shown in mean and variability of temporospatial gait measures between fallers and non-fallers in an elderly population (Callisaya et al., 2011; Verghese et al., 2009).

Elderly persons presenting with mild cognitive impairments demonstrate similar gait deficiencies to those with a history of falls, suggesting that executive function, gait control, and fall risk may be linked (Verghese et al., 2009). This has led to studies using dual-task [DT] conditions, in which walking is performed in conjunction with a cognitive task. Differences have been demonstrated in DT gait metrics between young and older persons, as well as between older fallers and non-fallers (Priest, Salamon, & Hollman, n.d.; Springer et al., 2006). However, it is unclear if the use of DT gait conditions increases the sensitivity in detecting fall risk (for review see (Menant et al., 2014; Schwenk et al., 2014)). Further, the contribution of differences between DT and single-task [ST] gait conditions for gait metrics has never been evaluated.

Most studies have separately evaluated mobility, balance, strength, physiologically based tests, and gait as fall risk indicators, and little work has concurrently evaluated the breadth of measures. A recent study employing principal components analysis determined seven components from measures of gait measures, strength, muscular control as well as postural sway during quiet standing. Using three of the factors related to mean and temporal variability of gait they found a sensitivity of 74% and specificity of 76% for classification of fallers and non-fallers (N. König, Taylor, et al., 2014a). However, this investigation did not include many of the clinical balance and mobility tests currently employed by clinicians, nor did it include DT gait conditions. Further, it did not include postural sway with vision removed or physiological measures often affected by age such as vision, or proprioception that have been linked to fall risk (Lord et al., 2003). To date, no study has concurrently evaluated the relative contributions of measures of clinical mobility and balance, postural sway, physiological indicators and gait (DT and ST and difference scores between them) to differentiate fallers from non-fallers. To that end, this study aims to determine the optimal components of a composite measure easily administered

in a clinical setting drawn from an extensive battery of outcome measures that retrospectively classify fallers and non-fallers with the highest sensitivity and specificity.

3.2 Methods

Participants

Forty-two community-dwelling older adults (75.8 yrs +/- 3.3) were recruited and classified into two groups based on self-report of having one or more falls in the previous 12 months (Fallers N=27, (19F, 7M) Non-Fallers N=15 (6F, 9M)). The circumstances of each reported fall were reviewed and classified as a fall if the participant came to rest on a lower surface as a result of a loss of balance. Exclusion criteria included: physician-diagnosed dementia, recent major illness or a neurological, sensory, or mobility impairment that would impede participation; Mini-Mental Status Examination score (MMSE) of less than 24; and non-fluent in English (See Table 1). Participants were screened with the Physical Activity Readiness Questionnaire (PAR-Q), and physician approval was obtained if participants reported 'yes' to any question. Participants provided written informed consent and all procedures were approved by the Human Research Ethics Board at the University of Victoria.

Table 3.1

Descriptive Participant Characteristics for Fallers (N=26) and Non-Fallers (N=15)

Descriptive Variable	Non-Fallers		Fallers		p-value
	Mean	SD	Mean	SD	
MMSE	28.5	1.1	28.5	1.6	0.14
Age (yrs)	75.8	3.4	75.9	3.3	0.97
Height (cm)	168.9	9.3	167.5	10.2	0.68
Weight (kg)	77.3	15.7	77.4	17.3	0.99
Leg Length (cm)	91.8	5.2	90.8	5.4	0.54

Protocol

Participants completed a battery of assessments to attain measures of gait during DT and ST gait, clinical balance and mobility, postural sway during quiet standing, as well as select physiological measures. The order of tests was randomized. All researchers conducting the testing were blinded to the participants' fall history. All participants wore a safety belt and were closely spotted for balance for the duration of testing. Height, weight, and limb segments lengths were measured.

Gait Measures

Spatiotemporal gait measures were recorded as participants performed 10 DT and 10 ST walking passes (i.e. there and back) at a self-selected preferred walking speed along a 6.4m GAITRite™ (CIR Systems INC, Sparta, NJ) instrumented walkway (sample rate 120hz) in walking shoes. The DT walking trails involved counting backward by serial sevens aloud from a randomly generated three-digit number. The order of the ST and DT conditions was randomized, and three practice passes were performed prior to each condition for familiarization. To account for acceleration and deceleration in gait velocity, participants walked 1.5 meters prior to and beyond the end of the mat. Gait measures included four sub-domains: Length, width, timing, and velocity (See Table 2). Within each gait sub-domain, there were measures representing the mean and variability (standard deviation) for DT scores, mean and variability of difference scores between single-task and dual-task gait trials (DS) for a total of 45 gait measures (See Table 2).

Table 3.2

Gait Measures and Clinical Assessments

	Gait Measures		Clinical Assessments
Length	**Stride Length (cm)**	Static Balance	**Single Leg Balance (s)**
	Stride Length Variability (cm)		**SPPB Tandem Stand (s)**
	*** Stride Length Difference (SLD) (cm)**		**CTSIB 1 (cm^2) [eyes open]**
	*** Stride Length Variability Difference (SLVD) (cm)**		**CTSIB 2 (cm^2) [eyes closed]**
	Base of Support (cm)		*** CTSIB 3 (cm^2) [visual conflict dome]**
Width	**Stride Width (cm)**		**CTSIB 4 (cm^2) [foam- eyes open]**
	Base of Support Variability (cm)		*** CTSIB 5 (cm^2) [foam- eyes closed]**
	Stride Width Variability (cm)		**CTSIB 6 (cm^2) [foam– visual conflict dome]**
	Base of Support Difference (cm)		Fab 6 (s) [stand on one leg]
	*** Stride Width Difference (SWD) (cm)**		**Fab 7 (s) [stand on foam with eyes closed]**
	Base of Support Variability Difference (cm)	Functional Mobility	**SPPB 2.44m Walk Time (s)**
	*** Stride Width Variability Difference (SWVD) (cm)**		**SPPB 2.44m Walk Score (ord)**
Timing	Stride Time (s)		**Timed Up and Go (s)**
	Stance Time (s)		**Functional Reach Test (ord)**
	Single Support Time (s)		**Fab 3 (ordinal) [turn 360]**
	Double Support Time (s)		**Fab 4 (ordinal) [step over 6" bench]**
	Cadence (stride/min)		**Fab 5 (ordinal) [tandem walk]**
	Swing % of Cycle (%)		**Fab 9 (ordinal) [walk with head turns]**
	*** Stride Time Variability (STV) (s)**	Strength	**SPPB Repeated Chair Stands (s)**
	Stance Time Variability (s)		**SPPB Repeated Chair Stands Score (ord)**
	Single Support Time Variability (s)		5x Sit to Stand (s)
	Double Support Time Variability (s)		**5-Step Test (s)**
	Cadence Variability (stride/min)		**Hand Grip (kg)**
	Swing % of Cycle Variability (%)	Physiological	**Knee Proprioception (Active) (º)**
	*** Stride Time Difference (STD) (s)**		**Knee Proprioception (Passive) (º)**
	Stance Time Difference (s)		**Peak Flow (L/min)**
	Single Support Time Difference (s)		**Visual Acuity (1/logMAR)**
	Double Support Time Difference (s)	Summary	**SPPB Total Time (ord)**
	Cadence Difference (stride/min)		**SPPB Summary Score (ord sum)**
	*** Swing % of Cycle Difference (SCD) (%)**		**Fab Total (ord sum)**
	Stride Time Variability Difference (s)		
	Single Support Time Variability Difference (s)		
	Double Support Time Variability Difference (s)		
	Cadence Variability Difference (stride/min)		
	Swing % of Cycle Variability Difference (%)		
Velocity	**Stride Velocity (cm/s)**		

Velocity (cm/s) **Stride Velocity Variability (cm/s)** Velocity Variability (cm/s) *** Stride Velocity Difference (SVD)** Velocity Difference (cm/s) ***Stride Velocity Variability Difference (SVVD) (cm/s)** Velocity Variability Difference (cm/s)	Endurance	**30s Sit-to-stand (Count)**

• Bolded variables were included for principal component analysis
• Asterisk indicates variables included in binary logistic regression
• ord: Ordinal

Clinical Mobility and Balance Measures

Ten clinical mobility and balance tests (with a total of 40 individual measures; see Table 2) were administered according to accepted standardized protocols comprising: Timed Up and Go (Podsiadlo & Richardson, 1991; Rose et al., 2006), Berg Balance Scale (Berg et al., 1992), Single Leg Balance (Vellas et al., 1997), Short Physical Performance Battery (Gawel et al., 2012), Functional Reach Test (Weiner et al., 1992), 5 Step Test (Murphy et al., 2003), Five-Times-Sit-to-Stand (Teo et al., 2013), 30 second Sit to Stand (Jones et al., 1999) and Modified Fullerton Advanced Balance Scale (FAB). All Berg Balance Scale items were excluded as there was insufficient variance due to ceiling effect to allow for statistical comparison between cohorts. FAB Items 8 and 10 were removed, as they were deemed unlikely to be carried out by a physician in a clinic setting. Clinical balance and mobility measures were classified into five domains comprising static balance, functional mobility, muscle strength, endurance, and summary test scores. Individual components of each clinical test (e.g. FAB) were classified into domains based on the theoretical construct they measured (See Table 2).

Postural Sway during Quiet standing

Postural sway was assessed with the Clinical Test of Sensory Interaction and Balance (CTSIB) (Cohen, Blatchly, & Gombash, 1993), and the conditions are listed in Table 2. Participants stood without shoes on an AccuSway force plate (AMTI™) with feet together for three conditions: eyes open, eyes closed, and wearing a visual conflict dome (view of vertical lines). These three conditions were repeated while standing on four inches of foam placed on the force plate. Centre of pressure displacement was recorded, and the 95% confidence interval area of ellipse was calculated for each condition. Postural sway was classified in the static balance domain (see Table 2).

Physiological Measures

Four physiological measures with known associations with fall risk or general health were tested. Visual acuity was tested with 10 foot Snellen Eye Chart; handgrip strength was tested using a dynamometer (Takei™ 5001) in the dominant hand, peak expiratory flow measured with a peak flow meter (Vitalograph®), and knee proprioception was measured using the Physiological Profile Assessment™ (Lord et al., 2003) (See Table 2). With the participant's eyes closed and each leg on either side a 60cm by 60 cm acrylic sheet inscribed protractor, the participants were asked to align their left lower limb to the position of their right, which in separate trials were moved into position actively and then passively. The difference between the positions of the right and left great toes was measured in degrees.

3.3 Data Analysis

Descriptive Statistics

Student's T-test was used to determine differences between fallers and non-fallers for leg lengths, age and MMSE scores (SPSS v. 20®). Spatiotemporal gait measures for right and left legs were averaged for statistical analysis. Statistical significance was set at $\alpha < 0.05$. Descriptive analyses include means and standard deviations for the faller and non-faller cohorts.

Data Reduction

Prior to data reduction, there were 76 measures (45 gait, 26 clinical and five physiological measures) which were classified into their respective domains (See Table 2). Within each domain, highly collinear (Pearson's product-moment correlations > .90 (StatSoft™)) and theoretically redundant measures were removed to reduce multi-collinearity. Principal component analysis (PCA) was then performed as a dimension reduction technique on this limited set of measures to determine the fewest measures that could reconstruct the highest portion of sample variance (StatSoft™). These measures were mean normalized, and the PCA variable selection followed the methods outlined in King and Jackson (1999) method B4. This process required performing iterative PCA and the highest contributing variable from each factor with an eigenvalue of 1.0 or greater was identified. These identified variables were retained as critical measures for subsequent modelling and removed from further PCA. The iterative PCA was repeated with the remaining measures until a single factor solution was achieved. PCA was performed using the covariance matrix to account for part-whole associations within the gait metrics (Aguilera, Escabias, & Valderrama, 2006) and varimax rotation to ensure orthogonality of measures (King & Jackson, 1999).

Retrospective Classification

Following data reduction, the key measures identified from the PCA were entered into a backward stepwise binary logistic regression using maximum likelihood estimation to assess the ability of the independent measures to classify the fall status of older adults to create a predictive model. Regression analysis was performed using raw data that were z-transformed and linearly converted to T-scores (M=50, SD=10). The dependent variable was fall status (non-faller or faller). The model with the highest sensitivity while minimizing the number of measures was chosen. The Hosmer-Lemeshow test was conducted to assess the goodness of fit of the logistic regression model.

3.4 Results

Participant descriptive characteristics were not significantly different between the fallers and non-fallers as outlined in Table 1. Mean and standard deviation for each variable are presented in Appendix A (100 stride gait metrics).

Data Reduction and Retrospective classification

Removal of highly collinear measures ($r \geq 0.9$) whose constructs were theoretically overlapping resulted in 18 gait measures (reduced from 45), 24 clinical measures (reduced from 25) and five physiological measures (none removed) which are bolded in Table 2. Elimination of highly collinear measures ensured a positive definite covariance matrix prior to conducting the PCA. A total of four iterations of the PCA was required to achieve a single factor solution. This resulted in the identification of eleven measures: nine gait measures spanning all four gait sub-domains (Stride Time Difference (STD), Stride Time Variability (STV), Stride Length

Difference (SLD), Stride Length Variability Difference (SLVD), Stride Width Difference (SWD), Stride Width Variability Difference (SWVD), Stride Velocity Difference (SVD), Stride Velocity Variability Difference (SVVD), and Swing % of Cycle Difference (SCD)) and two clinical measures from the static balance domain (CTSIB 3 and 5). These measures are indicated with an asterisk in Table 2.

The 11 measures were entered into the logistic regression, with the resulting model comprised of five measures: STD, SWD, SLD, SWVD, and SVVD (See Table 3). This model achieved 92.3% sensitivity (correctly classified fallers) and 66.7% specificity (correctly classified non-fallers) with a total model classification of 82.9%. Mean scores for fallers and non-fallers are presented for the five measures. The logistic regression revealed that SLD ($p=0.042$) and STD ($p=0.047$) significantly and uniquely contribute to the prediction of fall status, with a larger DS indicating increased fall risk. SWD and SWVD were approaching significance at $p=0.056$ and $p=0.058$ respectively. Goodness of fit for the model was supported by the Hosmer-Lemeshow test (Chi-square; 7.643; $p=0.469$).

For each T-Score unit increase in the STD participants were 1.19 times (19%) more likely to experience a fall; for each T-score unit increase in SWD, participants were 1.14 times (14%) more likely to experience a fall; for each T-score unit increase in STD, participants were 1.64 times (64%) more likely to experience a fall; and for each T-score unit increase in SWVD, participants were 1.12 times (12%) less likely to experience a fall.

The binary logistic regression resulted in the following equation derivation where Fall experience is the dichotomous dependent variable Faller group=1 and Non-faller group =0 (See Table 3):

$$\log\left(\frac{p}{1-p}\right) = -34.022 + (0.170 \times SLD) + (0.134 \times SWD) - (0.114 \times SWVD) +$$

$$(0.498 \times STD) - (0.035 \times SVVD)$$

Table 3.3

Results of Binary Logistic Regression at an alpha Level of p < 0.05

							95% CI	
Variable	B	S.E	Wald	df	Sig	Exp(B)	Lower	Upper
Stride Length Diff	.17	.08	4.13	1	**.04**	1.19	1.0	1.4
Stride Width Diff	.13	.07	3.65	1	.06	1.14	1.0	1.3
Stride Width Var Diff	-0.11	0.06	3.59	1	.06	0.90	0.8	1.0
Stride Time Diff	0.50	0.25	3.93	1	**.05**	1.65	1.0	2.7
Stride Velocity Var Diff	-.035	.04	.70	1	.40	0.97	0.9	1.0
Constant	-34.02	15.60	4.76	1	.03	0.00		

• Bolded variables are significant predictors of fall status

3.5 Discussion

After concurrently evaluating a comprehensive battery of measures, we found that 11 of these were able to capture the salient characteristics of this cohort of fallers and non-fallers. The set of measures comprised clinical mobility and balance, postural sway, physiological indicators as well as mean and variability gait measures and difference scores. Of the 11 measures, five gait measures were sufficient for classifying fallers from non-fallers with 92.3% sensitivity (correctly classified fallers) and 66.7% specificity (correctly classified non-fallers) with a total model classification of 82.9%. Remarkably, the five gait measures were all difference scores between ST and DT trials (DS) comprising mean stride timing, stride width, and stride length and the variability for stride width and stride velocity. This highlights the important interplay between cognition, gait and fall risk.

Causes of falls in older adults are multifactorial including deficits in bio-mechanical components (e.g. muscular strength and endurance, balance), sensory input (e.g. vision, proprioception and vestibular system), cardiorespiratory function, and cognition (e.g. executive function to manage dual-tasks) all leading to changes in walking ability, particularly under cognitive load (Menant et al., 2014; Rubenstein, 2006). Thus when evaluating measures relevant for fall prediction, it is important to include a representative, comprehensive battery of measures spanning these diverse domains to allow each the opportunity to emerge as key indicators of fall risk. Further, the importance of both mean and variability of temporospatial gait features (Callisaya et al., 2011)(Verghese et al., 2009) as well as the effect of cognitive load on gait for differentiating fallers from non-fallers has been demonstrated (Springer et al., 2006). To this end we included 76 initial measures that embodied these domains, which necessitated a data reduction process. Though Lord and colleagues developed a tool representing multiple domains(Lord et al., 2003), these measures were selected based on theoretical constructs rather than allowing a statistical data reduction process to guide the selection such as employed in the current study (King & Jackson, 1999). Though König et al. (2014) used statistical data reduction, their battery was less inclusive, making our study, the first to our knowledge, to include this comprehensive a battery of measures.

Our data reduction process involved removal of highly collinear measures and an iterative PCA process prior to modeling the classification of fall risk with binary regression. The PCA reduced the 18 gait and 24 clinical and five physiological measures to nine, two and zero respectively. The 11 measures in the reduced data set, which contain the salient characteristics of both cohorts, map on to the functional domains of gait and static balance. The sub-domains within gait comprised stride length, stride width, stride time, and stride velocity. Interestingly,

König and colleagues, who also used PCA for data reduction, arrived at seven similar representative domains (N. König, Taylor, et al., 2014a). The first component was static balance, and the other six were related to gait. König and colleagues' temporospatial gait measures included mean and variability of ST gait, while our gait measures included variability of DT gait measures as well as mean and variability of DS.

König et al. (2014) identified only gait measures as significant from their predictive fall risk binary logistic regression model (N. König, Taylor, et al., 2014a). This is corroborated by the overwhelming evidence, that gait domains (Menant et al., 2014) and variability during DT gait (Springer et al., 2006) are strongly predictive of fall risk. We enhanced this model by identifying that an increase in the DS for gait measures better discriminated fallers in our predictive model. Similarly, Priest et al. (2008) found a larger difference between DT and ST gait tasks for gait velocity and stride velocity in the older subjects than younger subjects (Priest, Salamon, & Hollman, 2008). Intriguingly, evidence from the neurocognitive arena has also shown that difference scores between cognitive tests of different challenge levels can be even more sensitive to performance deficits than the individual test scores (Strauss, Sherman, & Spreen, 2006). This addition of DS for gait measures afforded a markedly more sensitive classification model of 92.3% compared to 74% sensitivity reported by König et al. (N. König, Taylor, et al., 2014a).

While we identified specific DS of mean and variability gait measures for stride width, length, velocity, and timing, DS from other measures that represent the identified gait domains may provide similar predictive models. Our work demonstrates that these gait measures significantly out-performed traditional clinical tests of strength, mobility and balance, as well as physiological assessments for fall risk prediction. This raises the question as to whether the long

standing use of clinical tests of mobility and balance employed by clinicians should be replaced by accurate measures of gait features during DT and ST trials for fall risk evaluation. The recent development of inexpensive, user-friendly gait measurement technologies, such as inertial measurement units with robust gait algorithms, make accurate gait measurement in the clinical setting feasible and attractive. This does not negate the fact that clinical tests of mobility and balance remain extremely useful for evaluating changes in individual's functional performance resulting from a clinical intervention or disease progression. Our future research will investigate the implementation of our fall risk model with longitudinal data to predict first time fallers.

Chapter 4: Determining the minimum number of strides required to accurately measure dual-task walking gait in older adult fallers and non-fallers

4.1 Introduction

Approximately 33%-45% of community-dwelling older adults over the age of 65 fall at least once each year (Parachute, 2015). Further, the severity of falls increases with age (Rogers, Rogers, Takeshima, & Islam, 2003; Rose et al., 2006; Verghese et al., 2009) and falls can have debilitating consequences including injury, hospitalization, loss of independence, and death (Rogers et al., 2003; Verghese et al., 2009). Thus, early identification of potential fallers and providing timely, effective interventions is critical (Callisaya et al., 2011; Rubenstein & Josephson, 2002; Stevens, Corso, Finkelstein, & Miller, 2006). Identifying key walking gait metrics that are related to falls has shown promise for predicting future fall risk (Hausdorff et al., 2001; A. König et al., 2017; N. König, Taylor, Armbrecht, Dietzel, & Singh, 2014b). Differences have been shown in the mean and variability of temporospatial gait measures between fallers and non-fallers in an elderly population (Callisaya et al., 2011; Faude et al., 2012; Rampp et al., 2015; Toole et al., 2007; Verghese et al., 2009). For example, slower gait speed, increased stride length variability, decreased swing time, increased stance time, and increased swing time variability were found to predict fall risk (Verghese et al., 2009). Decreased dual-task gait velocity and a positive association between gait variability and dual-task complexity were noted for fallers and particularly in those with mild cognitive impairment (Montero-Odasso, Muir, et al., 2012). Further, it has been shown that dual-task paradigms are more sensitive than single-task walking at distinguishing fallers from non-fallers (A. König et al., 2017; Montero-Odasso, Verghese, et al., 2012). Findings presented in Chapter 3 demonstrated that the calculated

differences between dual-task and single-task walking gait metrics (difference score) were better than dual-task values alone for classifying fallers. While the value of walking gait metrics (single- and dual-task) has gained research support as a viable clinical fall assessment task, there is no consensus on the minimum number of strides required to obtain valid and reliable results with recommendations for minimum number of strides ranging from 6-400 (Hollman et al., 2010; N. König, Singh, et al., 2014; Kressig & Beauchet, 2005; Owings et al., 2003). For a fall risk assessment tool to be clinically viable, several important factors need to be considered such as limited space, time required for assessments, and physical limitations of older adults, all of which facilitate the need to determine the minimum number of strides required to differentiate walking gait metrics between older adult fallers and non-fallers (Mody et al., 2008). Further, the minimum number of strides required to accurately assess dual-task gait metrics and difference scores has also yet to be determined.

Several attempts have been made to quantify the minimum number of walking strides required to accurately and reliably measure a limited number of gait metrics in healthy young adults (N. König, Singh, et al., 2014; Owings et al., 2003) and healthy older adults (Hollman et al., 2010). To date, no investigation has determined the minimum number of strides required to accurately characterize the gait metrics that identify older adult fallers. Therefore, the aim of this study is to determine the minimum number of strides required to accurately and reliably measure temporospatial dual-task and difference score gait parameters in older adult fallers and non-fallers as well as discriminate between them.

4.2 Methods

Participants

Forty-one community-dwelling older adults (74.8 ± 3.5 yrs) were recruited and completed a single- and dual-task walking experiment following the experimental protocol outlined in Chapter 3. The participants were classified into two groups based on their one-year fall history (Fallers N= 18, Non-Fallers N=23). The circumstances of each reported fall were reviewed and classified as a fall if the participant came to rest on a lower surface as a result of a loss of balance. Participant exclusion criteria included: physician-diagnosed dementia, recent major illness or a neurological, sensory, or mobility impairment that would impede participation; Mini-Mental Status Examination score (MMSE) of less than 24; and non-fluent in English (See Table 5.1). Participants were screened with the Physical Activity Readiness Questionnaire (PAR-Q), and physician approval was obtained if participants reported 'yes' to any question. Participants provided written informed consent and all procedures were approved by the Human Research Ethics Board at the University of Victoria.

Protocol

Participants performed 10 single-task (ST) and 10 dual-task (DT) walking passes (approximately 10 strides per pass) across a 6.4m instrumented GAITRite™ pressure sensing walkway with an additional 1.5m acceleration and deceleration zone before and after the walkway. Dual-task trials consisted of counting backward by serial 7's from a randomly generated 3-digit number. In addition to the full data set consisting of 100 strides of ST and DT walking, four reduced datasets were created by taking the first 10, 30, 50, and 70 strides from the

original 100 stride data. These four data sets were compared to the full 100 stride data set to assess the level of agreement.

Assessing Measurement Agreement

Agreement between the four reduced datasets and the original 100 stride dataset were assessed using 3 different statistical approaches. First, the agreement between each individual measure was assessed visually through the use of Bland-Altman plots to characterize the concurrent validity (Bland & Altman, 1986). These plots compare the mean between the 100 strides and each of the reduced stride counts (abscissa) vs the difference between the two (ordinate). Differences in measurement are characterized by a bias (mean difference) which does not equal zero, and limits of agreement were assessed by the proportion of observations contained within the 95% confidence intervals (dotted lines) and spread from the bias (solid line). Second, Cronbach's alpha was used to assess the internal consistency for each gait measure across all data sets separately for each group (fallers and non-fallers) with reliability coefficients of 0.90 considered excellent, 0.80 considered good and a minimum of 0.70 considered acceptable (Tavakol & Dennick, 2011). Third, repeated measures ANOVA were performed for each gait measure between the five data sets (10, 30, 50, 70, and 100 strides) to determine the minimum number of strides required to identify differences between cohorts as well as between full and reduced stride datasets. Main effects for fall status and number of strides were assessed, as well as the interaction between fall status and number of strides. For measures derived from overall trial averages (cadence and swing % of cycle), there is no measure of variability for 10 strides as there is a single value output for the average of each trial.

4.3 Results

Participant descriptive characteristics were not significantly different between the fallers and non-fallers as outlined in Table 4.1. Mean and standard deviation for each variable are presented for each data set in Appendix A.

Table 4.1

Descriptive Participant Characteristics for Fallers (N=18) and Non-Fallers (N=23)

Descriptive Variable	Non-Fallers		Fallers		p-value
	Mean	SD	Mean	SD	
MMSE	28.5	1.2	28.5	1.3	0.36
Age (yrs)	75.7	3.3	75.9	3.3	0.84
Height (cm)	169.1	10.5	166.6	8.8	0.43
Weight (kg)	79.1	15.1	78.9	18.5	0.61
Leg Length (cm)	91.7	5.5	90.5	5.0	0.46

Concurrent Validity

Results of the Bland Altman Plot assessment of concurrent validity across the full and reduced stride count data sets showed that for all gait measures, at least 90% of observations were within the 95% confidence intervals except stride length (SL) for 10, 30, and 50 strides (88%), stride length difference (SLD) for 10, 30, 50, and 70 strides (88%), and base of support variability difference (BOSVD) for 10 strides (85%). There was no apparent bias in measurement for any of the gait measures (bias line centred at 0), indicating no systematic measurement error (Bland & Altman, 1986). Bland-Altman plots for each variable are presented in Appendix B, selected plots for characteristic average plots and those with less than 90% of observations within the 95% confidence intervals can be seen in Figure 4.1 below.

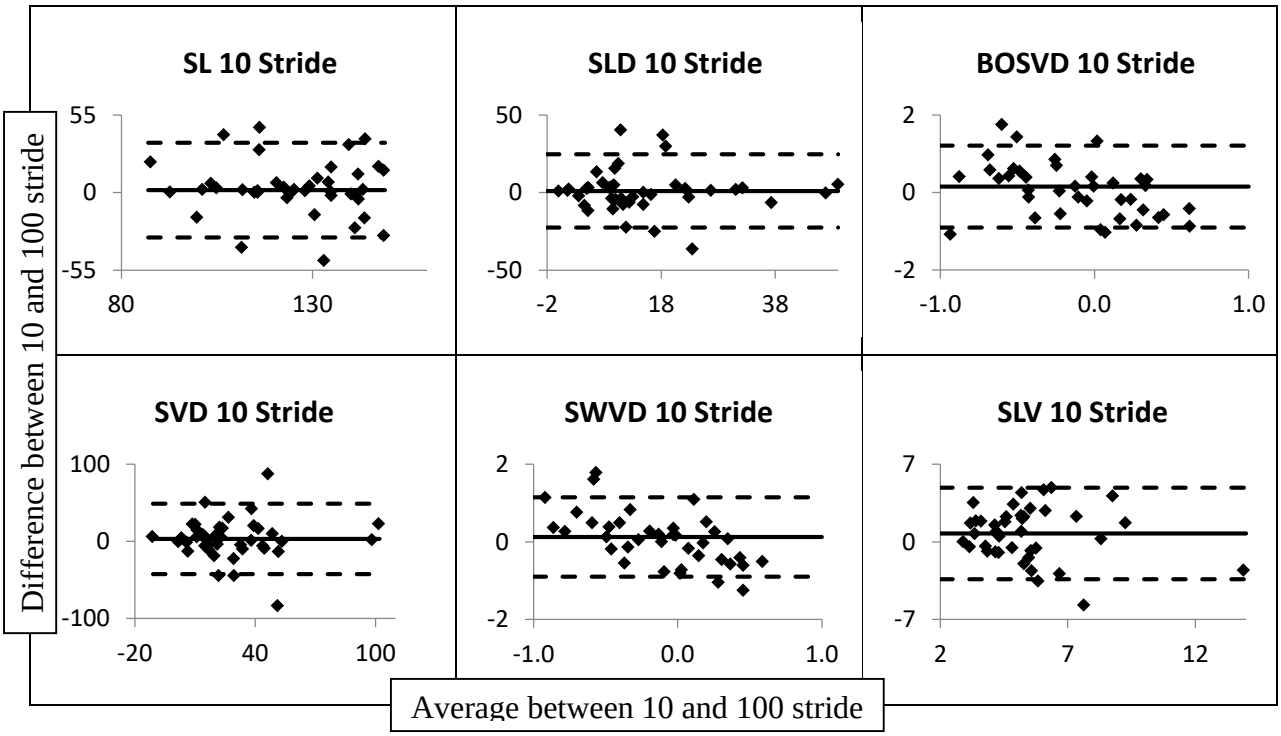

Figure 4.1. Bland-Altman plots of 10 stride vs 100 stride gait metrics which show examples of less than 90% of observations within the 95% confidence intervals (SL (cm), SLD (cm), BOSVD (cm)) and examples of 90% or more observations within the 95% confidence intervals (SVD (cm/s), SWVD (cm), SLV (cm)).

Internal Consistency

Cronbach's alpha (α) was used to assess the internal consistency of each measure for each group. All gait measures in the Faller group had average α of 0.96 with values between 0.85 and 1.0. For Non-Fallers, average α was 0.88 and all but three measures (stride width variability difference (SWVD) [α=0.79], swing % of cycle variability (SOCV) [α=0.77], and swing % of cycle variability difference (SOCVD) [α=0.78]) had α values >0.80. (See Figures 4.2a-4.2d below).

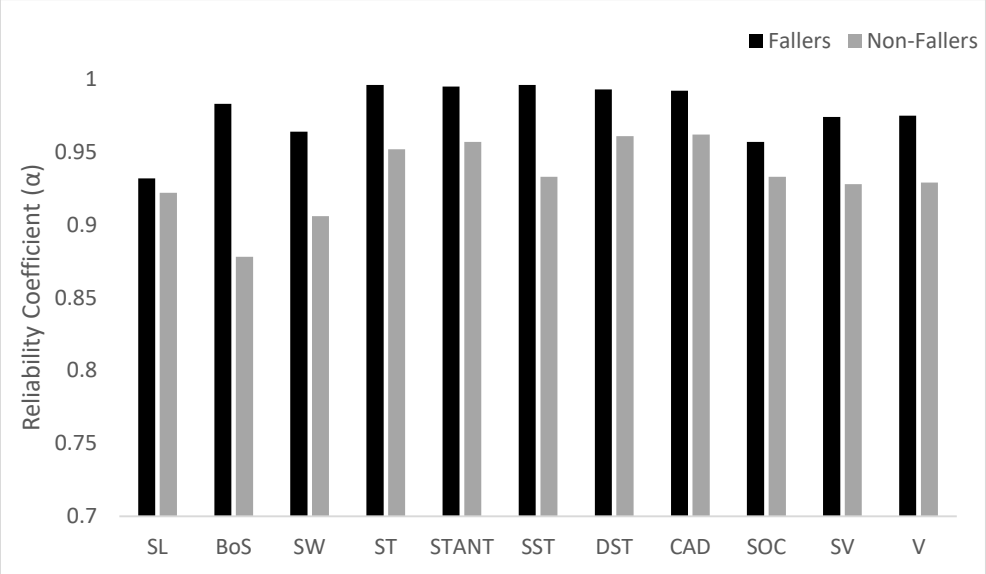

Figure 4.2a. Cronbach's alpha for temporospatial measures of mean gait metrics in older adult fallers (N=18) and non-fallers (N=23).

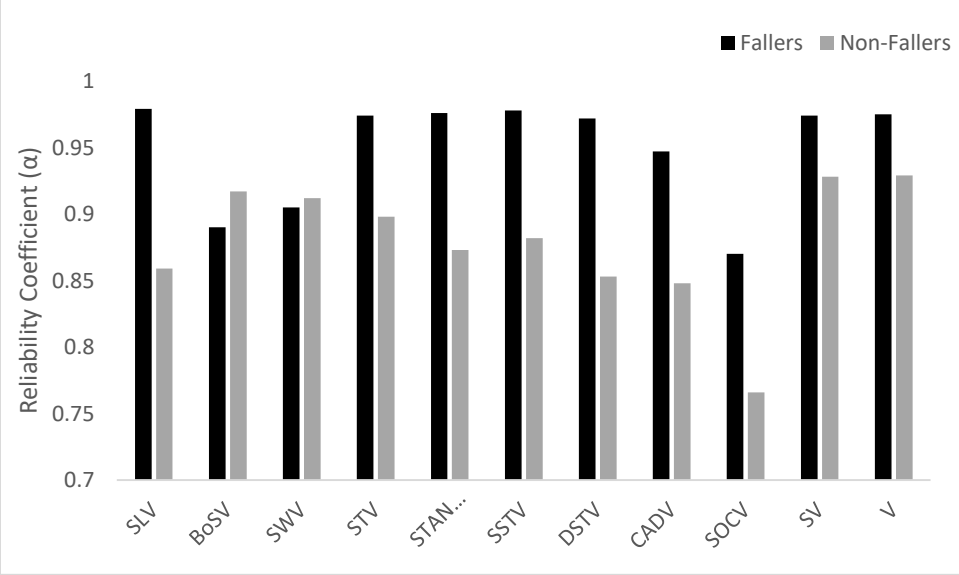

Figure 4.2b. Cronbach's alpha for temporospatial measures of gait variability metrics in older adult fallers (N=18) and non-fallers (N=23).

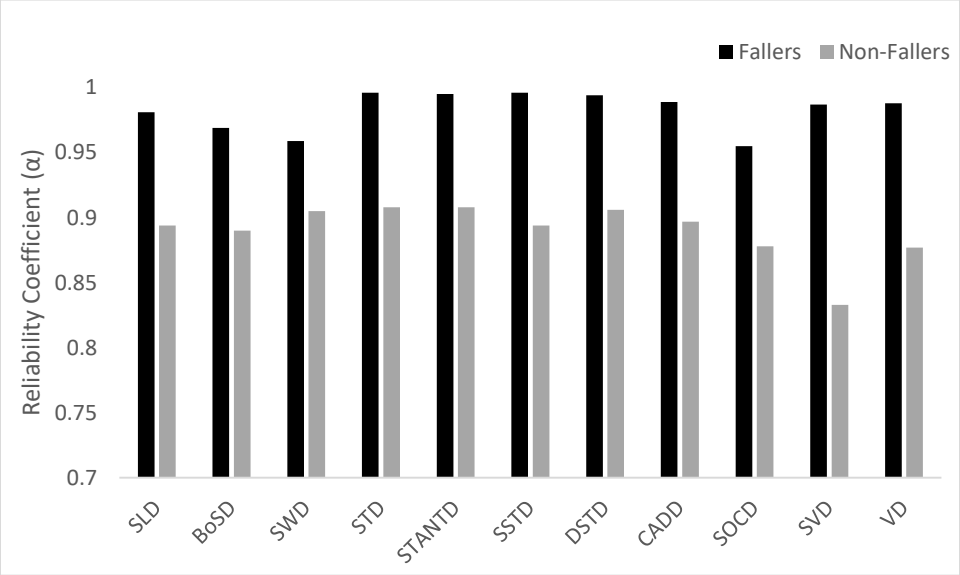

Figure 4.2c Cronbach's alpha for temporospatial measures of gait difference scores in older adult fallers (N=18) and non-fallers (N=23).

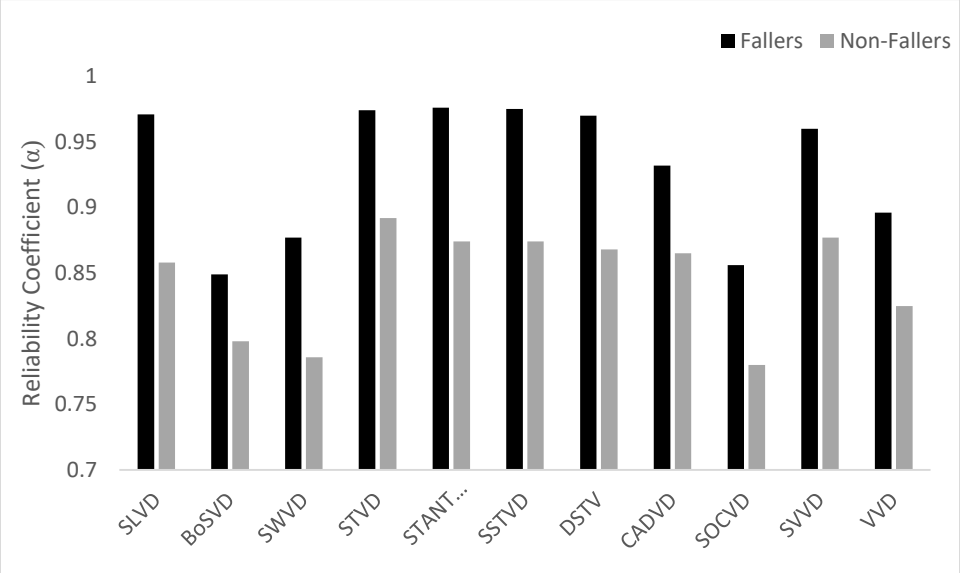

Figure 4.2d Cronbach's alpha for temporospatial measures of gait variability difference scores in older adult fallers (N=18) and non-fallers (N=23).

Differences Between Cohorts and Stride Count

Differences between fallers and non-fallers for each stride count are reported in Table 4.2 and are the result of separate repeated measures ANOVA for each stride count. For each measure not included in Table 4.2 there were no significant main effects or interactions ($p > 0.05$). Table 4.3 displays the main effect for stride count of the overall ANOVA comparing all data sets, post-hoc comparisons for the main effect of number of strides revealed that 10 strides were different from 30 and 50 strides for SSTV and SVV, 10 strides were different from 70 strides for: Stride length variability (SLV), stride time variability (STV), single support time variability (SSTV), stride velocity variability (SVV), and stride velocity variability difference (SVVD). 10 strides were different from 100 strides for: SLV, STV, stride time variability difference (STVD), stance time variability (STANTV), stance time variability difference (STANTVD), single support time variability (SSTV), double support time variability (DSTV), double support time difference (DSTD), double support time variability difference (DSTVD), stride velocity variability (SVV), and stride velocity variability difference (SVVD). Additionally, for cadence variability (CADV) both 30 strides and 50 strides were different from 100 strides. There were no post-hoc differences for the number of strides in DSTD or DSTVD. Table 4.4 presents significant results for the overall comparison of all data sets, post-hoc comparisons for the interaction between number of strides and fall status revealed significant differences only in fallers where 10 strides were different than 50 strides for STV and STVD, 10 strides were different than 70 strides for STV, STVD, and STANTV, and 10 strides were different from 100 strides for STV, STVD, STANTV, STANTVD, and DSTV.

Table 4.2

Differences in Gait Metrics Between Fallers and Non-Fallers for Each Stride Count. Significance was set at α < 0.05. All Significant Comparisons Are Indicated by a ***Bold X*****.**

Gait Metric	10 Strides	30 Strides	50 Strides	70 Strides	100 Strides
Stride Length	**X**	**X**	**X**	**X**	**X**
Stride Velocity	**X**	**X**	**X**	**X**	**X**
Velocity	**X**	**X**	**X**	**X**	**X**
Stride Velocity Difference			**X**	**X**	**X**
Velocity Difference			**X**	**X**	**X**

Table 4.3

Differences Between Stride Count Data Sets. No Differences Found Between 70 vs 100 (not displayed). The Grey Bar Represents Comparisons Which Cannot Be Made Due to Single Measurements Providing No Variability. Significance was set at α< 0.05. All Significant Comparisons Are Indicated by a ***Bold X****. This Table is a Quick Reference for Significant Results Presented in Table 4.4.*

Gait Metric	Comparison of Stride Number					
	10 vs 30	10 vs 50	10 vs 70	10 vs 100	30 vs 100	50 vs 100
SLV				**X**		
STV			**X**	**X**		
STVD				**X**		
STANTV				**X**		
STANTVD				**X**		
SSTV	**X**	**X**	**X**	**X**		
DSTV				**X**		
CADV					**X**	**X**
SVV	**X**	**X**	**X**	**X**		
SVVD			**X**	**X**		

Table 4.4

*Main Effects for Differences Between Cohorts, And Number of Strides Data Sets, And Interactions for Differences Between Cohorts Within Each Number of Stride Data Set. Significance was set at $\alpha < 0.05$. Significant Comparisons are in **Bold**.*

	Fall Status (p)	# Strides (p)	# Strides * Fall Status (p)
SL	**0.00**	0.90	0.94
SLV	0.23	**0.02**†*	0.78
BOS	**0.03**	0.95	0.85
BOSD	**0.00**	0.20	0.70
SWD	**0.00**	0.26	0.69
STV	0.10	**0.00**†*	**0.02**#†*
STVD	0.11	**0.01***	**0.03**#†*
STANTV	0.11	**0.01***	**0.03**†*
STANTVD	0.12	**0.02***	**0.04***
SSTV	0.09	**0.04**‡#†	0.07
DSTV	0.12	**0.03***	**0.03***
DSTD	0.10	**0.03ND**	0.11
DSTVD	0.13	**0.05 ND**	0.053
CADV	0.14	**0.01*¥**	0.74
CADD	**0.05**	0.65	0.90
SOC	**0.02**	0.99	0.99
SOCV	**0.03**	0.93	0.88
SOCD	**0.01**	0.34	0.96
SOCVD	**0.04**	0.89	0.83
SV	**0.02**	0.95	0.99
SVV	0.41	**0.00**‡#†*	0.38
SVVD	0.92	**0.01**†*	0.93
V	**0.02**	0.94	0.99

‡ - 10 different from 30 strides
† - 10 different from 70 strides
¥ - 30 & 50 different from 100 strides
- 10 different from 50 strides
***** - 10 different from 100 strides
ND – No post-hoc difference

4.4 Discussion

This is the first study to assess the minimum number of strides required to reliably measure dual-task and difference score gait metrics for a comprehensive set of gait measures using the GAITRite™ pressure sensing mat. We found that for all metrics except CADV the

minimum number of strides that was comparable to 100 strides in quantifying dual-task and difference score gait metrics was 30 strides for non-fallers and fallers. Additionally, for mean gait metrics, only 10 strides were required to result in highly reliable measurements while measures of variability required at least 30 strides. Further, we found that only five variables were able to discriminate fallers from non-fallers regardless of the stride count and that for two of these metrics 50 strides were needed to detect group differences. The following discussion will present contemporary findings related to current stride count recommendations and the use of dual-task gait metrics to discriminate older adult fallers from non-fallers.

Stride Count Recommendations

Good to excellent reliability was observed between 10, 30, 50, 70, and 100 strides using Cronbach's alpha for all measures except SLVD, SOCV, and SOCVD which were acceptable but very close to good (0.77-0.79). There is a clear trend of highly reliable mean gait measures from a very limited number of strides and increasing reliability for measures of gait variability with increasing stride count demonstrated in our findings and those of others (Hollman et al., 2010; N. König, Singh, et al., 2014). Hollman et al. (2010) provided stride count recommendations for characterising walking gait based on assessments of the reliability of dual-task stride velocity (ICC = 0.93), cadence (ICC = 0.83) and stride velocity variability (0.23) in healthy older adults. Based on these results they determined that in order to obtain accurate and reliable measures of stride velocity nine strides were required, 20 strides were required for cadence, and as many as 370 strides were required for gait variability. While we observed similar results for stride velocity and cadence for healthy older adults, stride velocity variability was substantially more reliable in our assessment requiring only 30 strides for all measures except

CADV which needed more than 50 strides. This discrepancy could be due to the differences in stride velocity variability calculation between studies. Hollman et al. (2010) calculated stride velocity variability as the average coefficient of variation over the whole trial while stride in the present study velocity variability was calculated as the average stride-to-stride standard deviation. Additionally, Hollman et al. only measured 14 strides for each participant (N=24) in the dual-task condition and used the Spearman-Brown prophecy formula to extrapolate reliability coefficients for a given stride count. Similar to our findings, König et al. (2014) employed ICC (2,1) analysis and found that only 10 strides were required for mean gait parameters (ICC= 0.88 (10 strides) to ICC= 0.98 (60 strides)) and they found that increasing stride counts resulted in improved reliability for variability measurements up to 50 strides (ICC= 0.60 (10 strides) to ICC= 0.90 (60 strides). Importantly, Konig et al (2014) directly measured 60 strides and results were not estimated from extrapolated data. In addition to measuring the accuracy of gait metric estimation from adequate stride counts, several studies have assessed test-retest reliability of gait metrics and found that mean gait metrics were more reliable than measures of variability (Brach, Perera, Studenski, & Newman, 2008; Hollman et al., 2010). Almarwani et al. (2016) examined gait measurement test-retest reliability in healthy older adults using ICC (2,1) and found that mean measures had excellent test-retest reliability, while measures of variability were fair to good. For both validity and reliability, mean gait measures perform well, while variability provides lower intraclass correlations. This may be due to the fractal nature of gait which leads to non-stochastic variability whereby the variability of each successive stride is related to the previous stride history, requiring a sufficient number of strides to achieve consistency (Hausdorff et al., 1996). While no other attempt has been made to determine the minimum number of strides required to measure gait in fallers, there is evidence supporting increased variability in fallers

which could require more strides to achieve consistent measurements (Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997; Hausdorff et al., 2001). The variability of gait in fallers further compound the fractal nature of gait variability and supports our post-hoc stride count * fall status results in which differences were noted in the falling cohort.

Discrimination of Fallers from Non-Fallers Using Dual-task Gait Metrics

While determining the validity and reliability of gait metrics is valuable when establishing data collection guidelines, it is also essential to determine the minimum stride count required to discriminate between cohorts. Differences in mean and variability gait metrics, including stride length, width, velocity, and timing, have been used to distinguish older adult fallers from non-fallers (Taylor et al., 2013). Fallers have been shown to have significantly slower gait velocity, increased stride time variability and stride length variability, and impaired stance-swing ratio (Verghese et al., 2009). Additionally, stride width has been observed to have an increased dual-task cost (difference between single and dual-task) in fallers (Nordin et al., 2010). Many researchers have examined various dual gait metrics for their ability to discriminate fallers from non-fallers (A. König et al., 2017; N. König, Taylor, et al., 2014b; Montero-Odasso, Muir, et al., 2012; Muhaidat et al., 2014), however, a meta-analysis by Menant et al. (2014) did not find any effect of dual-task gait speed increasing the sensitivity of fall classification when compared to single-task gait speed despite reported claims that dual-task paradigms provided improvements over single-task. Importantly, the number of strides recorded were not reported in most studies they examined, however, the distance walked was reported and ranged from 4.6m to 25m. This would correspond to an approximate stride count of 5-25 strides, which as we have

shown is not sufficient to obtain reliable measures for all gait metrics, especially for measures of variability. In the present study, we compared older adult faller and non-faller cohorts across a number of measures and stride counts. Table 4.2 and 4.3 present the minimum number of strides required to discriminate differences between cohorts and the interaction between stride count and fall status respectively. As can be seen in Table 4.2, only five variables were able to discriminate fallers from non-fallers, and differing stride counts were required. For SL, SV, and V 10 strides were required to discriminate fallers, while 50 strides were required for SVD and VD. Table 4.3 indicates that there was an interaction effect between the number of strides used and fall status. In each case, these differences were only observed in the faller group. These findings indicate the potential for dual-task gait variables to identify fall risk, however, as can be observed in contemporary literature and supported by Chapter 3, a multivariate approach to fall risk classification is recommended (A. König et al., 2017; N. König, Singh, et al., 2014).

Limitations

Limitations of our study include the limited spatial and temporal resolution of the GAITRite™ pressure mat which may increase the variability of measurements. The use of Cronbach's alpha to assess internal consistency between data sets may increase the reliability coefficient when compared to ICCs as Cronbach's alpha is the equivalent of ICC (2,k) consistency, rather than ICC (2,k) absolute agreement (Koo & Li, 2016). Our recommendation for the minimum number of strides is limited to overland walking on a smooth flat surface, and footwear may have an influence on the number of strides required to reach gait steady state which is a consideration when designing research protocols (Najafi, Miller, Jarrett, & Wrobel, 2010). Additionally, having more stride count datasets with increments of 10 strides between

datasets would allow for more accurate identification of the minimum number of strides required to measure each dual-task gait metric reliably. Gait data in the current study were collected during non-continuous walking due to constraints of GAITRite™ mat length and findings may be different with a continuous overland walking paradigm.

Conclusion and Future Direction

We found that a minimum of 30 overland strides are required for accurate and reliable measurement of gait measures in older adult fallers and non-fallers. If only non-fallers are being studied, or only measures of mean dual-task and difference scores are being measured, then as few as 10 strides are required. Future research should investigate the minimum number of strides to accurately and reliably measure gait in older adult fallers and non-fallers using alternate data collection techniques, including 3D motion capture, and for treadmill walking. Continuous overland walking should also be examined, however, technical limitations of systems such as GAITRite™ or optoelectronic 3D motion capture preclude them from this analysis.

Chapter 5: 3D Depth Sensor Based Gait Cycle Detection Algorithm

5.1 Introduction

This project developed an algorithm to detect and quantify gait cycle events during walking gait using 3D depth-sensing technology (DST), specifically the Microsoft Kinect V2 camera. In order to characterise the gait cycle, two main events must be identified, heel-strike and toe-off. The gait cycle is defined as the events happening between right-to-right and left-to-left heel-strike. The Microsoft Kinect has previously been shown to accurately measure stride length and stride width when external sensors or the complex proprietary biomechanical joint model (Microsoft™) were used to identify the gait cycle (Clark, Bower, Mentiplay, Paterson, & Pua, 2013; Mentiplay et al., 2015). In order to create a self-contained temporospatial measurement system, the algorithm must accurately locate heel-strike and toe-off events using only features of the signal collected from the DST. Our algorithm achieved this using data from the ankles are used, as the foot signals are more prone to errors due to obstruction of line-of-sight due to the camera position which must be offset and parallel to the walking path.

5.2 Methods

Three university aged participants performed 10 walking trials for a total of ~20 recorded strides per participant. The camera was positioned at a vertical height of 1.3m and placed approximately 4.5m away (maximum recording distance) from the starting position and 40cm perpendicular to the right side of the participants' walking path. The camera was set facing parallel to the walking path while participants walked toward and continued past the camera so as not to modify their gait velocity. Stride detection was performed only for strides which were

between the maximum and minimum (1.25m) recording distance. A force sensing resistor (FSR) was placed in the heel and toe of the right shoe to record heel-strike and toe-off events. Custom written LabVIEW software was used to track the ankle joint using the infrared camera space sampling at ~30Hz while simultaneously recording heel-strike events from the FSR sampling at 128Hz. MK data were re-sampled to 128Hz using unequal time series interpolation (LabVIEW TSA resample-unequal) and heel-strike and toe-off events from the FSR were compared to features identified in the DST depth stream. A quadratic trend was removed from the DST ankle data and the displacement signal was low-pass filtered at 3Hz. The valleys and peaks of the filtered de-trended displacement signal were identified using multiscale wavelet peak detection to identify heel-strike and toe-off respectively. The DST identified stride times were compared using paired sample t-tests to the measured stride times from the FSR.

Stride Detection Algorithm

The first function of the algorithm is to take the DST Ankle data and crop it so that it only contains a short static stance followed by the walk and removes all data after the participant is within 1.25m (the minimum recording distance) of the camera.

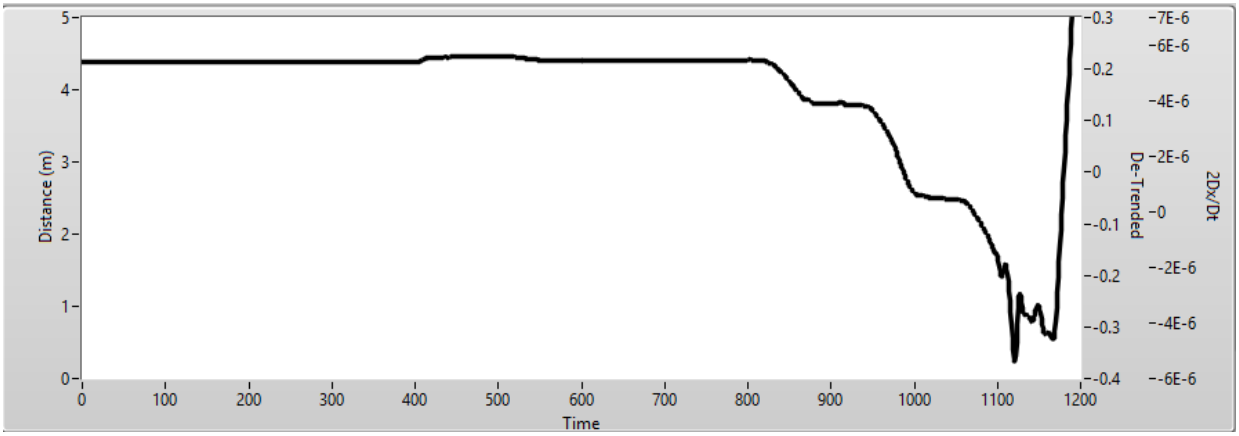

Figure 5.1. Original Signal

Step 1 – Load Kinect Ankle Joint Z displacement data (distance from camera in metres)

- Re-sample data to 128Hz (see Figure 5.1).

Step 2 – Determine initial stance phase

- Calculate array differences and identify the threshold when $X_{i+1} - X_i > 0.005$m to determine initial stance phase and then crop signal 1 second prior to movement. Identify array minimum between 1.5m and 1.25m to determine terminal position and crop beyond this point (see Figure 5.2).

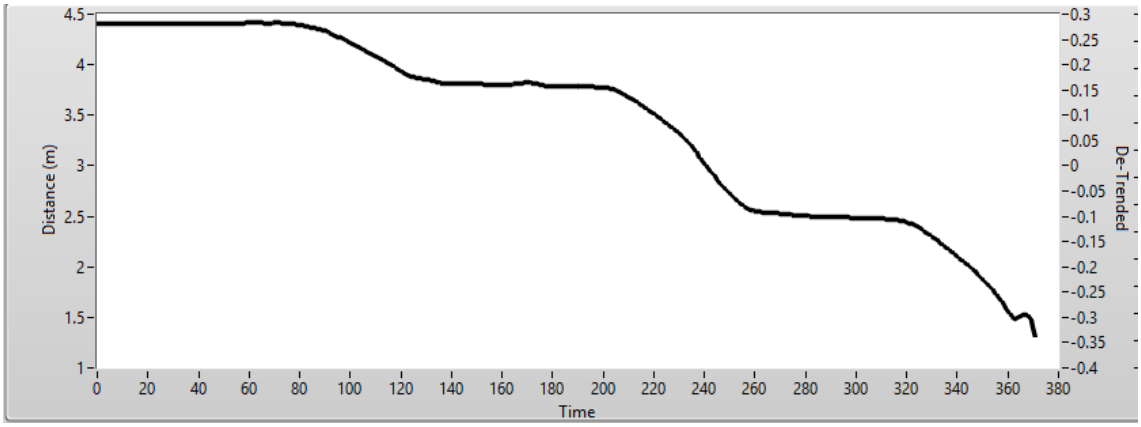

Figure 5.2. Cropped Trial

- **Step 3** – Quadratic de-trend of the original signal to remove the step-down trend (see Figure 5.3) and then filter de-trended signal using zero-phase low pass Butterworth filter at 3Hz (see Figure 5.3 teal line).

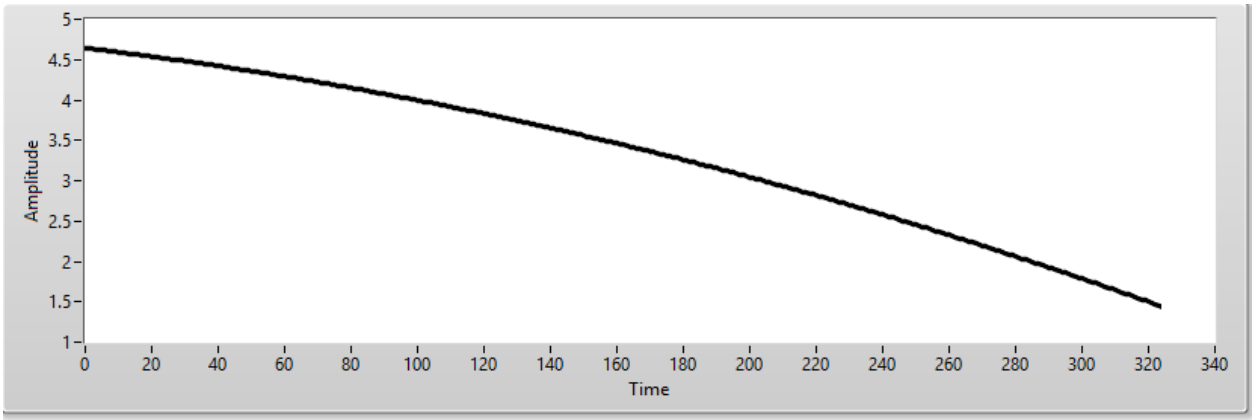

Figure 5.3. Quadratic trend removed

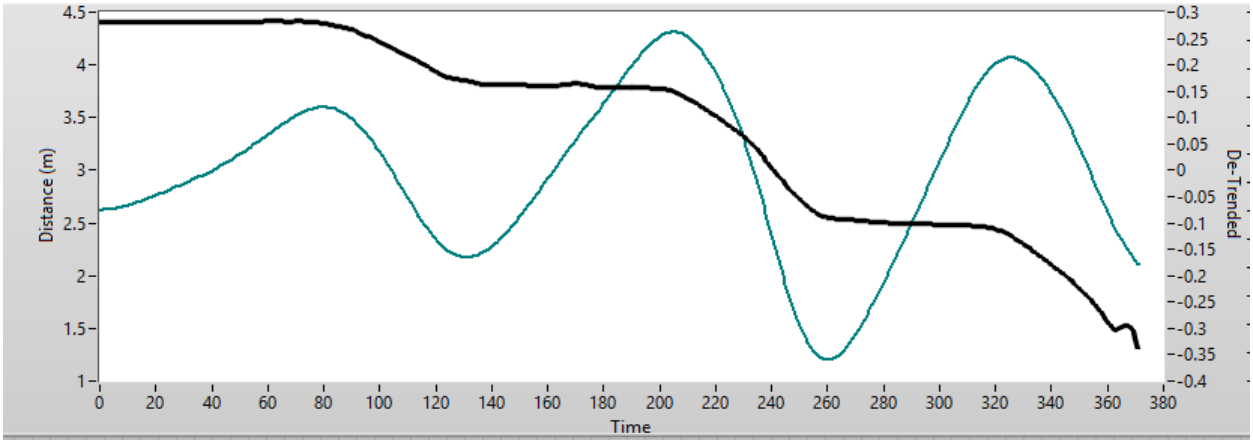

Figure 5.4. Cropped signal (black) and filtered de-trended signal (teal)

- **Step 4** – Identify valleys and peaks in filtered de-trended signal using multiscale wavelet peak/valley detection (valleys correspond to areas of least forward progression (heel-strike) and peaks correspond to initiation of movement (toe-off)) (see Figure 5.5).

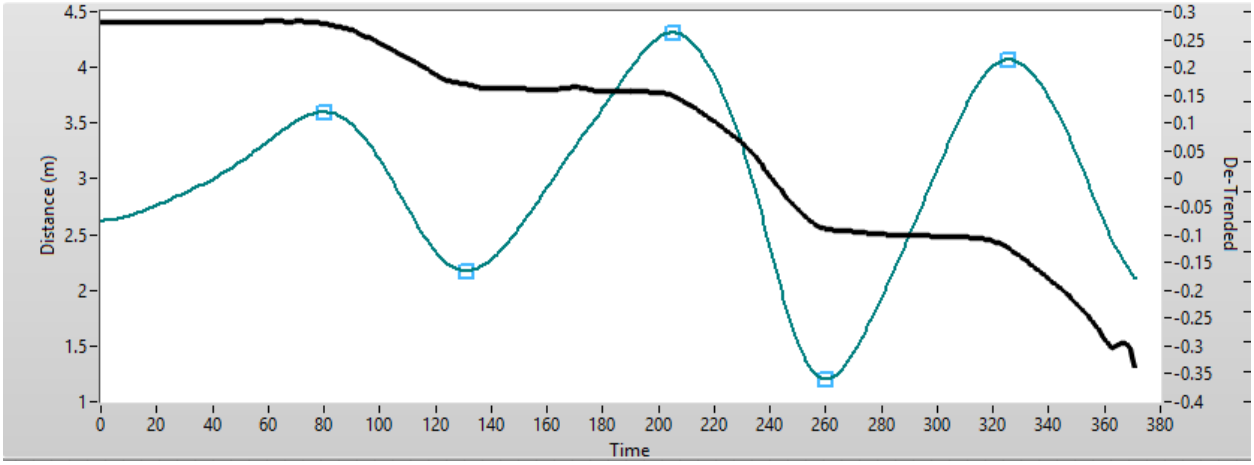

Figure 5.5. Peaks and valleys identified on filtered de-trended signal

Step 5 – The peaks and valleys of the filtered de-trended signal represent the toe-off (peak) and heel-strike (valleys) events (see Figure 5.6).

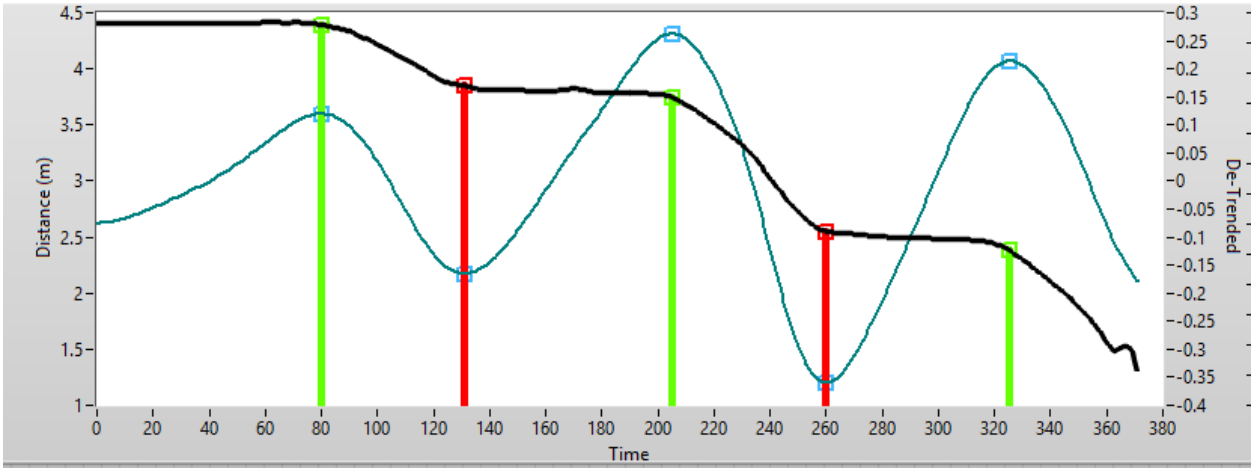

Figure 5.6. Toe-off (green) and heel-strike (red) indicated on cropped filtered signal

Step 6 – The heel-strike and toe-off locations can be used to determine the index of the ankle Z data to calculate stride (right to right/left to left) and step (right to left/left to right) length and

velocity, and the ankle x data can be used to calculate step width, and the index of the gait markers can be used calculate stride and step time.

Results

Of the 56 recorded FSR strides, 54 strides were identified by the DST algorithm (96%). The two strides that were missed by the algorithm were near the minimum recording distance of the DST where the entire body model will not be constructed due to proximity to the camera. Stride times were similar between the DST and FSR with a mean difference of 8.4ms ± 2.3ms ($p=0.08$).

Discussion

While Microsoft Kinect ankle joint data were used in this analysis, the features identified by the algorithm for measurement of temporospatial gait rely only on point distance from the camera depth stream. This allows for the broad application of this algorithm to any depth sensing technology which can be used to track a single point, such as an infrared marker, placed on the lower leg. Although two strides were not detected by the algorithm, this is likely due to an error in estimation of whether the footfall happened within the 1.25m minimum recording distance when FSR strides were manually selected for inclusion. Assuming the two missed footfalls are due to inclusion of two extraneous FSR strides, then 100% accuracy was achieved for measurement of strides of healthy young participants using this algorithm. Stride time accuracy was acceptable as the error was approximately ¼ of a single frame interval for the DST (33ms). Further improvement for temporal accuracy is expected with future development of the algorithm which will explore wavelet decomposition to further refine the feature extraction for

heel-strike and toe-off events as well as centre of mass oscillation. Improvements to technology including increased framerate and resolution will also improve accuracy of measurement. These future iterations of this algorithm will be refined to measure gait in individuals with irregular step and stride patterns such as older adults, older adult fallers, and other clinical populations.

Chapter 6 Dissertation Discussion

6.1 Summary of Dissertation

Assessment of fall risk in older adults is multifactorial. Many methods are available which show promise including: self-assessments, physiological assessments, clinical assessments, and gait assessments. Recently, dual-task gait paradigms which include a cognitive load have proven to be very effective for discriminating fallers in community-dwelling older adults. This dissertation adds to the current literature by 1) reviewing the availability and sensitivity of current fall risk self-assessments, 2) developing a multivariate gait measure assessment which is highly sensitive for classification of older adult fallers, 3) determining minimum stride count standards for reliable measurement of dual-task gait measurement, and 4) developing a stride detection algorithm for use with portable infrared depth sensing technology.

Chapter 2 investigated the available fall risk self-assessments and found varied results for their ability to accurately classify fallers. While many survey and physical assessments were used, the tests which showed the most promise included objective measures of physical performance (Bongers, Schoon, Graauwmans, Schers, et al., 2015; Marston et al., 2015; Yamada, Aoyama, Nakamura, et al., 2011) and especially the inclusion of technology for more accurate assessment (Marston et al., 2015; Yamada, Aoyama, Nakamura, et al., 2011). Based on our findings, a more thorough systematic review of self-assessment tools is required, and with the adoption of technological assessments, frequent updates to the ever expanding list of tools will be required.

Chapter 3 supported the use of physical assessments for fall risk classification. While many clinical tests and gait measures were assessed for their ability to identify fallers in a multivariate model, it was measures of the difference between normal walking and dual-task

walking which showed the greatest sensitivity. Clinical tests may have more trouble discriminating potential fallers in this population due to the inclusion of subjective measurements as seen in the FAB, SPPB, and BBS, and the non-instrumented CTSIB (Berg et al., 1992; Guralnik et al., 1994; Rose et al., 2006; Shumway-cook et al., 1986). Additionally, self-reported items which are included as part of an assessment may affect the reproducibility and accuracy of tests such as the EFST. In Chapter 3, we observed a ceiling effect in the BBS which prevented inclusion in the analysis (Berg et al., 1992).

Dual-task walking gait has shown promise as an important fall risk indicator, however, there is currently no consensus on the minimum standards for collection of gait data. Chapter 4 sought to determine minimum number of strides required for accurate and reliable gait measurements. Contrary to commonly cited results from Hollman et al. (2010) who determined that as many as 370 strides are required for measurement of gait variability, we found that as few as 10 strides, and no more than 50 strides are required to obtain reliable and accurate measures. Importantly, we measured a broad selection of gait variables compared to Hollman et al. (2010) who chose a very limited subset of only three variables. Additionally, we recorded 100 strides while Hollman et al. recorded 14 strides and then used Spearman-Brown Prophecy formula to predict the approximate number of strides required to achieve an ICC of 0.90 using test-retest methods for ICC calculation (ICC 2,1).

Technological advances have created opportunities for affordable and novel applications of gait assessment, including in-home fall risk monitoring. In order to increase access to affordable fall-risk monitoring, affordable technologies which can be broadly adapted to in-home environments are essential. Gait metrics have shown much promise in fall risk prediction, and

technology innovations have been rapidly gaining acceptance as useful fall risk assessment tools in community settings (Ni Scanaill, Garattini, Greene, & McGrath, 2011).

The goal of this dissertation was to refine the use of gait metrics as a clinical tool for fall risk classification. This document adds to the literature in fall risk assessment by addressing the accurate classification of older adult fallers using multivariate assessments, to suggest minimum standards for accurate and reliable gait measurement, and to begin the development of novel fall risk assessments utilizing emerging technologies such as the Microsoft Kinect V2.

6.2 Practical Applications and Future Directions

Chapter 2

Understanding the current options for self-assessment of fall risk helps to guide the development of more sensitive fall risk tools. When suggesting fall risk self-assessments to older adults, healthcare professionals should focus on tools with objective measures of physical performance. Not only does this allow for long-term tracking of health status, but these tools have demonstrated the greatest sensitivity for classifying fallers. Additionally, the broad application of technologies such as smartphone and smartwatches which contain accelerometers and gyroscopes provides unlimited opportunities for daily tracking of fall risk (Howcroft et al., 2016). Future research into fall risk self-assessments should leverage these technologies to provide accurate real-time and longitudinal monitoring of gait and balance metrics which can provide objective measurements of fall risk. In order to ensure adoption of these tools, operation should be intuitive and simple, and interpretations should be clear and rely on minimal jargon to

provide older adults with information that they can utilize to monitor their own fall risk without the aid of a caregiver.

Chapter 3

In Chapter 3 we developed a retrospective fall risk classification tool using a multivariate approach including clinical and gait metrics. This classification tool could be utilized by clinicians as an assessment to help identify older adults who are at increased risk of falling. The metrics contained within the final classification tool represent each of the four functional domains of gait: length, width, timing, and velocity. Similar gait metrics have been identified in prospective models of fall risk classification which utilized principal component loading scores representing combinations of gait metrics (A. König et al., 2017; N. König, Singh, et al., 2014). Prospective validation of our fall risk classification tool is currently underway and will help determine the clinical utility of our multivariate gait model for prediction of fall risk. Further investigation will also include measures of step initiation using multiple force plates. Gait initiation time and time to first lateral movement during both single and dual-task walking were associated with increased risk of multiple falls in older adults (Callisaya, Blizzard, Martin, & Srikanth, 2016). Additionally, we will re-introduce the CTSIB conditions 3 and 5 into future classification models as it demonstrated potential as an indicator of variance in the principal component model. We will also include measures of the Community Mobility and Balance Scale (CB&M) which has been show to eliminate the ceiling effect observed with other traditional clinical tests, such as the effect we observed with the FAB in Chapter 3. The future direction of this research is to refine the metrics which best predict fall risk in older adults so that preventive measures can be taken to reduce the incidence of falls. Presently, exercise interventions focused

on increasing strength, balance, and walking speed have shown excellent results for reducing the risk of falls in community dwelling older adults (Gillespie et al., 2012). Thus, the early identification of fall risk can be used to suggest exercise interventions for those at the greatest risk of falling in the hopes of reducing falls and fall related injuries.

Chapter 4

Chapter 4 sought to determine the minimum number of strides required to accurately and reliably measure walking gait. While further replication is necessary, and a larger sample size is recommended, our findings can serve as guidelines for similar research, and have established a standard for many gait measures which previously had no recommended guidelines. Researchers should seek to measure at least 30 strides for most measures, especially measures of variability, though as many as 50-70 may be required for certain metrics. When feasible, more strides can be collected for increased reliability, however if participant fatigue, discomfort, or time constraints warrant a more limited approach, we recommend following the guidelines established in Chapter 4. We demonstrated a clear trend of excellent reliability for measures of mean dual-task gait metrics with as few as 10 strides, and good reliability for measures of variability which became more reliable with increasing stride count. Our recommended minimum stride counts are similar to those suggested by N. König et al. (2014) who's recommended minimum ranged from nine to 60 strides depending on the variable, and they also agree with some, but not all, of the recommendations by Hollman et al. (2010). Future research should investigate the number of strides required to measure gait using devices other than the GAITRite™ pressure mat, such as 3D motion capture, wearable accelerometers, and portable motion capture devices such as the Microsoft Kinect.

Chapter 5

To fully utilize emergent technologies for the development of comprehensive fall risk assessment and training tools, it is essential to ensure accurate and reliable measurement of walking stride parameters. Currently, most methods employing the Microsoft Kinect for measurement of gait rely on external devices, such as accelerometers, for temporal identification of key gait phases, such as heel-strike, mid-stance, and toe-off (Clark et al., 2013). While this does not preclude the use of Microsoft Kinect, and similar technologies, for assessment and monitoring of fall risk, it does increase the cost and complexity of use. In order to circumvent the requirement for additional devices, we developed a stride detection algorithm which relies only on information provided by the depth sensing camera. Importantly, this technique is not exclusive to Microsoft Joint Kinematics models which allows the broad application of the algorithm to any depth sensing technology with sufficient temporal and spatial accuracy. Passive in-home measurement of gait has been previously attempted with Microsoft Kinect, however, the method of stride identification was not indicated (Stone & Skubic, 2011). The result of this assessment was that Microsoft Kinect was less reliable than an web camera based system when compared to Vicon 3D motion capture, though without the specific algorithm used it is unknown whether this is a failing of the device or the technique used to calculate gait metrics. Future research from these authors investigated the use of Microsoft Kinect for fall detection in the homes of older adults and found that it performed well when falls happened near the camera and the faller began in standing position, but sensitivity was reduced in situations where falls happened from a seated or lying down position, when falls were occluded by the background, when falls happened far away from the camera, and in situations with bright natural light (Stone

& Skubic, 2015). While fall detection is a valuable application for in-home monitoring, the ability to accurately and reliably measure key gait metrics may lead to the ability to predict fall risk before a fall occurs. This is ultimately the goal for the reduction of falls in older adults, and the current focus on measures of gait for prediction of fall risk combined with the potential for affordable technologies to constantly monitor gait characteristics in-home creates the opportunity for convenient fall-risk prediction and fall monitoring, in older adults.

6.3 Limitations

Chapter 2

- Only two databases were searched, self-assessment tools may exist which are not present on those databases.
- The assessment tools identified are limited to those which were available during the included timeframe
- Only assessments used specifically for identification of fall risk were included, it is possible that tools designed to identify frailty may be relevant to identify fall risk as well

Chapter 3

- The sample size of 41 individuals is small for the number of variables included in the logistic regression model, though as stated in chapter 3, there is support for this approach being reasonable
- Findings are limited to smooth and level over-ground walking while wearing comfortable shoes.

Chapter 4

- Results are only generalizable to populations which reflect our sample, as the number of older adults recruited in each group was ~20 our results must be interpreted conservatively.
- Findings are limited to smooth and level over-ground walking while wearing comfortable shoes.
- Recommendations are limited to gait metrics derived from the GAITRite™ pressure sensing mat.
- Cronbach's α is a less rigorous assessment of internal consistency than if intraclass correlation (ICC 2, k) were used

Chapter 5

- Chapter 5 is presented as a technical white paper and only details the current sequence of calculations used to recognize key gait events such as toe-off and heel-strike.
- The algorithm presented in Chapter 5 is designed for stride detection in healthy individuals with a "normal" gait pattern which does not involve shuffling, stopping, or other clinical presentations
- The Microsoft Kinect has a limited measurement range of 4.5m to 1.5m
- The Microsoft Kinect has a maximum sampling rate of 30Hz which may lead to missed or inaccurate detection of gait events

6.4 Conclusion

This dissertation advances fall prevention research on many fronts. By providing a synthesis of the available methods for fall risk self-assessment through a scoping review it was determined that future development of self-assessments should focus on the implementation of technology for physical assessments in conjunction with traditional survey assessments. Additionally, further analysis in the form of a systematic or meta review on this topic is warranted. The next major contribution was a comprehensive assessment of common clinical fall risk assessments in conjunction with dual-task walking gait assessments to determine which measures are best for classification of fallers in community dwelling older adults. Difference scores between dual-task and single-task walking proved to be the most sensitive metrics for classification of fall risk providing a model which included only five gait metrics and accurately classified fallers 92% of the time; the only clinical measures which showed promise in our assessment were the components of the CTSIB which challenged vestibular and proprioceptive control of balance. Since gait metrics have been identified as potential sources of fall prediction, as evidenced by the excellent ability to classify fallers in Chapter 3 as well prospective studies which have used gait metrics for prediction of falls (N. König, Taylor, et al., 2014b), it was prudent to develop minimum standards for the quantity of gait data required to reliably measure each gait metric. While earlier works by Hollman et al. 2010 and N. König, et al. (2014) provided suggestions for a limited number of gait metrics, our comprehensive set of gait variables, as well as the number of strides we measured, demonstrated that for mean gait metrics as few as 10 and up to 30 strides are required, depending on the variable, however, for gait variability more strides are required for reliable measurements with a recommended minimum of 30 strides for most metrics and up to 50+ strides for some. The final contribution of this

dissertation is the preliminary development of a stride detection algorithm for use with portable 3D depth sensing cameras. This innovation will allow for accurate measurement of temporospatial gait metrics using affordable technologies, and is the first method which does not require external devices or proprietary (Microsoft™) joint model calculations to identify key gait events such as heel-strike and toe-off.

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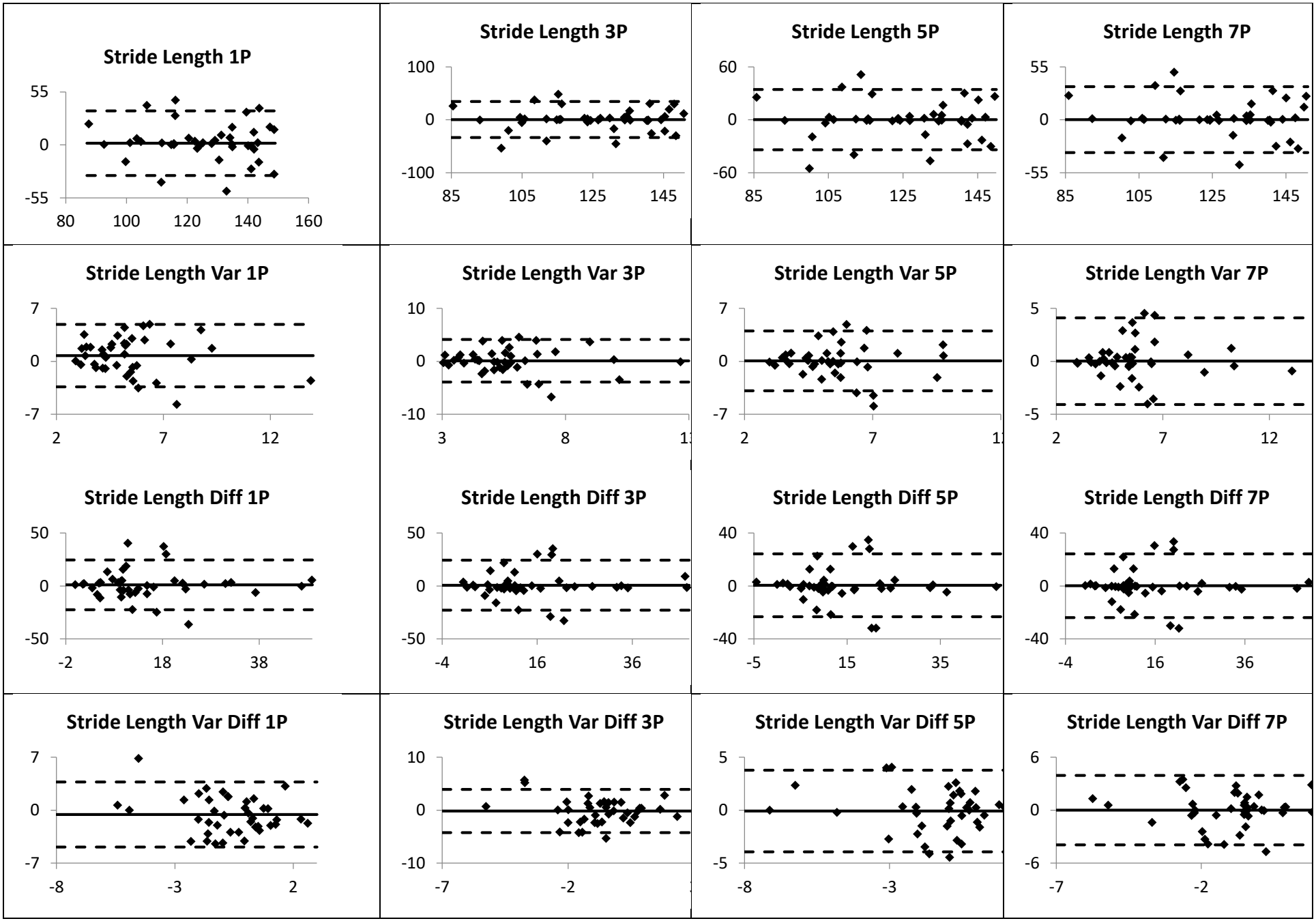
Appendix A: Gait Metrics

Gait Metric	10 Stride		30 Stride		50 Stride		70 Stride		100 Stride	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Stride Length (cm)	124.11	19.60	125.40	19.65	125.72	19.89	125.74	19.87	125.65	16.84
Base of Support (cm)	11.25	3.54	11.02	3.51	11.07	3.49	11.05	3.42	11.05	3.00
Stride Width (cm)	13.49	3.55	13.23	3.51	13.27	3.55	13.25	3.52	13.26	2.95
Stride Time (s)	1.24	0.46	1.25	0.50	1.26	0.55	1.26	0.58	1.26	0.54
Stance Time (s)	0.83	0.37	0.83	0.39	0.84	0.44	0.85	0.48	0.84	0.43
Single Support Time (s)	0.41	0.10	0.42	0.11	0.42	0.12	0.42	0.11	0.42	0.11
Double Support Time (s)	0.42	0.28	0.42	0.31	0.43	0.35	0.44	0.38	0.43	0.34
Cadence (step/min)	102.02	18.01	102.50	18.15	102.46	18.37	102.21	18.45	102.22	17.70
Swing % of Cycle (%)	34.08	2.74	33.97	3.49	34.02	3.25	33.99	3.27	33.97	3.02
Stride Velocity (cm/s)	107.15	27.53	108.67	27.00	108.93	27.53	108.73	27.41	108.64	24.90
Velocity (cm/s)	106.39	27.63	107.98	27.22	108.29	27.71	108.11	27.53	108.00	25.14
Stride Length Var (cm)	4.98	2.51	5.64	2.41	5.67	2.26	5.73	2.30	5.69	1.99
Base of Support Var (cm)	2.30	0.78	2.27	0.59	2.24	0.55	2.24	0.57	2.26	0.51
Stride Width Var (cm)	2.25	0.76	2.22	0.61	2.18	0.56	2.18	0.57	2.21	0.53
Stride Time Var (s)	0.06	0.10	0.09	0.20	0.10	0.24	0.11	0.25	0.10	0.23
Stance Time Var (s)	0.05	0.11	0.07	0.16	0.08	0.21	0.09	0.23	0.09	0.20
Single Support Time Var (s)	0.03	0.05	0.04	0.08	0.04	0.08	0.04	0.08	0.04	0.08
Double Support Time Var (s)	0.05	0.09	0.06	0.14	0.07	0.18	0.07	0.21	0.07	0.19
Cadence Var (step/min)			2.59	2.28	2.65	1.77	2.97	2.09	2.94	2.04
Swing % of Cycle Var (%)			1.11	2.34	1.02	1.79	0.99	1.54	1.05	1.52
Stride Velocity Var (cm/s)	6.25	3.57	7.68	3.63	7.78	3.26	8.03	3.63	8.00	3.08
Velocity Var (cm/s)			4.75	3.52	4.91	3.05	5.19	3.23	5.25	3.06
Stride Length Diff (cm)	14.03	13.74	14.37	13.29	14.59	13.44	14.90	13.60	14.72	11.66
Base of Support Diff (cm)	-0.85	2.29	-1.04	2.06	-1.21	1.92	-1.24	1.83	-1.16	1.76
Stride Width Diff (cm)	-0.88	2.10	-1.03	1.95	-1.19	1.80	-1.21	1.70	-1.15	1.65
Stride Time Diff (s)	-0.20	0.44	-0.21	0.49	-0.22	0.53	-0.12	0.28	-0.23	0.52

Stance Time Diff (s)	-0.16	0.35	-0.16	0.38	-0.17	0.43	-0.18	0.46	-0.18	0.42
Single Support Time Diff (s)	-0.05	0.09	-0.05	0.11	-0.05	0.11	-0.05	0.11	-0.05	0.10
Double Support Time Diff (s)	-0.11	0.27	-0.12	0.29	-0.13	0.33	-0.14	0.37	-0.13	0.33
Cadence Diff (step/min)	13.80	16.57	14.04	16.49	14.48	16.54	15.04	16.66	14.77	15.41
Swing % of Cycle Diff (%)	1.47	2.03	1.75	2.31	1.77	2.19	1.82	2.32	1.81	2.12
Stride Velocity Diff (cm/s)	26.48	26.14	27.40	25.77	28.13	25.95	29.03	26.14	28.55	22.65
Velocity Diff (cm/s)	26.48	26.11	27.47	26.04	28.18	26.18	29.06	26.31	28.59	22.94
Stride Length Var Diff (cm)	-0.58	2.78	-1.00	2.59	-1.07	2.24	-1.16	2.25	-1.07	2.02
Base of Support Var Diff (cm)	-0.28	0.81	-0.09	0.56	-0.08	0.48	-0.09	0.42	-0.10	0.43
Stride Width Var Diff (cm)	-0.27	0.78	-0.11	0.56	-0.09	0.47	-0.10	0.40	-0.13	0.43
Stride Time Var Diff (s)	-0.04	0.10	-0.07	0.20	-0.07	0.24	-0.08	0.25	-0.08	0.23
Stance Time Var Diff (s)	-0.03	0.11	-0.05	0.15	-0.06	0.21	-0.07	0.22	-0.06	0.20
Single Support Time Var Diff (s)	-0.02	0.05	-0.02	0.08	-0.03	0.08	-0.03	0.08	-0.03	0.08
Double Support Time Var Diff (s)	-0.03	0.09	-0.04	0.13	-0.04	0.17	-0.05	0.20	-0.05	0.18
Cadence Var Diff (step/min)			-1.20	2.65	-1.12	2.05	-1.28	2.07	-1.38	2.15
Swing % of Cycle Var Diff (%)			-0.62	2.34	-0.53	1.75	-0.46	1.52	-0.55	1.47
Stride Velocity Var Diff (cm/s)	-0.48	4.09	-1.34	3.52	-1.47	3.17	-1.68	3.54	-1.62	3.03
Velocity Var Diff (cm/s)			-1.50	3.89	-1.57	3.14	-1.62	3.36	-1.78	3.18

Appendix B: Bland-Altman Plots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85
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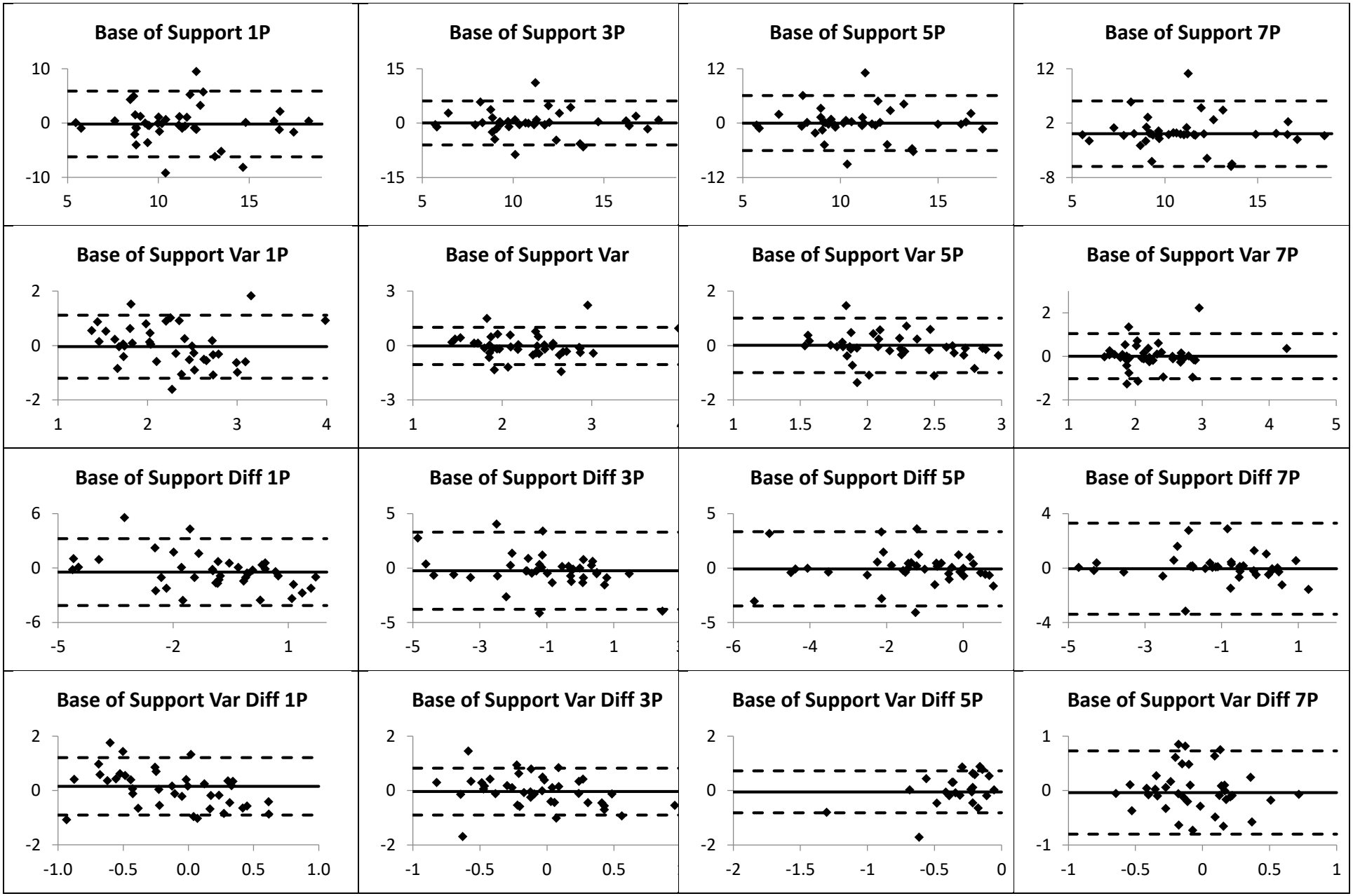
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Base of Support 5P
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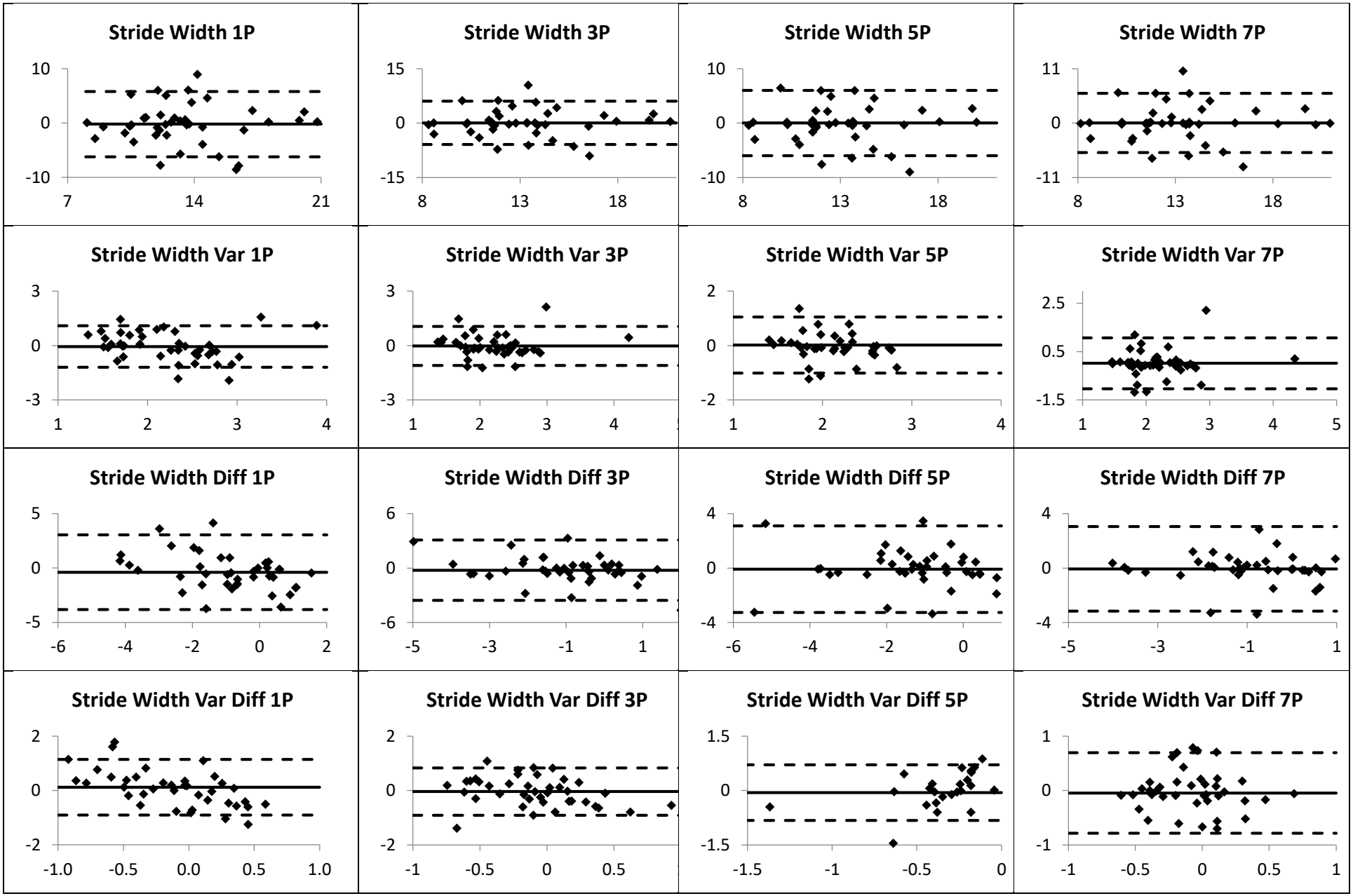
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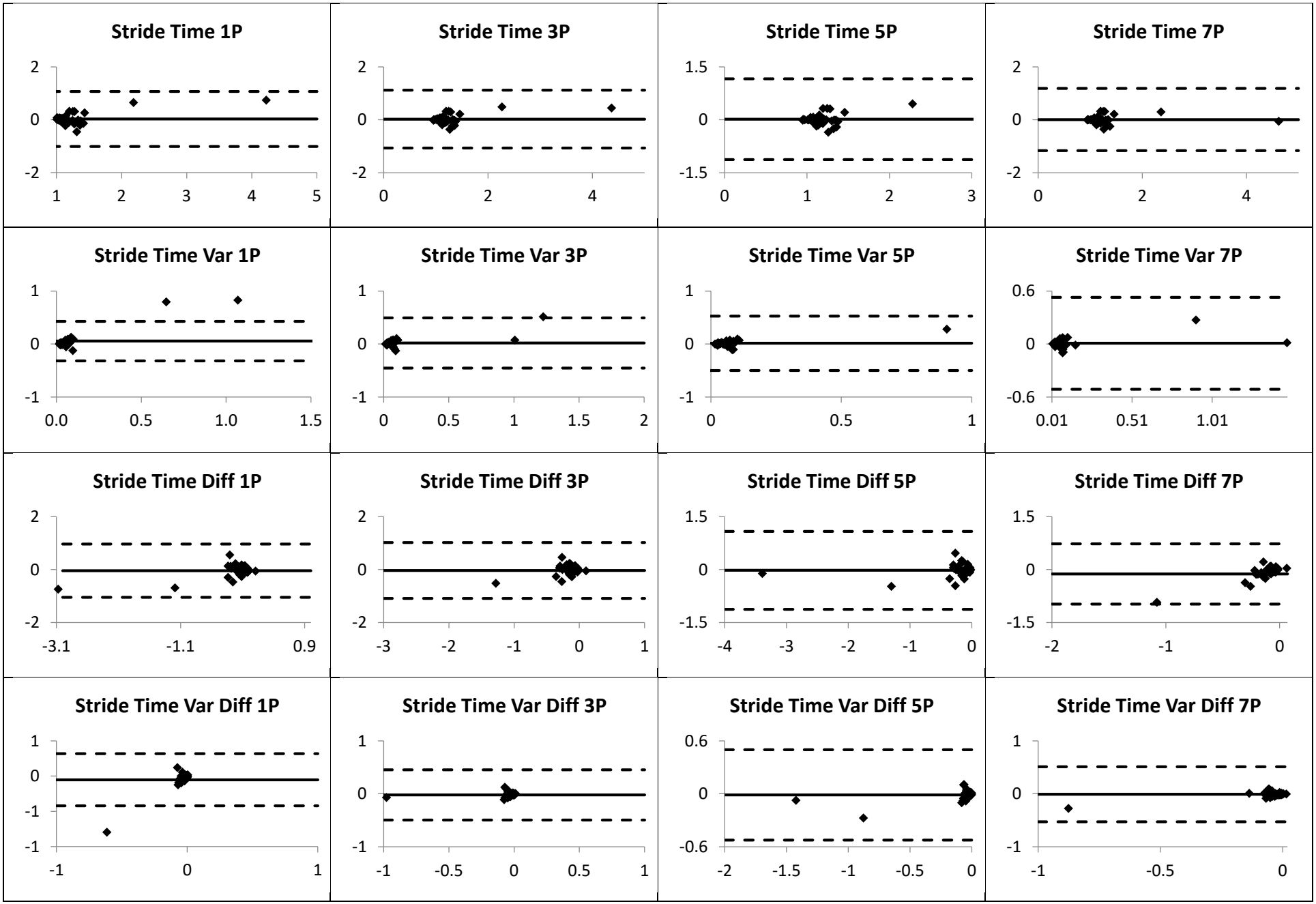
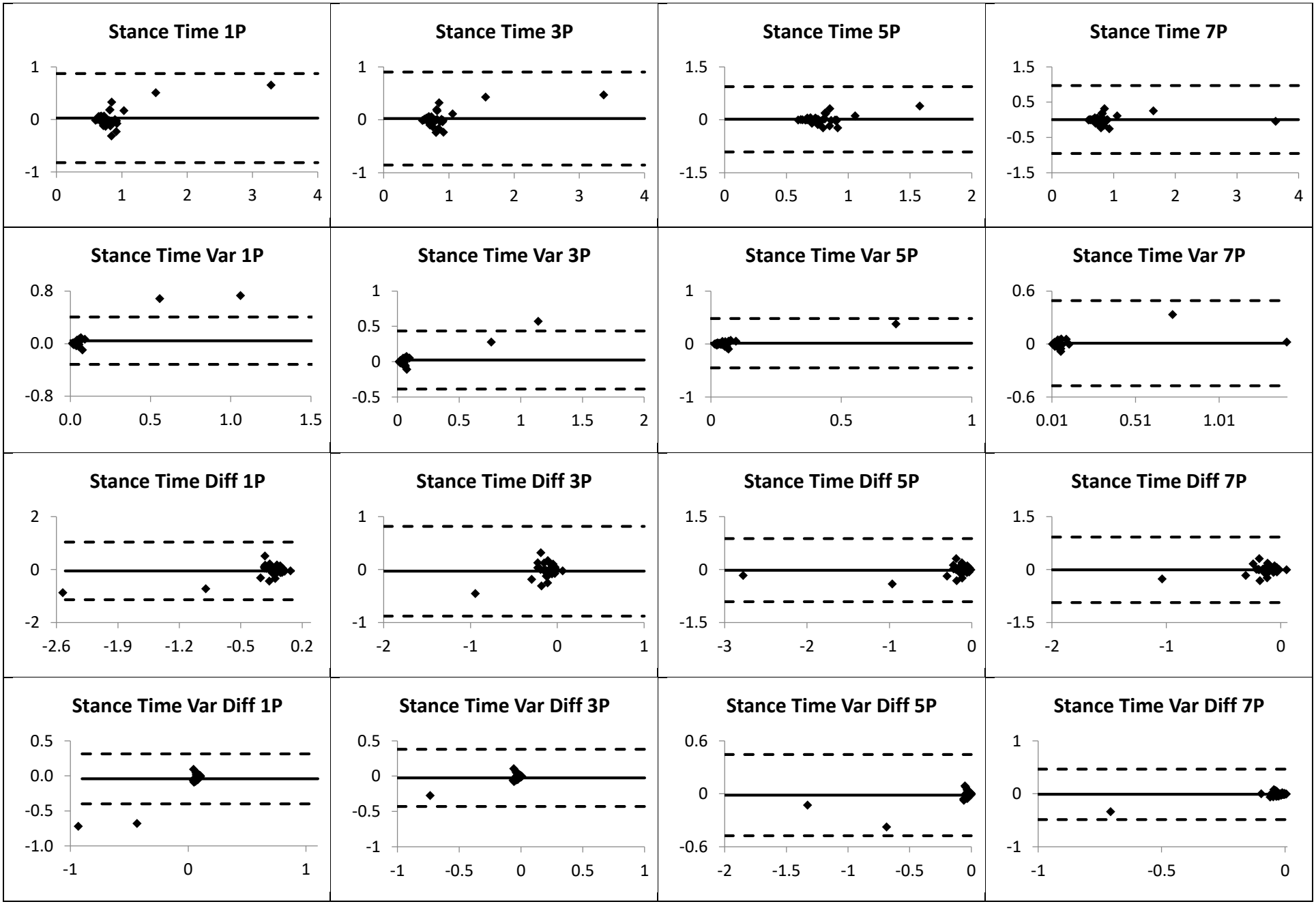
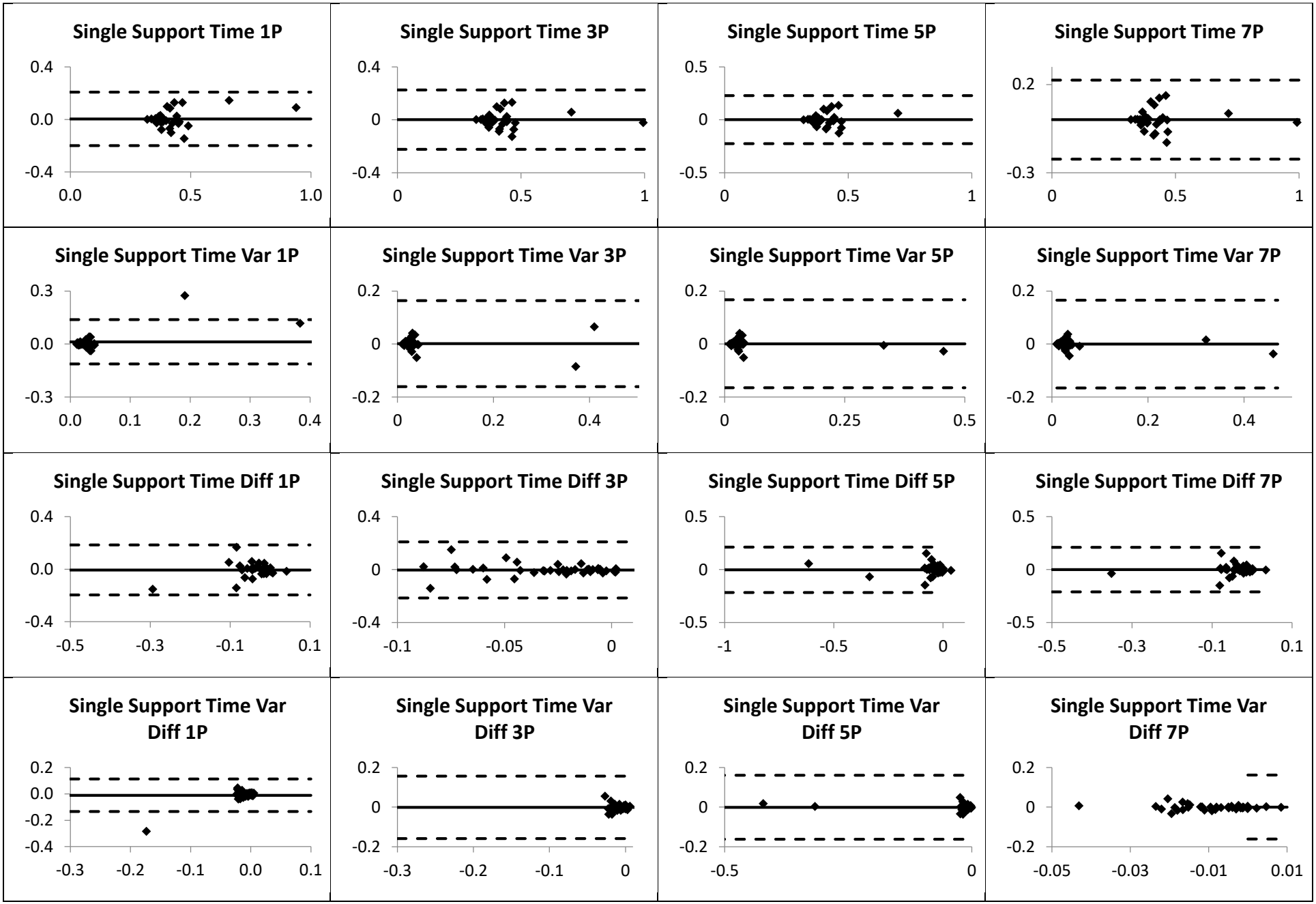
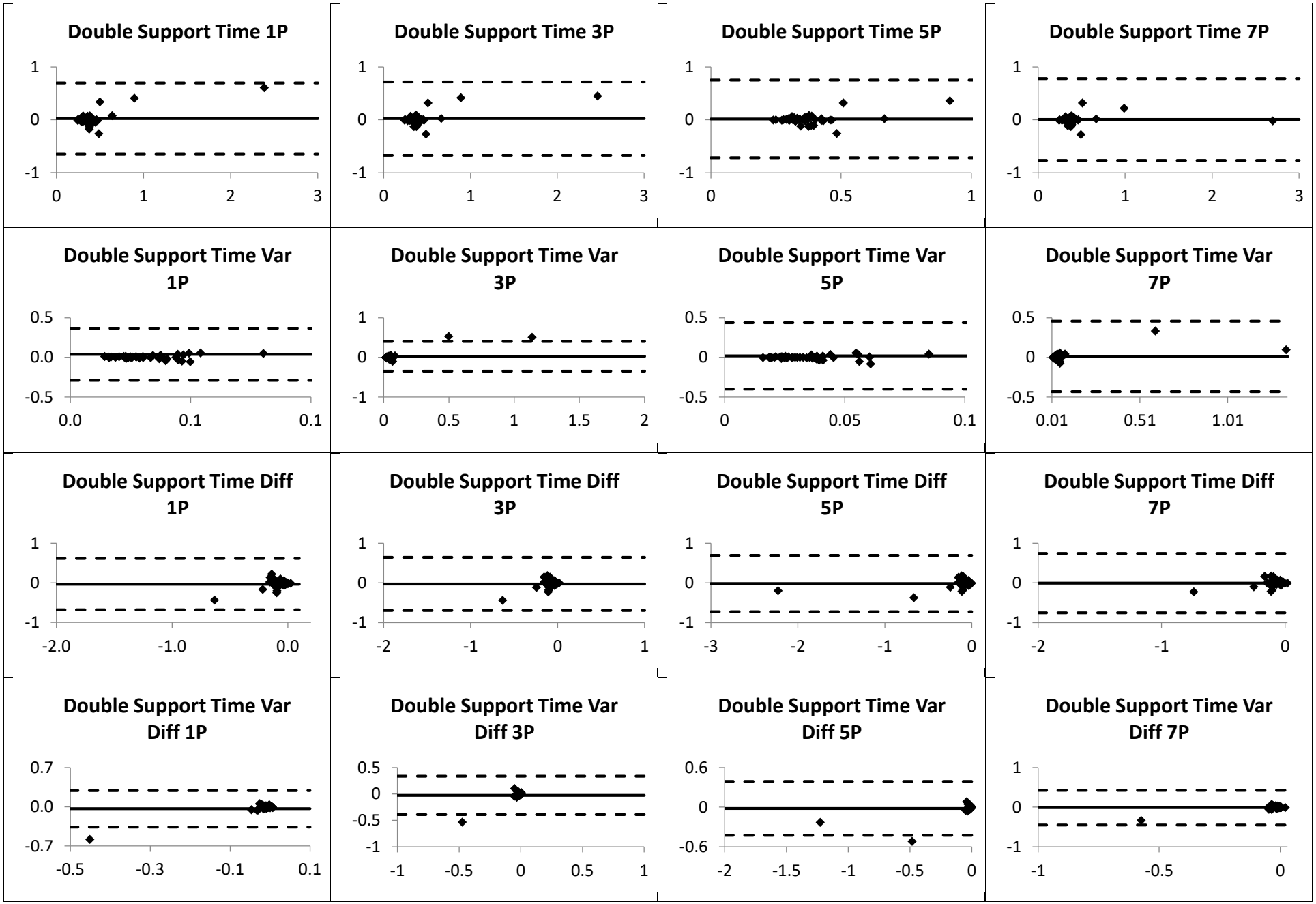
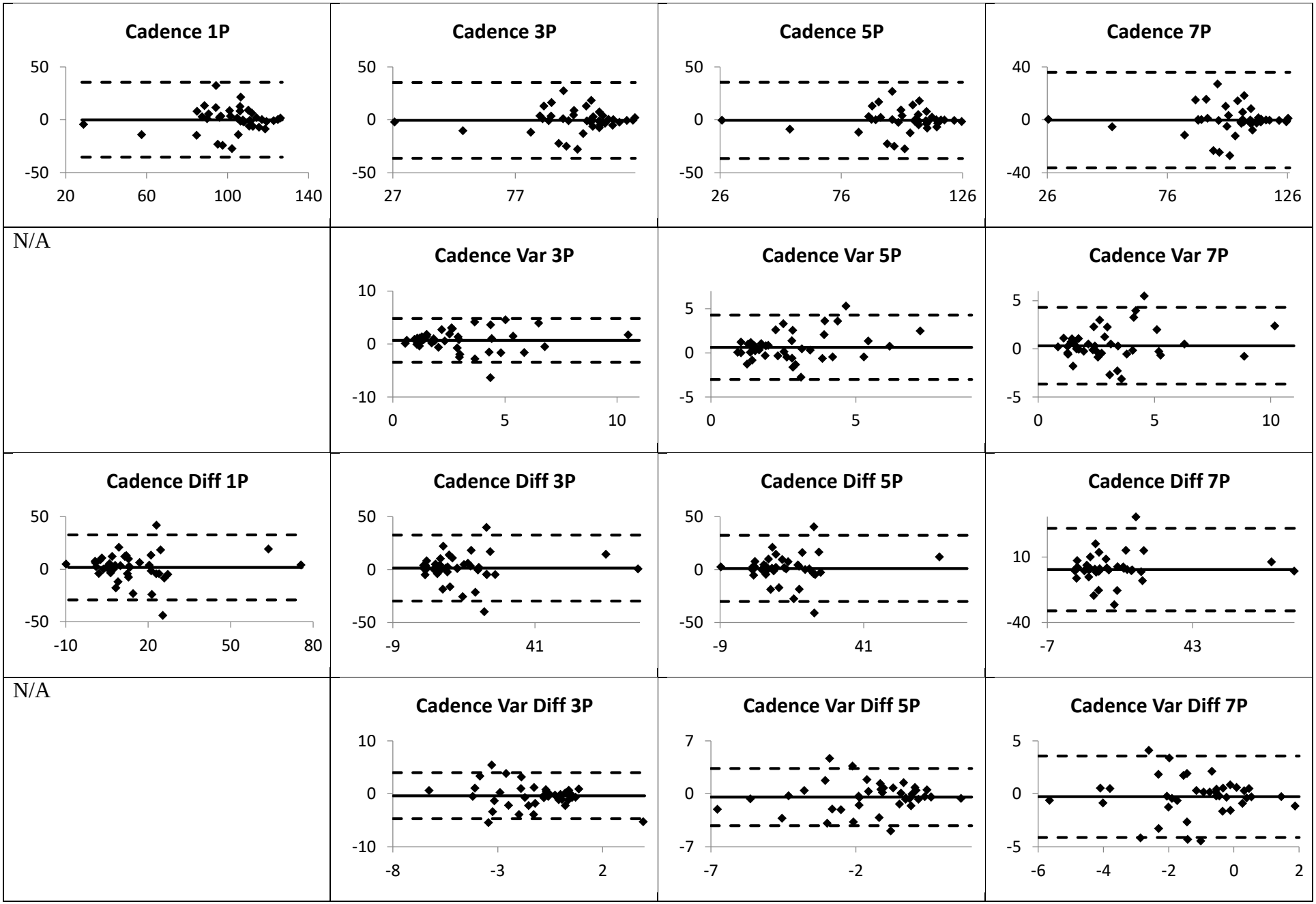
1
0
-1
-1
-0.5
0
0.5
1

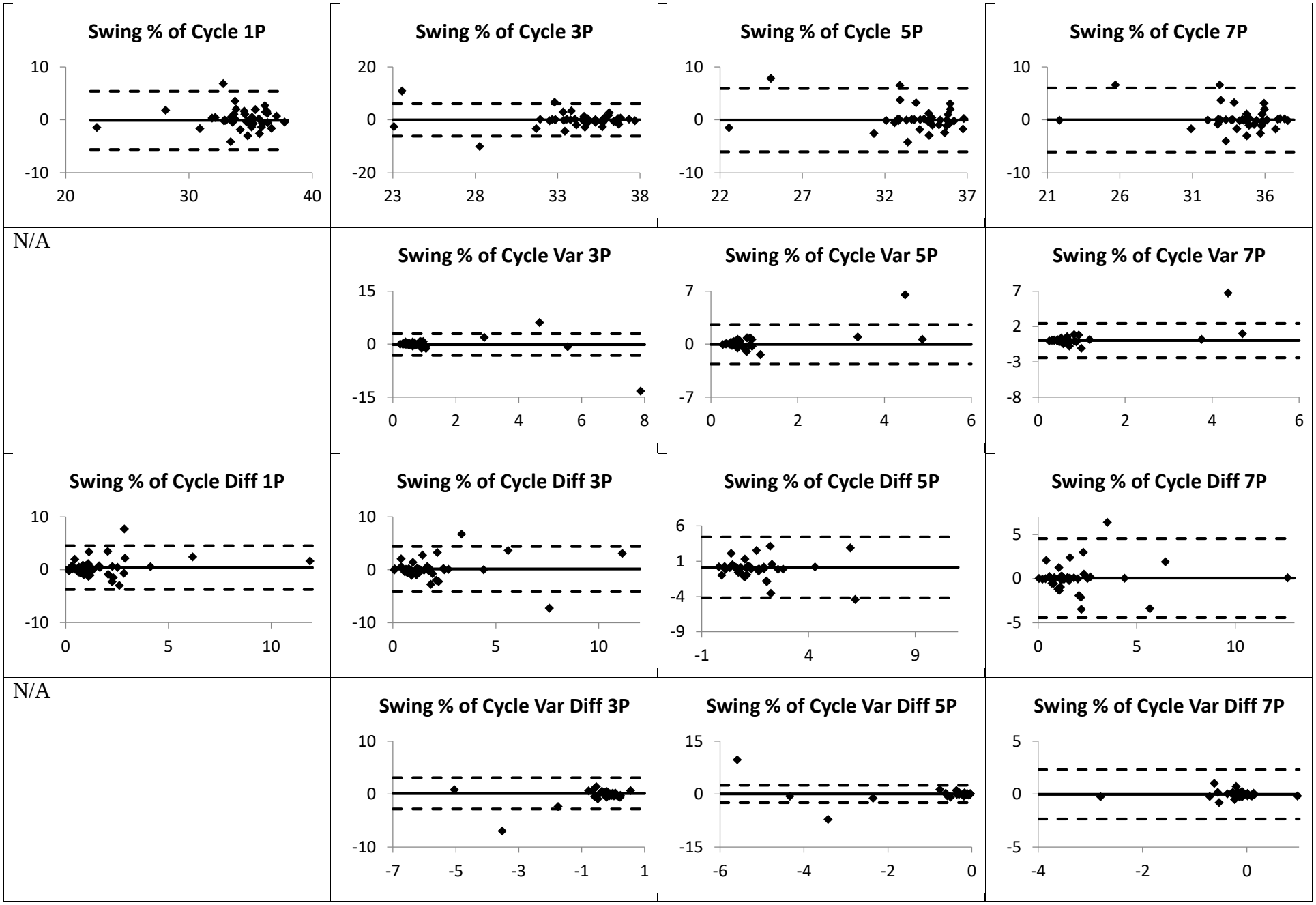

Stride Time 1P
Stride Time 3P
Stride Time 5P
Stride Time 7P
Stride Time Var 1P
Stride Time Var 3P
Stride Time Var 5P
Stride Time Var 7P
Stride Time Diff 1P
Stride Time Diff 3P
Stride Time Diff 5P
Stride Time Diff 7P
Stride Time Var Diff 1P
Stride Time Var Diff 3P
Stride Time Var Diff 5P
Stride Time Var Diff 7P

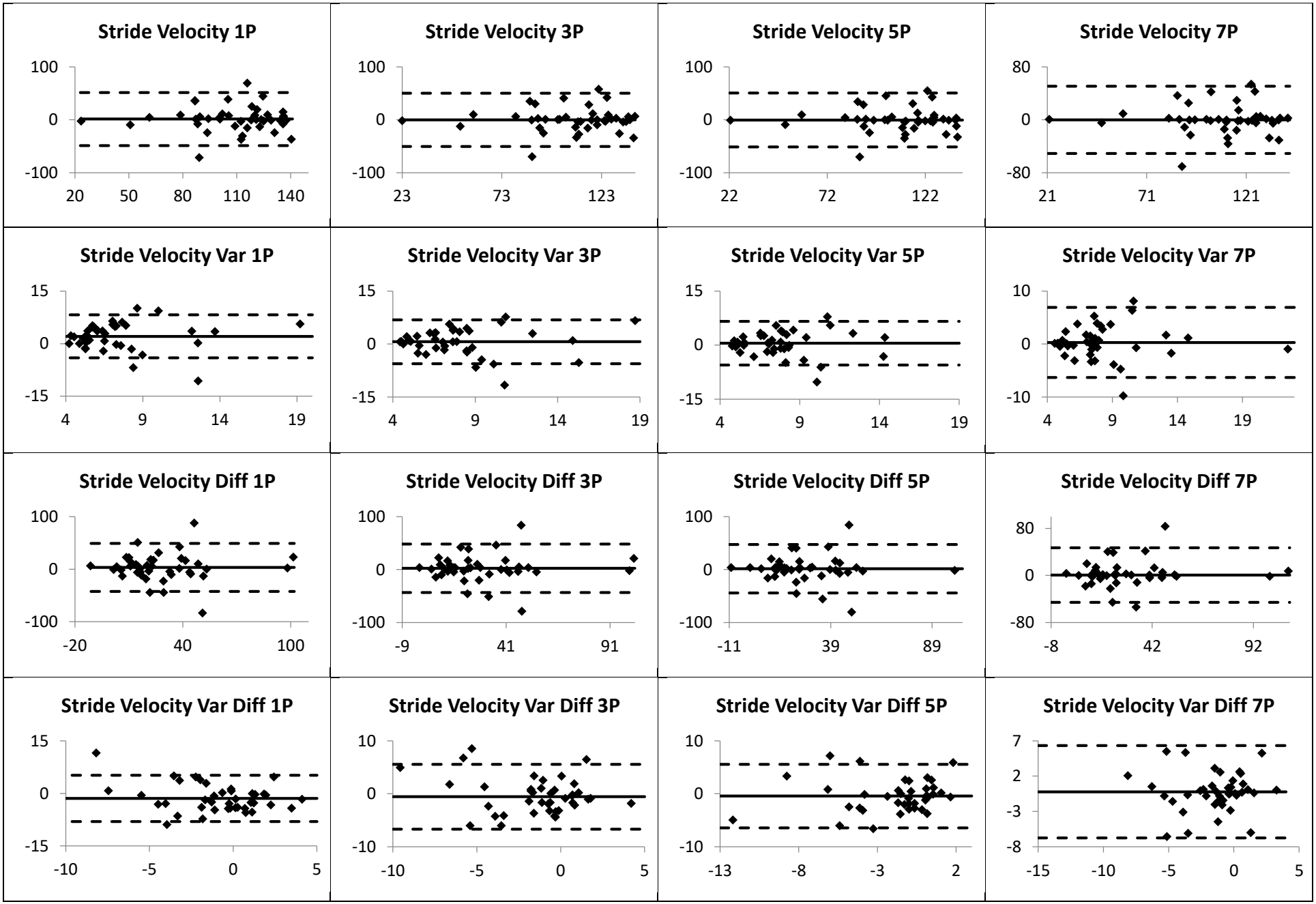

Stance Time 1P
Stance Time 3P
Stance Time 5P
Stance Time 7P
Stance Time Var 1P
Stance Time Var 3P
Stance Time Var 5P
Stance Time Var 7P
Stance Time Diff 1P
Stance Time Diff 3P
Stance Time Diff 5P
Stance Time Diff 7P
Stance Time Var Diff 1P
Stance Time Var Diff 3P
Stance Time Var Diff 5P
Stance Time Var Diff 7P

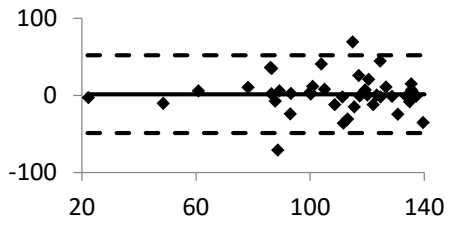
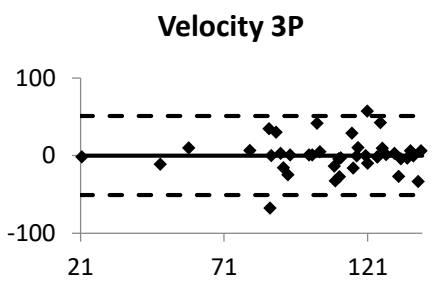
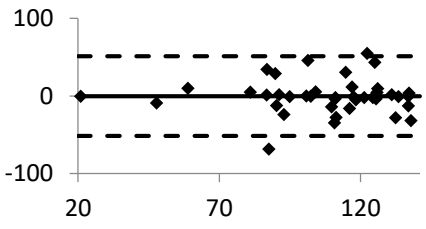
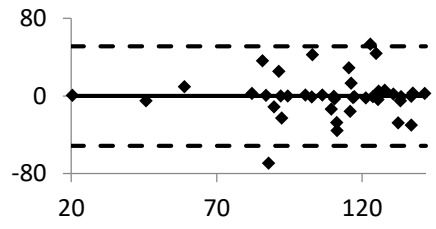
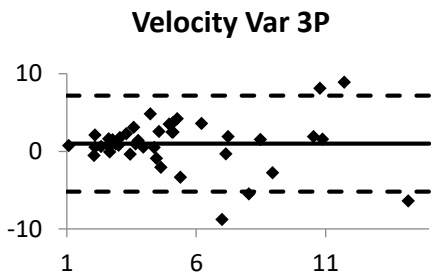
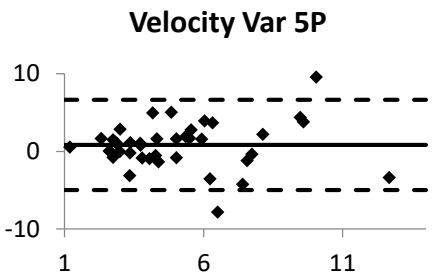
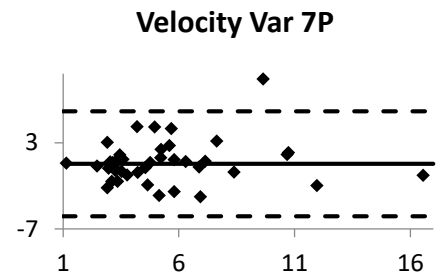
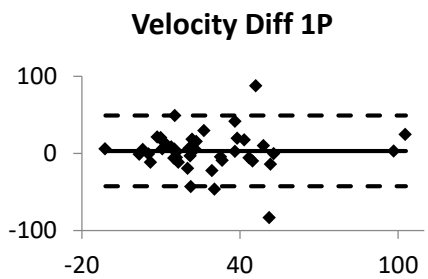
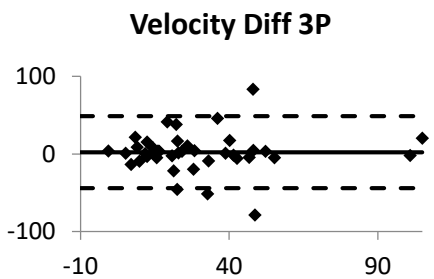
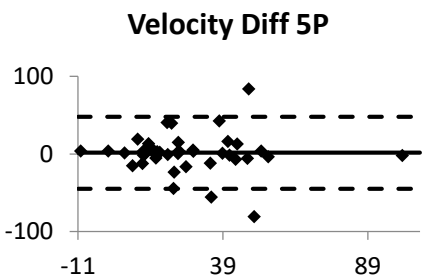
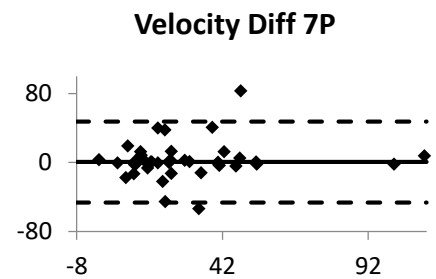
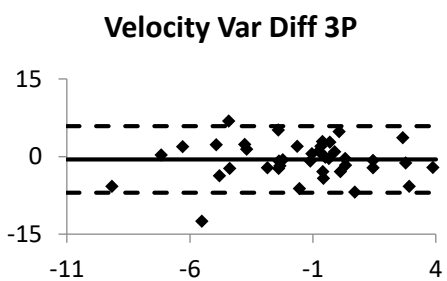
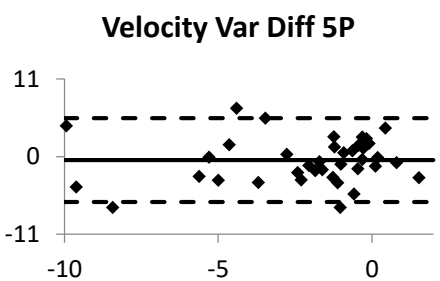
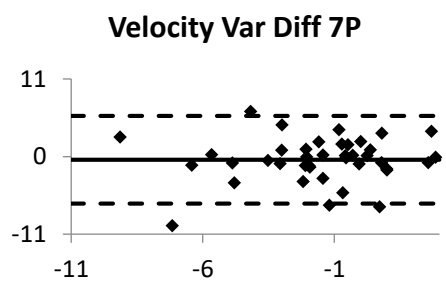

Single Support Time 1P
Single Support Time 3P
Single Support Time 5P
Single Support Time 7P
Single Support Time Var 1P
Single Support Time Var 3P
Single Support Time Var 5P
Single Support Time Var 7P
Single Support Time Diff 1P
Single Support Time Diff 3P
Single Support Time Diff 5P
Single Support Time Diff 7P
Single Support Time Var Diff 1P
Single Support Time Var Diff 3P
Single Support Time Var Diff 5P
Single Support Time Var Diff 7P


Double Support Time 1P
Double Support Time 3P
Double Support Time 5P
Double Support Time 7P
Double Support Time Var 1P
Double Support Time Var 3P
Double Support Time Var 5P
Double Support Time Var 7P
Double Support Time Diff 1P
Double Support Time Diff 3P
Double Support Time Diff 5P
Double Support Time Diff 7P
Double Support Time Var Diff 1P
Double Support Time Var Diff 3P
Double Support Time Var Diff 5P
Double Support Time Var Diff 7P


Cadence 1P
50
0
-50
20
60
100
140
Cadence 3P
50
0
-50
27
77
Cadence 5P
50
0
-50
26
76
126
Cadence 7P
40
0
-40
26
76
126
N/A
Cadence Var 3P
10
0
-10
0
5
10
Cadence Var 5P
5
0
-5
0
5
Cadence Var 7P
5
0
-5
0
5
10
Cadence Diff 1P
50
0
-50
-10
20
50
80
Cadence Diff 3P
50
0
-50
-9
41
Cadence Diff 5P
50
0
-50
-9
41
Cadence Diff 7P
10
-40
-7
43
N/A
Cadence Var Diff 3P
10
0
-10
-8
-3
2
Cadence Var Diff 5P
7
0
-7
-7
-2
Cadence Var Diff 7P
5
0
-5
-6
-4
-2
0
2


Swing % of Cycle 1P
Swing % of Cycle 3P
Swing % of Cycle 5P
Swing % of Cycle 7P
N/A
Swing % of Cycle Var 3P
Swing % of Cycle Var 5P
Swing % of Cycle Var 7P
Swing % of Cycle Diff 1P
Swing % of Cycle Diff 3P
Swing % of Cycle Diff 5P
Swing % of Cycle Diff 7P
N/A
Swing % of Cycle Var Diff 3P
Swing % of Cycle Var Diff 5P
Swing % of Cycle Var Diff 7P


Stride Velocity 1P
100
0
-100
20
50
80
110
140
Stride Velocity 3P
100
0
-100
23
73
123
Stride Velocity 5P
100
0
-100
22
72
122
Stride Velocity 7P
80
0
-80
21
71
121
Stride Velocity Var 1P
15
0
-15
4
9
14
19
Stride Velocity Var 3P
15
0
-15
4
9
14
19
Stride Velocity Var 5P
15
0
-15
4
9
14
19
Stride Velocity Var 7P
10
0
-10
4
9
14
19
Stride Velocity Diff 1P
100
0
-100
-20
40
100
Stride Velocity Diff 3P
100
0
-100
-9
41
91
Stride Velocity Diff 5P
100
0
-100
-11
39
89
Stride Velocity Diff 7P
80
0
-80
-8
42
92
Stride Velocity Var Diff 1P
15
0
-15
-10
-5
0
5
Stride Velocity Var Diff 3P
10
0
-10
-10
-5
0
5
Stride Velocity Var Diff 5P
10
0
-10
-13
-8
-3
2
Stride Velocity Var Diff 7P
7
2
-3
-8
-15
-10
-5
0
5

 Velocity 1P 100 0 -100 20 60 100 140	 Velocity 3P 100 0 -100 21 71 121	 Velocity 5P 100 0 -100 20 70 120	 Velocity 7P 80 0 -80 20 70 120
N/A	 Velocity Var 3P 10 0 -10 1 6 11	 Velocity Var 5P 10 0 -10 1 6 11	 Velocity Var 7P 3 -7 1 6 11 16
 Velocity Diff 1P 100 0 -100 -20 40 100	 Velocity Diff 3P 100 0 -100 -10 40 90	 Velocity Diff 5P 100 0 -100 -11 39 89	 Velocity Diff 7P 80 0 -80 -8 42 92
N/A	 Velocity Var Diff 3P 15 0 -15 -11 -6 -1 4	 Velocity Var Diff 5P 11 0 -11 -10 -5 0	 Velocity Var Diff 7P 11 0 -11 -11 -6 -1