THE INFLUENCE OF DUAL-TASK CONDITIONS ON POSTURAL CONTROL
AND INSTRUMENTED TIMED UP AND GO PERFORMANCE
IN FALLERS AND NON-FALLERS

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THE INFLUENCE OF DUAL-TASK CONDITIONS ON POSTURAL CONTROL
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ABSTRACT

THE INFLUENCE OF DUAL-TASK CONDITIONS ON POSTURAL CONTROL
AND INSTRUMENTED TIMED UP AND GO PERFORMANCE
IN FALLERS AND NON-FALLERS

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One in three older adults fall each year; many falls resulting in moderate to severe
injuries. Falls are a multi-faceted problem, with risk factors that include balance and gait
impairments. Balance and movement assessments are often used to identify individuals at
risk of falls by identifying a change in the center of pressure excursions or movements.
This study examined two fall risk assessments, posturography analyzed through
traditional time-domain measures and newer non-linear measures and the instrumented
Timed Up and Go (iTUG), under standard and dual-task conditions, to determine better
ways to distinguish individuals with subtle deficits contributing to fall risk.

One hundred fifty older adult fallers and non-fallers performed quiet-standing
posturography and iTUG methodologies. Test conditions included standard testing
conditions, cognitive dual-task, manual dual-task, and cognitive+manual dual task. Five
traditional postural sway parameters, four non-linear postural sway parameters were calculated, and eight iTUG parameters were calculated. One-way multivariate analysis of variance (p<0.05) was used to compare fallers versus non-fallers and to compare each type of dual task. Effect sizes were calculated using the Cohen’s d method. Stepwise logistic regression was performed to identify the postural sway and iTUG parameters that best differentiated fallers from non-fallers for the traditional Timed Up and Go Test, iTUG test, posturography test and a combined model including the iTUG and posturography tests.

Results demonstrated that not just one dual-task prevailed over the others, rather when analyzing posturography data through traditional measures the manual dual-task provided greater differentiation between fall risk groups, when analyzing posturography data through non-linear measures the cognitive dual-task provided greater differentiation between fall risk groups, and when utilizing the iTUG test the cognitive+manual dual-task affected the iTUG parameters the most, with fall risk differentiation seen in the sit-to-stand measures. A stepwise logistic regression model was created, with all of the posturography, traditional and nonlinear, parameters and all iTUG output parameters input into the model. The resulting fall risk model has a max re-scaled R² value of 0.3244, sensitivity of 54.3% and specificity of 82.7%. The parameters included in the model are height, sit-to-stand duration, stand-to-sit duration, turn peak velocity, and A/P sway range. Dual-tasks and non-linear analysis measures were valuable additions to posturography and iTUG fall risk assessments. Future work is necessary to extend exploration of dual-tasks and how they affect fallers and non-fallers differently.
I would like to dedicate my work to Timothy Jon Beach – father, mentor, role model, friend, and guardian angel.
ACKNOWLEDGMENTS

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I would like to extend my gratitude to all my study participants for their time and interest in my research. I also want to share my appreciation for all those who assisted in subject recruitment for my study, including University of Dayton Osher Lifelong Learning Institute, especially Julie Mitchell and Bethany Village, especially Judy Budi,
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CHAPTER I

INTRODUCTION

Importance of Fall-Risk Identification

One in three older adults fall each year, many resulting in severe to moderate injuries.\textsuperscript{1,2} As of 2012, falls have been the leading cause of injury-related death in adults age 65 and older, and since 2013, unintentional falls are the leading cause of nonfatal injuries in this population.\textsuperscript{3} Falls often result in hip fractures, a reduction in physical activity and mobility, increase in medications, decrease in quality in life, reduced self-confidence and fear of falling, and therefore an increased risk of future falls or death.\textsuperscript{2,4,5} A history of falling also increases the likelihood of future falls.\textsuperscript{6,7} If individuals can be more accurately identified as at-risk fallers, precautions and interventions could be put in place to target the risk factors for an individual’s risk of falls.\textsuperscript{7} Earlier identification of fall risk can help decrease not only fall-related injuries, but also the financial burden incurred due to a fall.\textsuperscript{1,7}

Posturography Assessment

One indicator of fall risk is a balance deficit; individuals are up to 5.4 times more likely to fall if they exhibit poor balance.\textsuperscript{8–10} One method for identifying balance deficits is posturography.\textsuperscript{11} Posturography is the method of using a force-measuring platform to
model the upright standing human body as an inverted pendulum and measuring the amount of center of pressure (COP) sway exhibited as the individual maintains and manipulates balance and posture.\textsuperscript{12–14} A force-measuring platform, such as a balance plate, uses strain gages to measure the vertical ground reaction force as well as two associated moments to determine COP in the anterior/posterior and medial/lateral directions.\textsuperscript{13} Center of pressure, which is related to the center of gravity (COG) of the individual, expresses the location of the resultant vector of the ground reaction force on the force plate.\textsuperscript{13} Traditional posturography output parameters such as anterior/posterior (A/P) sway range, medial/lateral (M/L) sway range and mean velocity have been successfully used in identifying individuals with a higher risk of falls.\textsuperscript{9,14–16}

**Timed Up and Go Assessment**

Force plates are typically used in static posturography studies in which participants stand on the plate while attempting to remain still. Although this has the benefit of identifying deficits without an individual moving, postural control during movements can also be insightful when studying fall-risk populations. In addition to deficits with postural control, many individuals who fall do so during a gait cycle, and these deficits can be identified through movement analyses.\textsuperscript{17–19} The Timed Up and Go (TUG) test is a frequently used clinical assessment of balance and mobility. The TUG test is a short evaluation where an individual is asked to start sitting in a chair, stand from the chair, walk a 3 meter path, turn around, walk back to the chair and sit down, all while a clinician uses a stop watch to time the total time duration of the task.\textsuperscript{20} This test has been used to identify individuals at risk of falling and has shown to be a practical, reliable
test of physical mobility that accurately represents activities commonly due in everyday living.\textsuperscript{20-22}

**Instrumented Timed Up and Go Assessment**

Although the TUG test is able to identify individuals at risk of falls with explicit balance differences, it has not always been consistent in identifying individuals with less pronounced differences.\textsuperscript{23} In order to create a more sensitive screening assessment, one recent addition to the TUG test is the use of accelerometry to measure trunk and limb movement during the TUG assessment.\textsuperscript{24} Known as the instrumented Timed Up and Go (iTUG), the addition of inertial measurement units (IMUs) adds extensive information over the sole outcome measure of the TUG assessment, total time duration. The iTUG assessment incorporates IMUs to measure trunk and limb movement during dynamic movements such as sit-to-stand, turn, and stand-to-sit. The iTUG provides more insight into the overall stability of the individual through collecting information about the acceleration, velocity, orientation and movement of the individual.\textsuperscript{22}

**Dual-Task Methodologies**

Although both posturography and TUG movement assessments have shown to identify individuals at risk of falling, there is room for improvements in discrimination in both analyses. One recent contribution to the field of fall identification is the introduction of dual-tasks. Dual-tasks give added benefit to traditional static posturography and the iTUG protocol by providing the individual with concurrent tasks to make maintaining equilibrium more involved and complicated.\textsuperscript{17,24-27} This requires individuals to rely on their innate ability to perform the primary task. Dual-tasking involves the execution of a
primary task which demands the majority of attention at the same time as a secondary
task.\textsuperscript{28} Research has shown that mental performance deteriorates during a demanding
balance task, but also that more research is needed to see exactly how balance is affected
by mental activity in complex ways.\textsuperscript{29} Dual-tasking lends itself well to studies with
patients of balance impairments and those with high fall risk.\textsuperscript{14,17} For example, existing
research shows that in a more impaired population, such as individuals with Parkinson’s
Disease, gait performance was diminished further during dual tasks as compared to the
traditional task condition.\textsuperscript{28} The most common type of dual tasking, cognitive
interference, have shown to provide an attentional demand to the individual and therefore
have shown impaired balance and a reduction in mobility.\textsuperscript{30} Recent research efforts have
proposed the incorporation of manual tasks as an alternative to help understand the
underlying motor control in various patient populations.\textsuperscript{30} In order to do so, a second type
of dual-task was introduced, yet not studied as in depth as cognitive tasks. A manual task
involves a task such as holding an object in their hand while also performing the primary
task like balancing or walking.\textsuperscript{22,30} Both cognitive and manual tasks have been identified
as a means of increasing attentional demand and have shown differences healthy and
non-healthy populations,\textsuperscript{30} yet there is a need for further research into manual dual-
tasks.\textsuperscript{30} To date there appears to be no studies that have utilized a task that requires a
combined cognitive and manual effort for the dual-tasking paradigm. It may be the case
that a combined task, cognitive+manual, may provide a greater amount of attentional
demand and therefore provide more insight than either type of dual-task alone. Although
this task may not be the most appropriate in some cases, such as when cognitive
contributions need to be isolated, this combined dual-task may be very beneficial to the real-life applicability of the fall risk assessments.

**Analysis Techniques**

Posturography and iTUG testing have a multitude of outcome parameters, which additionally increases with the addition of a dual-tasking paradigm. Because of the large number of parameters for each type of testing, studies often report varying outcome measures.\(^\text{13,31}\) Due to the variety of outcome parameters reported in published literature, the comparison across studies is difficult to determine which measures are the best to differentiate between fallers and non-fallers. Center of pressure data can be analyzed through traditional linear or newer non-linear measures. Commonly used traditional linear parameters are able to describe the trajectory of the center of pressure on the plate during posturography testing.\(^\text{31}\) Traditional posturography parameters based on linear analyses help describe the magnitude and speed of sway of the center of pressure. Common linear parameters reported for posturography are area of COP displacement (sway range), COP root mean square (RMS), COP mean velocity, and area of 95% confidence ellipse.\(^\text{13}\)

Although traditional linear parameters provide information into the amount of sway and stability or instability an individual exhibits, more recent nonlinear measures may provide greater insight into the natural human movement variability and complexity of an individual’s inherent sway pattern.\(^\text{32}\) Human movement variability encompasses the normal variability in motor performance across repetitions of a task over time.\(^\text{32}\) Human movement variability is present in every physiologic system and can be seen even in
static tasks, such as quiet standing. During quiet standing, an individual sways around a central point as they are maintaining upright posture and reacting to internal or external perturbations. Contrary to traditional linear measures, increases in variability are not necessarily signs of an impaired balance system, but variability should lie somewhere between complete chaos and complete repeatability. Linear measures can mask the structure of variability in the movement pattern while nonlinear measures give more information about the structure of variability, which describes the development of the movement over time. Increases in linear measures are typically seen as an indication of instability, yet through nonlinear analyses, researchers were able to determine that variability in movement is actually very important to a person’s equilibrium and a decrease in variability can make the system more rigid and less adaptable. Therefore analyses including nonlinear techniques can be very beneficial over linear measures. Kang et al. and Kirchner et al. have utilized non-linear methods of analyses for dual tasking during quiet standing, yet did not include manual tasks and included limited nonlinear outcome parameters. This warrants the need for further research with non-linear analyses and various dual-task methodologies.

Various types of nonlinear analyses have been used in posturography assessments. Two types that have been successful are Sample Entropy (SampEn) and Detrended Fluctuation Analysis (DFA). Sample Entropy (SampEn) is a means of describing the degree in which complexity is present and has been used to describe changes in postural control, physical activity measures and other movements. Data that proves to be too rigid (low SampEn) or erratic (high SampEn) can reveal important information about motor control processes associated with aging, and therefore possibly
fall risk. Another nonlinear analysis is Detrended Fluctuation (DFA). DFA describes the structure within the data series and the degree of randomness present in a set of data. DFA has also proven to be an effective method of analysis for posturography data, even differentiating between non-fallers and recurrent fallers. In addition to the measure of the magnitude of sway that traditional posturography analysis measures, non-linear analysis provides an insight into the natural variability and complexity of an individual’s inherent sway patterns.

**Fall-Risk Screening Model**

Due to the mass amount of posturography linear and non-linear and iTUG outcome parameters that could be used to identify an individual at risk of falling, a recommendation as to which parameters add the most benefit to fall risk differentiation is needed. To date, only a few papers sought to do something similar. Two of these studies include: Bigelow et al. and Kang et al. Bigelow et al. carried out statistical modeling to determine which of four posturography testing conditions revealed the best differentiation between fallers and non-fallers, and which parameters (traditional and/or non-linear) contributed to that differentiation. Kang et al. incorporated both balance and gait measures in their model to find the best prediction. The current work seeks to advance these findings by improving the model based on advancements in the field known to improve discrimination between fallers and non-fallers but previously not included into modeling. For example, the increased differentiations observed through instrumenting movements during the iTUG have the potential to greatly improve the discrimination between fallers and non-fallers.
Study Aims

Through the use of dual-task posturography and dual-task iTUG procedures and traditional linear and non-linear analyses, this study aims to:

a) Determine how postural sway measures differ between fallers and non-fallers under standard conditions and various dual-task conditions

b) Determine which analysis techniques (linear or non-linear) are most appropriate for the different types of posturography testing conditions (traditional single task, cognitive dual-task, manual dual-task, or a combined cognitive+manual dual-task)

c) Determine how the type of testing condition (traditional single task, cognitive dual-task, manual dual-task, or a combined cognitive+manual dual-task) affected performance on the subcomponents of the iTUG test

d) Determine which of the iTUG subcomponent outputs differed between fallers and non-fallers

e) Determine which combination of iTUG and posturography parameters during traditional or dual-tasking conditions best differentiated fallers from non-fallers by creating a fall-risk screening tool utilizing a step-wise logistic regression model

Therefore, this dissertation includes three individual studies, based off the same protocol and data collection. The first study titled “Manual and Cognitive Dual-Tasks Contribute to Fall-Risk Differentiation in Posturography Measures” intended to address aims a) and b). The second study titled “Sit-to-Stand iTUG Transition Contributes to Fall-Risk Differentiation in Older Adults” intended to address aims c) and d). The final
study titled “Posturography and iTUG Assessments Contribute to a Fall Risk Screening Model” sought to address aim e). Chapters 2, 3, and 4 of this dissertation present the above three studies in succession.
CHAPTER II

MANUAL AND COGNITIVE DUAL-TASKS CONTRIBUTE TO FALL-RISK DIFFERENTIATION IN POSTUROGRAPHY MEASURES

Abstract

Falls occur in 33% of older adults each year, some leading to moderate to severe injuries. To reduce falls and fall related injuries, it is important to identify individuals with subtle risk factors elevating their likelihood of falling. The objective of this study was to determine how postural sway measures differed between fallers and non-fallers under standard and dual-task conditions. Quiet-standing posturography measures were collected from 150 older adults during standard, cognitive, manual and cognitive+manual tasks, and analyzed through traditional and non-linear analyses. Of the traditional measures, M/L sway range and 95% confidence ellipse sway area showed statistically significant differences in all four test conditions between fallers and non-fallers. Although the manual dual-task showed the most stable balance, effect sizes demonstrated larger differences between fallers and non-fallers. Non-linear analysis revealed M/L sample entropy and M/L $\alpha$-scaling exponent differentiating between fallers and non-fallers with the cognitive task demonstrating larger differences. Based on the results, it is recommended to: 1) utilize the manual task and M/L sway range and 95% confidence
ellipse area to differentiate between fallers and non-fallers when using traditional analyses, and 3) utilize the cognitive task and M/L alpha and M/L sample entropy to differentiate between fallers and non-fallers when using non-linear analyses.

**Introduction**

One in three older adults fall each year, often resulting in moderate to severe injuries.\(^1,2\) As of 2012, falls have been the leading cause of injury-related death in adults age 65 and older, and since 2013 unintentional falls in this population have been the leading cause of nonfatal injuries.\(^3\) Falls have greatly increased since the year 2000, also increasing the cost of medical care and direct medical expenses.\(^36\) Individuals fall for a number of intrinsic and extrinsic reasons such as: muscle weakness, poor vision, or uneven floors.\(^45\) When an individual does fall, this can result in: hip fractures, head injuries, reduction in physical activity, reduction in mobility, increase in medication, loss of confidence, increased fear of falling, death, and an increase in the likelihood of future falls.\(^2,4,5,10\) Improvements to already existing predictive technologies and techniques are crucial in identifying older adults at risk of falls.\(^36\) If an individual can be accurately assessed as having a high fall risk, precautions and interventions could be implemented to decrease the likelihood of falls and fall-related injuries.\(^1,7\)

Balance deficits are among the most commonly identified risk factors contributing to falls, with individuals being up to 5.4 times more likely to fall if they exhibit poor balance.\(^8,9,46,47\) An individual’s balance can be assessed using several methods; posturography is one of them.\(^11\) Posturography uses a force-measuring platform to infer postural stability based on an inverted pendulum assumption.\(^12-14\) The force measuring
platform uses load cells to record the amount of center of pressure (COP) displacement that is exhibited as the individual maintains an upright stance. A body is considered to be in mechanical equilibrium when the sum of all of the forces and the sum of the moments of the forces on the body equal to zero. Due to the internal and external forces on the body (heart rate, breathing, activation of muscle fibers, etc), the body is never in a true state of perfect balance. The COP recorded from the force plate expresses the location of the resultant vector of the ground reaction force on the force plate, indicating postural sway. Posturography studies using traditional analyses such as anterior/posterior (A/P) sway range, medial/lateral (M/L) sway range and mean velocity have found conflicting results on whether sway parameters can differentiate between individuals with balance impairments and those without balance impairments. A/P sway range measures the max excursions of the sway in the front to back direction while the M/L sway range measures the max excursions of the sway from side to side. Mean velocity measures the average velocity of the COP trajectory during the trial. Other common parameters included in analysis of the COP trajectory include M/L mean velocity, 95% confidence ellipse area, and root-mean-square.

Improvements have been made to standard posturography methods in order to better differentiate fallers from non-fallers; one improvement is the inclusion of dual-tasking during posturography measurements. Dual-tasking involves the execution of a primary task that demands the majority of the body’s attention while also completing a secondary task, such as walking and talking at the same time. Employing an attentional demand through dual-tasks introduces an interference to the primary task and can help measure the attentional demand required of the primary task. Many older
adults incur falls while performing two activities at the same time; therefore, dual-tasking lends itself well to the assessment of individuals with potential balance impairments and fall risk. Dual-tasking during posturography assessments has been shown to be better at identifying fall risk than static posturography alone. One popular method of dual-tasking that adds difficulty to a postural stability test is the cognitive task of counting - generally by having individuals count backward from a number, for example 100, by 3’s. Cognitive dual-tasks have been shown to provide an attentional demand to the individual that impairs balance. In order to fully understand an individual’s abilities and fall risk, assessing individuals under dual-tasking activities representative of typical tasks faced during daily living (e.g. holding and/or carrying objects) may be valuable. This type of dual-task would be a manual task. Research has reported that dual-tasks may have varying levels of complexity and therefore place differing levels of demand on the individual. This has led individuals conducting research in attentional demands and dual tasking to incorporate a range of cognitive and motor tasks. However, due to the conflict between the static nature of posturography testing and the movements typically required for a manual task, little work has been done to evaluate manual tasks during posturography analysis.

Although cognitive tasks have been used predominantly for dual-task assessments in posturography, gait related studies have explored the use of a manual dual-task and found them to be beneficial and discriminative. Toulotte et al. identified the manual task of carrying a glass of water as beneficial to detecting walking disorders and planning therapy based on results. Lundin-Olsson et al. identified a manual task during the Timed Up and Go (TUG) test as a predictor of individuals prone to falls. Since the
manual task has a known benefit to gait testing, the real-life applicability of the manual task and/or a combined cognitive+manual task could help determine which type of dual-task most affects an individual. Incorporating dual-tasking into posturography could offer better insight in differentiating fallers and non-fallers because they will be faced in more realistic scenarios where they must multi-task and divide their attention. A real world example of this dual-task scenario would be an individual standing at a sink washing dishes while talking to someone. As far as the authors are aware, no work has been done to test the manual task in posturography or to combine the cognitive task of counting with a manual task for posturography testing.

Therefore, the overall objective of this study was to determine how postural sway measures differed between fallers and non-fallers under standard conditions and various dual-task conditions. We hypothesized that fallers and non-fallers would demonstrate significant differences from each other in performances (p<0.05) on each the cognitive, the manual, and the cognitive+manual tasks and that the more attentionally demanding cognitive+manual would exhibit the largest between-group differences as indicated by effect size. In all cases we hypothesized that fallers would exhibit larger sway ranges and speed of sway (traditional measures) and greater irregularity and persistence (non-linear measures), suggesting poorer postural control.

Methods

One hundred fifty participants over the age of 60 were recruited from local retirement communities, senior centers, community exercise groups and various interest groups. Individuals were excluded if they had balance or mobility deficits as defined by:
use of a lower limb brace such as a prosthetic limb or ankle foot orthotic, inability to stand unassisted for 5 minutes, or inability to walk 50 feet without assistance. Exclusion criteria were kept to a minimum so that individuals with a wide range of health and activity levels, more typical of the older population, would be included. Study participants were asked to report the number of falls they had sustained in the past 12 months, using the definition of “any time you came to rest on a lower surface unintentionally”.

Study participants were then categorized as a faller if they reported experiencing at least one fall in the past year; and a non-faller if they had not sustained any falls in the past 12 months. While more conservative definitions for fallers were considered (e.g. 2 or more falls in the last year; at least one fall in the last six months), the definition of at least one fall in the past 12 months was used as it aligns with fall prevention guidelines from the American Geriatrics Society and others. These recommendations support that individuals who self-report even a single fall in the past year warrant further gait and balance evaluation for fall risk to be most effectively managed.

This study was approved by the University of Dayton Institutional Review Board and all participants gave written, informed consent.

Preliminary data collection included a fall history and activity level questionnaire as well as the Activity Balance Confidence (ABC) Scale questionnaire. The fall history questionnaire not only asked if the participant had fallen in the past year, but also how the fall happened, under what circumstances, and if any injuries were incurred. The general healthy history and activity level questionnaire included questions concerning current balance disorders or known neurological disorders, seizure history, numbness of the feet, lower joint replacement or lower leg surgery, taking four or more medications,
involvement in physical therapy, intensity level of physical activity each week, and inclusion/exclusion of muscle strength or flexibility exercises each week. Fall history and activity questionnaire information was used not only for fall risk classification, but also to explain any outlier information in the data.

Posturography was used to assess quiet-standing balance under four testing conditions: standard (single task), cognitive dual-task, manual dual-task, and a combined cognitive+manual dual task. For all testing conditions study participants were asked to stand with their feet approximately shoulder width apart on a force plate (Model 5046, Bertec Corporation, Worthington, Ohio). In order to provide as much real-life applicability as possible, participants wore their own shoes, since wearing shoes has been recommended over being barefoot to reduce fall risk. However, to best control for the potential effect of differing shoe wear, all participants were instructed to wear comfortable walking shoes with medium thickness soles and the researcher confirmed the acceptability of the shoes prior to initiating testing. For all trials study participants were told to stand still, looking straight ahead at a blank wall for the duration of each trial. The balance plate was located in the same position in the same room for all study participants in order to eliminate variability due to testing site location. Trials were discarded and repeated if the individual talked or accidentally moved during the trial, as observed by the researcher. Force plate center of pressure (COP) data were collected at 1000 Hz. For each testing condition three 60-second trials were taken for a total of 12 trials. The four testing conditions were conducted in a randomized order and at the initiation of each testing condition the task-specific directions were given and demonstrated. Participants
were given plenty of time to ask any questions or ask for clarification at any point during testing. Participants wore a gait belt during testing and were spotted by a researcher.

During the standard quiet-standing task, participants were asked to keep their arms at their sides with the instructions to stay as still and quiet as possible. For all of the dual tasks, study participants were instructed to stand as still and as quiet as possible (primary task) while also doing the best they could to carry out the additional cognitive and/or manual task (secondary). The cognitive dual-task required the study participant to count backward from 200 by a specified number (2 or 3 depending on the subject’s comfort level with the task). For the manual task participants were instructed to try to keep a 2.5” tennis ball contained on a lipped serving tray. The participants were not instructed to keep the ball at any particular location on the tray. Participants were instructed to hold the tray with both hands, with elbows at a 90-degree angle. For the cognitive+manual task study participants were asked to count backward from 200 by 2 or 3, while also holding the tray with the ball. No instructions were provided as to whether to place more attention on counting or on holding of the tray.

All COP data collected from the force plate were down-sampled to 100 Hz based on results of the power spectral density. To calculate the traditional parameters, COP data were filtered with a 4th order low-pass Butterworth filter with 5 Hz cut-off. The following traditional COP parameters were then calculated: anterior/posterior (A/P) sway range, medial/lateral (M/L) sway range, mean velocity, and 95% confidence ellipse area (95%-CEA). Additionally, because past research has identified the M/L component of mean velocity as a useful tool in fall risk populations, this traditional parameter was also calculated. Whereas traditional measures provide information about the amount of
sway, nonlinear measures provide complementary information about the structure and underlying patterns of sway. To calculate nonlinear measures, the down-sampled COP data were used but filtering was not employed since filtering affects the structural content that nonlinear analysis seeks to characterize. Sample Entropy, as described by Richman et al., was used to calculate the non-linear measures of A/P SampEn and M/L SampEn. Sample Entropy measures the regularity, or predictability, of an individuals’ COP movement. Values close to 0 indicate highly regular and repeatable (e.g. periodic) movement; while higher values (with no limit) indicate highly irregular (e.g. random) movements. Additionally, Detrended Fluctuation Analysis (DFA), as described by Blazquez et al., was used to calculate the A/P $\alpha$-scaling exponent and M/L $\alpha$-scaling exponent. Detrended Fluctuation Analysis measures the underlying trends, or persistence in the data. DFA values between 0 and 0.5, the signal is anti-persistent (smaller DFA = more anti-persistent). When the DFA value is between 0.5 and 1, the signal is persistent (larger DFA = more persistent). Additional information and specific COP calculations can be found in Appendix A.

The three trials for each condition per participant were averaged for statistical analysis. IBM SPSS (Armonk, New York) was used to perform a one-way multivariate analysis of variance ($p \leq 0.05$) to compare fallers versus non-fallers for each type of task (standard, cognitive, manual, and cognitive + manual) for all outcome measures. Effect sizes were calculated using the Cohen’s $d$ method. Cohen $d$ ($d$) values were quantified as: $d \approx 0.2$, effect size is small, $d \approx 0.5$, effect size is moderate, and $d \approx 0.8$, effect size is large.
Results

Of the 150 recruited participants, two participants decided not to participate after completing the consent form process. All remaining 148 participants were able to complete balance testing, all without a loss of balance and were included in the analysis. There were 59 individuals who reported sustaining at least one fall in the last 12 months and were categorized as fallers, and 91 non-fallers (Table 1). Fallers reported experiencing between 1 and 24 falls over the past 12 months, with a mean fall incidence of 2.27 +/- 3.17. Significant differences were found between groups for age, height, and gender.

**Table 2.1.** Faller and Non-faller Group Subject Characteristics, Mean (St. Dev.)

<table>
<thead>
<tr>
<th></th>
<th>FALLER (n=59)</th>
<th>NON-FALLER (n=91)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AGE (years)</strong></td>
<td>77.17 (8.17)</td>
<td>74.35 (9.00)</td>
</tr>
<tr>
<td><strong>HEIGHT (cm)</strong></td>
<td>164.41 (8.21)</td>
<td>169.81 (10.91)</td>
</tr>
<tr>
<td><strong>WEIGHT (N)</strong></td>
<td>743.39 (166.76)</td>
<td>764.65 (148.31)</td>
</tr>
<tr>
<td><strong>MALE/FEMALE</strong></td>
<td>15 Male/44 Female</td>
<td>47 Male/44 Female</td>
</tr>
</tbody>
</table>

In each of the four testing conditions, the traditional sway measures M/L sway range and 95% confidence ellipse area were statistically larger for fallers compared to non-fallers (Table 2.1). All effect sizes for these statistically significant parameters were considered “moderate” ($d \approx 0.5$). Although all in a moderate range, effect sizes were higher for the manual task ($d=0.47, d=0.48$ for M/L sway range and 95% confidence ellipse area, respectively) and cognitive+manual ($d=0.48, d=0.48$) than the standard ($d=0.34, d=0.33$) and cognitive ($d=0.33, d=0.37$) tasks (Table 2.2). Additionally, a
statistically significant difference ($p=0.044$) of low-moderate effect size ($d=0.34$) was found for A/P sway range in the manual dual-task condition.

Table 2.2. Comparison of Fallers vs. Non-Fallers for All Testing Conditions for the Traditional Postural Sway Parameters, Mean and 95% Confidence Interval (Lower bound, Upper bound)

<table>
<thead>
<tr>
<th></th>
<th>FALLERS</th>
<th>NON-FALLERS</th>
<th>$P$</th>
<th>$d$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A/P SWAY RANGE (MM)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>41.99 (39.02, 44.96)</td>
<td>40.15 (37.73, 42.58)</td>
<td>0.345</td>
<td>0.16</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>43.56 (40.33, 46.78)</td>
<td>41.72 (39.08, 44.35)</td>
<td>0.383</td>
<td>0.15</td>
</tr>
<tr>
<td>MANUAL</td>
<td>42.90 (39.78, 46.02)</td>
<td>38.77 (36.22, 41.31)</td>
<td>0.044*</td>
<td>0.34</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>42.78 (39.52, 46.03)</td>
<td>41.15 (38.49, 43.81)</td>
<td>0.445</td>
<td>0.13</td>
</tr>
<tr>
<td><strong>M/L SWAY RANGE (MM)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>23.60 (20.99, 26.21)</td>
<td>20.08 (17.95, 22.21)</td>
<td>0.041*</td>
<td>0.34</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>31.02 (26.39, 35.66)</td>
<td>24.87 (21.08, 28.65)</td>
<td>0.044*</td>
<td>0.33</td>
</tr>
<tr>
<td>MANUAL</td>
<td>22.44 (20.35, 24.53)</td>
<td>18.53 (16.82, 20.24)</td>
<td>0.005*</td>
<td>0.47</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>30.16 (25.91, 34.41)</td>
<td>21.79 (18.32, 25.25)</td>
<td>0.003*</td>
<td>0.48</td>
</tr>
<tr>
<td><strong>MEAN VELOCITY (MM/S)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>18.02 (15.92, 20.11)</td>
<td>18.41 (16.70, 20.12)</td>
<td>0.777</td>
<td>0.05</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>22.90 (20.10, 25.69)</td>
<td>22.82 (20.53, 25.10)</td>
<td>0.965</td>
<td>0.01</td>
</tr>
<tr>
<td>MANUAL</td>
<td>18.15 (15.99, 20.31)</td>
<td>17.56 (15.80, 19.32)</td>
<td>0.676</td>
<td>0.07</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>21.81 (19.03, 24.59)</td>
<td>21.58 (19.32, 23.85)</td>
<td>0.902</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>M/L VELOCITY (MM/S)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>5.92 (5.06, 6.79)</td>
<td>5.92 (5.21, 6.62)</td>
<td>0.99</td>
<td>0.00</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>9.00 (7.43, 10.58)</td>
<td>7.96 (6.68, 9.25)</td>
<td>0.313</td>
<td>0.17</td>
</tr>
<tr>
<td>MANUAL</td>
<td>5.91 (5.21, 6.62)</td>
<td>5.39 (4.81, 5.97)</td>
<td>0.258</td>
<td>0.19</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>8.09 (6.73, 9.44)</td>
<td>7.02 (5.91, 8.12)</td>
<td>0.229</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>95% CEA (MM²)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>382.22 (312.31, 452.13)</td>
<td>287.41 (230.33, 344.49)</td>
<td>0.04*</td>
<td>0.33</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>513.93 (410.33, 617.53)</td>
<td>354.94 (270.35, 439.53)</td>
<td>0.02*</td>
<td>0.37</td>
</tr>
<tr>
<td>MANUAL</td>
<td>362.99 (312.00, 413.99)</td>
<td>265.64 (224.01, 307.29)</td>
<td>0.004*</td>
<td>0.48</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>475.03 (386.95, 563.11)</td>
<td>299.88 (227.96, 371.80)</td>
<td>0.003*</td>
<td>0.48</td>
</tr>
</tbody>
</table>

95% CEA = 95% confidence ellipse area; $d$ = Cohen’s $d$ for effect size

*p<0.05, significant difference between groups

For the non-linear analysis measures, M/L SampEn and M/L $\alpha$-scaling exponent were statistically different for the cognitive and cognitive+manual testing conditions (Table 2.3). No other statistically significant differences were observed. For both the cognitive and cognitive+manual testing conditions, the M/L SampEn values were significantly smaller and the M/L $\alpha$-scaling exponents were significantly larger for fallers.
than non-fallers. Focusing on those two measures where statistically significant differences were observed, all effect sizes were considered “moderate” \((d \approx 0.5)\).

Cognitive \((d=0.56, d=0.37)\) and cognitive+manual \((d=0.44, d=0.49)\) showed moderate effect sizes for M/L alpha and M/L sample entropy, respectively (Table 2.3).

**Table 2.3.** Comparison of Fallers vs. Non-Fallers for All Testing Conditions for the Non-linear Postural Sway Parameters, Mean and 95% Confidence Interval (Lower bound, Upper bound)

<table>
<thead>
<tr>
<th></th>
<th>FALLERS</th>
<th>NON-FALLERS</th>
<th>(P)</th>
<th>(d)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>M/L ALPHA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>1.53 (1.45, 1.60)</td>
<td>1.52 (1.46, 1.59)</td>
<td>0.982</td>
<td>0.00</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>1.57 (1.53, 1.61)</td>
<td>1.49 (1.45, 1.52)</td>
<td>0.001*</td>
<td>0.56</td>
</tr>
<tr>
<td>MANUAL</td>
<td>1.52 (1.49, 1.56)</td>
<td>1.49 (1.46, 1.52)</td>
<td>0.202</td>
<td>0.21</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>1.54 (1.50, 1.58)</td>
<td>1.47 (1.44, 1.51)</td>
<td>0.009*</td>
<td>0.44</td>
</tr>
<tr>
<td><strong>A/P ALPHA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>1.41 (1.34, 1.48)</td>
<td>1.42 (1.36, 1.48)</td>
<td>0.905</td>
<td>0.02</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>1.43 (1.39, 1.47)</td>
<td>1.39 (1.36, 1.43)</td>
<td>0.206</td>
<td>0.22</td>
</tr>
<tr>
<td>MANUAL</td>
<td>1.41 (1.38, 1.45)</td>
<td>1.39 (1.36, 1.42)</td>
<td>0.287</td>
<td>0.19</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>1.41 (1.37, 1.45)</td>
<td>1.38 (1.34, 1.41)</td>
<td>0.179</td>
<td>0.23</td>
</tr>
<tr>
<td><strong>M/L SAMPLE ENTROPY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>0.07 (0.07, 0.08)</td>
<td>0.09 (0.08, 0.09)</td>
<td>0.054</td>
<td>0.33</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>0.08 (0.07, 0.10)</td>
<td>0.10 (0.09, 0.11)</td>
<td>0.037*</td>
<td>0.37</td>
</tr>
<tr>
<td>MANUAL</td>
<td>0.07 (0.07, 0.09)</td>
<td>0.09 (0.08, 0.10)</td>
<td>0.058</td>
<td>0.33</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>0.08 (0.07, 0.09)</td>
<td>0.10 (0.09, 0.11)</td>
<td>0.005*</td>
<td>0.49</td>
</tr>
<tr>
<td><strong>A/P SAMPLE ENTROPY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STANDARD</td>
<td>0.10 (0.09, 0.11)</td>
<td>0.11 (0.10, 0.12)</td>
<td>0.083</td>
<td>0.31</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>0.12 (0.11, 0.14)</td>
<td>0.14 (0.13, 0.16)</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>MANUAL</td>
<td>0.10 (0.09, 0.11)</td>
<td>0.11 (0.10, 0.12)</td>
<td>0.115</td>
<td>0.28</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>0.12 (0.10, 0.14)</td>
<td>0.14 (0.13, 0.16)</td>
<td>0.134</td>
<td>0.26</td>
</tr>
</tbody>
</table>

\(d\) = Cohen’s \(d\) for effect size

*p<0.05, significant difference between groups
Discussion

Determining fall risk in older adults is an important goal of healthcare providers, and there is past evidence that conditions requiring some form of dual-tasking may negatively impact balance and gait. However, most current balance tests used for fall risk assessment do not include dual-task activities. This study was the first to evaluate postural control between fallers and non-fallers under dual-task conditions that included a cognitive task, a manual task, and a combined cognitive plus manual task using both traditional postural sway measures and non-linear analysis methods. The results of this study indicate that certain measures and conditions may differentiate fallers from non-fallers better than others during quiet standing. These results also suggest that a greater negative impact on balance does not necessarily provide a greater difference between fall risk groups. Rather, results emphasize that certain tasks can affect the two populations differently, providing a greater difference in their outcomes. The results of this study also further support the growing belief that postural control does require attention, and is thus not strictly automatic. This is evidenced by the impact attention-dividing dual tasks seem to have on performance.

When using traditional posturography measures of sway range, sway velocity, and 95%-CEA, it was evident that M/L sway range and 95%-CEA demonstrated the largest and most consistent differences between fallers and non-fallers during all four of the task conditions. Traditional measures seek to describe the amount of sway without accounting for the time-varying changes that are often observed in postural control. As such, traditional measures are useful and commonly employed, but are now being used more often in conjunction with nonlinear measures that quantify the underlying structural
patterns of the data to provide a more complete understanding of postural stability.\textsuperscript{32,62} Values for both of these identified traditional measures were significantly greater in the fallers for every condition, with these larger values indicating greater postural instability and poorer balance. Reduced postural control in the faller group indicates that the faller group has more trouble employing movement strategies to achieve equilibrium position, whether it be to control direction of their sway or the speed at which their body sways. In addition, significant differences between fallers and non-fallers were observed in A/P sway range, though only in the manual dual-task condition. The identification of M/L sway range and 95\%-CEA as the most promising fall risk discriminators is in-line with existing literature for traditional posturography measures.\textsuperscript{12,26,36} In particular, past research has identified the medial-lateral stability as being an important difference between fallers and non-fallers.\textsuperscript{12,26} The findings of this study suggest that this is not only true under standard testing conditions but also under various dual-task conditions examined; additionally, these two traditional sway parameters should be the primary traditional outcomes reported in future studies.

The largest differences between fallers and non-fallers, as indicated by effect size for the traditional sway measures, were elicited during the manual and cognitive+manual conditions for both M/L sway and 95\% confidence ellipse area. This suggests that the manual and cognitive+manual conditions may be more likely to show differences between fallers and non-fallers even though they did not elicit the greatest overall amounts of sway. This suggests that the cognitive+manual task may affect executive function differently in fallers than non-fallers and therefore affect the amount of attention placed on the primary task. Effect sizes for M/L sway and 95\%-CEA were nearly
identical ($d=0.47-0.48$) for both the manual and cognitive+manual conditions, indicating that these conditions were similar in their ability to demonstrate differences between the groups and was likely due to the nature of the manual task. While M/L sway and 95%-CEA were also significantly greater in the fallers for the standard and cognitive task conditions, they exhibited smaller effect sizes ($d = 0.33-0.37$). This seems to suggest that while the manual task itself is not overtly challenging (with individuals exhibiting, on average, better balance while holding the tray than the standard (single task) condition), it does require an attentional demand that affects fallers and non-fallers differently. In contrast, the cognitive task resulted in the highest mean value for the traditional sway measures for all four test conditions, indicating poorer performance, but the differences between fallers and non-fallers was much smaller. It is possible that the cognitive task did not demonstrate as strong of a difference between the groups because the task required an increased attentional demand that was equally challenging for all individuals, regardless of fall status. This may suggest that a greater balance impairment is not necessarily an ideal attempt at differentiating between fallers and non-fallers. This suggests that finding a dual-task that provides the appropriate amount of attentional deficit to each subject group is pertinent. Similar findings have been observed in posturography studies that manipulated sensory conditions. These studies have found an eyes closed, foam pad testing condition was so challenging for all subjects that that condition did not differentiate well between fallers and non-fallers, though easier testing conditions did. In this study, we found a similar trend that many of the individuals participating in the study, both fallers and non-fallers, reported difficulty and a lack of confidence counting
backward. In fact, the two individuals who chose not to complete the study did so because they were not comfortable performing the counting task.

It was outside the scope of the current study to determine the underlying reason for the differences observed between fallers and non-fallers. However, research in the attentional demands field has sought to address why these differences between fallers and non-fallers might be observed under dual-task conditions. Much of this research has focused on the potential role of differences in executive function. It has been hypothesized that fallers may exhibit deficits in executive function that may be identifiable through cognitive or executive function assessments (e.g. Mini Mental Status Exam or trail making test), and that these deficits may contribute to a poorer ability to appropriately allocate attention. Future studies in this area may therefore want to characterize an individual’s cognitive and/or executive function abilities to provide additional insight.

In contrast to the traditional postural sway findings, this study found that there were fewer and less consistent significant differences between fallers and non-fallers when considering nonlinear analysis findings. Nonlinear measures seek to describe how postural control is regulated and controlled over time. Significant differences between fallers and non-fallers were found for M/L alpha and M/L SampEn in only the cognitive and cognitive+manual conditions. Fallers demonstrated a higher M/L $\alpha$-scaling exponent, indicative of a more persistent sway pattern for the cognitive and cognitive+manual conditions; whereas, the non-faller group showed more of an anti-persistent pattern. This means that fallers seemed to experience a consistent drift away from equilibrium without recovery back, but non-fallers exhibited a more oscillatory, corrective pattern. Fallers
also demonstrated lower M/L SampEn values during the cognitive and cognitive+manual
tasks than non-fallers. Lower SampEn values indicate a greater degree of regularity and
predictability, with a SampEn value of 0.0 indicative of periodic motion. The findings of
this study suggest that fallers appear to be more rigid than non-fallers in the cognitive
condition, and as such would likely be less able to adapt within their environment during
the cognitive tasks.

It may seem that the findings of this study are contradictory, with traditional
measures demonstrating potentially more influence on the manual tasks and non-linear
measures demonstrating more influence on the cognitive tasks. However, we feel that
these findings reflect inherent differences in the measures and how they might be affected
by task. In the case of the manual task, we propose that it makes sense that a manual task
is highly related to the overall mechanics of an individual’s sway. For example, the tactile
feedback provided by holding the tray may ground the individual, as previous research
has demonstrated that even light touch has been shown to improve quiet-standing sway.66
Because of this, it makes sense that the manual task may affect the amount of sway more
so than the underlying structure of the sway. This would be observed best in the
traditional measures, as found in this study. A cognitive task like counting backward by
3’s, however, likely requires additional and/or different resources than a manual task.
Non-linear analyses seek to quantify the underlying structure of human movement and
how it changes over time. As this evolution of movement is controlled by a coordinated
effort of multiple regions of the brain, the impact of the cognitive demands from the
counting task may be more likely to interfere. Assuming so, it makes sense that
differences caused by the cognitive task might be best observed in the non-linear
analyses. Past work in principal component analysis of COP data indicate that traditional and non-linear measures characterize different aspects of the COP, further supporting this point. As there has been limited work done using non-linear analyses under dual-tasking conditions, the findings of this study are both important and insightful and continue to support the use of considering traditional and non-linear measures jointly.

Our findings for both the linear and non-linear measures demonstrated that manual tasks and cognitive tasks seem to influence performance differently. This is interesting and may motivate additional work in the attentional demands research field. The attentional demands literature has focused in recent years on trying to identify which of several attentional demands models might best explain the information processing that occurs when individuals are asked to dual task and divide their attention. Findings that a cognitive dual task affects performance differently than a motor dual task seems to support the proposed “multiple resource model”. This theory supposes that dual tasks only affect the primary task if they are competing for the same resources. While we want to be conservative in the interpretation of all of our findings due to the relative sizes and similarity of our moderate effect sizes, we do believe that future work in the area of dual tasking during posturography testing could continue to explore and contribute to this area.

When comparing the two groups, differences between the faller and non-faller group in age, gender, and height may initially be seen as a limitation to this study; however, these differences further reinforce that the groups were representative sampling of the older adult population. Of the study participants, 39% reported sustaining a fall in the twelve months prior to testing, which aligns with Center for Disease Control and
Prevention reporting 33% of older adults incurring a fall each year.\textsuperscript{3} Also consistent with published literature, the faller group was generally older and had a higher percentage of women than men.\textsuperscript{2,68} Not only does a decline in functional ability and greater risk of falls occur as age increases, but a loss in height is also reported.\textsuperscript{69,70} The differences seen between groups help illustrate the realistic characteristics of the two populations.

One of the limitations of this study was the unexpected challenge of the counting instructions provided during the cognitive task. Although each participant was asked to count backward by 3’s, some individuals did not feel comfortable doing this and instead counted backward by 2’s. While consistency is generally desired, in this case the difference in counting actually served as an equalizer – those who counted by 2 did so because the challenge was maximal for them at that level, while the remaining were able to count by 3’s comfortably. Another potentially confounding aspect of this study was the choice of a manual task that involved balancing a tennis ball on a serving tray. Initially, it was expected that this task would lead to greater sway but the opposite was true. In retrospect, participants likely demonstrated less sway because they were restricting movement in their effort to balance the ball and had additional visual feedback from the ball moving on the tray. Despite the manual condition leading to a decrease in overall sway for both fallers and non-fallers it was still more effective than other conditions in demonstrating differences between groups.

Although this study identified postural sway parameters and dual-task conditions that provide promise in identifying differences between fallers and non-fallers, it was not the intention of the study to identify a single dual-task condition that should be used exclusively in future testing. Because this is the first study to examine some of these
dual-task conditions, we sought to demonstrate whether there was potential usefulness in their inclusion and demonstrate how they compared to more commonly used testing conditions. The results of this study indicate when using traditional sway measures for assessing balance under a variety of single and dual-task conditions, M/L sway and the 95% confidence ellipse area demonstrate greater and more consistent differences in performance between fallers and non-fallers than other sway measures. Furthermore, dual-tasking conditions involving a manual task may accentuate those differences. When using non-linear analysis methods, the findings of this study indicate that only M/L alpha and M/L SampEn during cognitive dual-task conditions identify differences between fallers and non-fallers. The findings of this study may be helpful in designing future prospective trials for determining fall risk.
CHAPTER III

PERFORMANCE ON THE INSTRUMENTED TIMED UP AND GO (iTUG) IS INFLUENCED BY DIFFERENT DUAL-TASK CONDITIONS AND FALLER STATUS

Abstract

The Timed Up and Go (TUG) test is a clinical assessment frequently used for identifying older adults at higher risk of falling. The TUG test has recently included dual-tasking, providing a second task (counting, carrying a tray, combination of counting and carrying a tray) to the primary task of the TUG test, in hopes of dividing the attention of the individual. Additionally, researchers have had study participants wear sensors while performing the TUG to create the instrumented Timed Up and Go (iTUG) test, allowing researchers to examine subcomponent movements within the TUG test such as the sit-to-stand and turning movements. The primary objective of this study was to determine whether significant differences in performance were observed for four different TUG test conditions (traditional, cognitive dual-task, manual dual-task, and combined cognitive and manual dual-task). A secondary objective was to identify which of the iTUG subcomponents seemed most promising in differentiating between fallers and non-fallers. 150 older adults, age 60 and above, were recruited from a local retirement community.
and various interest groups. Four inertial measurement units were placed on the individual’s shoes, chest, and lower back. Individuals performed the iTUG test under four conditions: standard, cognitive, manual, and cognitive+manual. Data analysis was performed through APDM’s Mobility Lab software followed by statistical analysis of a one-way multivariate analysis of variance (p<0.05). Results indicate there was no significant effect for the Group*Task interaction. Performance on the iTUG during the cognitive+manual task was significantly poorer than the traditional task on the majority of the iTUG outcomes. It was also significantly worse than the individual cognitive and manual tasks for several outcomes. For the main effect of Group, considering all of the testing conditions pooled together, the outcomes related to the sit-to-stand transition were significantly different between fallers and non-fallers, suggesting this might be an area to concentrate attention on in the future. Results suggest that the cognitive+manual dual-tasks presents a greater difficulty to older adults. Differences seen between fallers and non-fallers suggest that the sit-to-stand movement is the movement involved in the iTUG test that best identifies an individual who had fallen in the past year, with significantly longer durations and greater lean angles. Results show that the incorporation of the cognitive+manual dual-task provides insightful information not redundant of the standard task condition, and therefore may be useful especially for high-performing individuals who may need more of a challenge before deficits are noticeable. Because the sit-to-stand transition appears to provide important insight that would not otherwise be detected through the traditional TUG, this supports the usefulness of the iTUG with future efforts focusing on this transition.
Introduction

The Timed Up and Go (TUG) is a frequently used clinical assessment of balance and mobility. The TUG is a short evaluation where an individual is instructed to rise from a seated position in a chair to a standing position, walk a 3 meter path, turn around, return to the chair and sit back in the chair, while the clinician uses a stop watch to time the duration of the total task. The TUG assessment represents activities commonly done in everyday living, and has not only been shown to be a practical, reliable performance test of physical mobility but it also has been commonly used to identify individuals at risk of falling. Community-dwelling individuals who take longer than 20 seconds to perform the TUG have been found to be at a higher risk of falling and may benefit from further evaluation and intervention to prevent future falls.

While the TUG has demonstrated potential in identifying individuals at risk of falls, there are limitations. For example, in elderly adults the assessment has been observed to have a floor effect that leads to poor reliability for lower-performing individuals. Sensitivity to falls in the older community-dwelling population has also been found to be poor, with a small effect observed for changes based on recent falls. Although the TUG has been successful in differentiating between individuals with obvious mobility deficits (e.g. healthy individuals from individuals with moderate to severe Parkinson’s disease), it has not always or consistently been able to identify individuals with more subtle and less pronounced differences (e.g. healthy individuals and individuals with early-stage Parkinson’s). The inability to identify subtle differences is one limitation of the TUG and drives the need for a more discriminative assessment.
One potential approach to increasing the discriminatory nature of the TUG is to utilize a dual-task activity. In this protocol, the individual is asked to perform the primary task, in this case the TUG, while also simultaneously performing a secondary task that is meant to cause an interference to divide their attention. Various secondary tasks that have shown promise in providing differences between faller and non-faller groups include counting, carrying a tray with a glass of water, or reciting from memory. The inclusion of a dual-task condition is beneficial on two levels. First, studying individuals under these distracted conditions is more representative of real-world performance during which multitasking is common. Secondly, research has shown that the inability to perform well under a dual-task condition is an important indicator of balance impairments and history of falls in older adults. Shumway-Cook et al. demonstrated that older adults with balance impairment perform similarly to healthy controls on the standard TUG but perform significantly worse during a cognitive and manual dual-task condition. This decrease in performance during the dual-task TUG can more easily differentiate individuals at risk of falls from those that are not at risk of falls.

While it has been found that the incorporation of a dual-tasking paradigm is useful, it is unclear what kind of dual-task might be most appropriate. The most common and consistently used dual-task paradigm is a cognitive task that requires individuals perform the primary assessment while doing subtraction, generally by 7’s or 3’s. Other cognitive tasks studied included naming animals, external information acquisition, and auditory-verbal and visual-verbal memory responses. Manual dual-tasks that require some level of motor control and object manipulation have also been used. For example, Lundin-Olsson et al. had people carry a tray holding a tumbler of water while
performing the TUG\textsuperscript{52}. The selection of these tasks must require careful consideration as they need to be realistic for the testing conditions, sufficiently challenging but achievable for a majority of the older adult population, isolated to the type of desirable interference (for example, a manual task that does not also include a cognitive load), and appropriate to be safely performed concurrently with the primary task.

Due to the nature of real-world multitasking activities that individuals perform daily while ambulating (e.g. ambulating while carrying objects and holding a conversation), utilizing an interfering task that requires both cognitive and manual performance simultaneously may be most representative of real-world multitasking. To date there appear to be no studies that have utilized a task that requires a combined cognitive and manual effort for a dual-tasking paradigm. While such a task would not be appropriate for all dual-task applications, such as when there is desire to isolate cognitive contributions to the overall performance, for real-world applicability a combined cognitive and manual task may be very beneficial. It is unclear, though, whether performance under the different types of dual-tasks would be different enough so as to provide new insight into fall differentiation, warranting the inclusion of a combined dual-task TUG assessment.

Concurrent with the use of dual-tasking paradigms during TUG assessments has been the addition of wearable sensors to provide additional insight into the various subcomponents of TUG performance. The instrumented Timed Up and Go (iTUG) test involves the individual performing the TUG, single or dual-task, while outfitted with wearable sensors\textsuperscript{23}. The iTUG assessment provides extensive information over total time duration, the sole outcome parameter of the TUG\textsuperscript{52}. The wearable sensors collect
information about the acceleration, velocity, orientation, and movements of the individual, providing additional data about the traditional TUG assessment and its individual components (sitting to standing, walking, and turning). To this end, various body worn sensor companies have developed clinical software and hardware options to monitor the transitional movements, such as identifying the onset and offset of turning, using accelerometry during the TUG. These systems can provide instant analysis of transitional movement and compare the individual’s results with normative values to better identify deficits. With the additional information about each task involved in the iTUG, clinicians can use this knowledge to better identify characteristics of an individual’s complex transitional movements. Information concerning individual transitions can help identify which real life movements individuals at risk of falls are struggling with in their day-to-day lives. If a specific transition is identified to be indicative of fall risk, clinicians can focus their testing and interventions on this specific movement.

To date, the iTUG is still relatively new and under-utilized. We believe that the iTUG test used in conjunction with a dual-tasking paradigm could provide new and important insight compared to the sole output of total time obtained under traditional (single-task) conditions. Coulthard et al. has shown that dual-task demands during the iTUG test provide discriminatory variables for a group of young and older adult participants and is an easily implemented protocol for the clinical setting, yet to the authors’ knowledge has not yet been examined in older adults. Due to dual-tasking being known to be discriminate fall risk in older adults during other applications (ie posturography and gait), the addition of dual-task to the iTUG protocol may be a valuable
addition in order to further improve iTUG’s ability to discriminate between fall risk populations.\textsuperscript{19,30,50} Incorporating the iTUG with the combined dual-task further improves the iTUG to be more similar to real-life situations of performing cognitive and manual tasks at the same time.

The first objective of this study was to determine how the type of testing condition (traditional single task, cognitive dual-task, manual dual-task, or a combined cognitive and manual dual-task) affected performance on the subcomponents of the iTUG. A secondary objective was to determine which of the iTUG subcomponent outputs differed between fallers and non-fallers. We hypothesized that the combined cognitive and manual dual-task would result in performance that was statistically significantly different than all of the other task conditions. We also hypothesize that due to muscular weakness being a significant risk factor for falls,\textsuperscript{83} the sit-to-stand iTUG subcomponents will differentiate fallers and non-fallers (p<0.05).

Methods

150 participants, age 60 and above, were recruited from local retirement communities, senior centers, and community exercise groups. In order to include individuals with a wide range of health and activity levels representative of the typical older population, exclusion criteria were kept to a minimum. Exclusion criteria included the use of a lower limb brace such as a prosthetic limb or ankle foot orthotic, the inability to stand unassisted for 5 minutes, and the inability to walk 50 feet without assistance or pain. Any participant that self-reported one or more falls incurred over the past 12 months was classified as a faller. A fall was defined to the participants as “any time you
come to rest on a lower surface unintentionally” 84. This study was approved by the University of Dayton Institutional Review Board and all participants gave written, informed consent.

Four inertial measurement units (Opal, APDM Inc, http://apdm.com) consisting of tri-axial accelerometers, tri-axial gyroscopes, and tri-axial magnetometers were used to conduct the iTUG protocol, which was part of a larger study protocol. The APDM Mobility Lab software that accompanied the sensors was used to carry out the iTUG protocol. This software protocol dictated the orientation and placement of the four sensors, directions given to each participant before testing, and distance for the walking portion of the iTUG. A sensor was placed at each of the four locations: left foot, right foot, lower back (waist strap) and chest and were secured using adjustable straps as shown in Figure 3.1. Data were collected and analyzed using developed algorithms through APDM’s Mobility Lab software.

Figure 3.1. Placement of APDM OPAL sensors for iTUG test
Before testing began, the researcher instructed participants to sit in the chair with their arms to their side (so not to use their arms for assistance in standing). When the researcher said “walk”, the participant was instructed to stand from the chair, walk straight for 3 meters (marked by a line on the floor), turn around just past the line, walk back to the chair and turn to sit down in the chair. The participants were not told which direction to turn for either turning movement and were asked to sit still once seated until told the test was complete by the researcher.

This iTUG protocol was used for four testing conditions: traditional (single-task), cognitive dual-task, manual dual-task, and cognitive+manual dual task. For all trials other than the traditional, the participants were asked to successfully complete the iTUG while also completing a secondary task. The cognitive task instructed the individuals to complete the iTUG while also counting backwards from 200 by 2 or 3, depending on the subject’s comfort level. The starting number of 200 was chosen in order allow participants to count the entire sixty seconds, without counting below zero. To complete the manual task, the participants were instructed to hold a clear plastic tray with their elbows at a 90-degree angle in front of their body while trying to keep a 2.5” tennis ball at any particular location on the tray. They were instructed to look ahead while walking and turning rather than looking down at the tray. The combined cognitive+manual task required the individuals to perform the iTUG while completing both of the dual-tasks, counting backward from 200 by 2 or 3 and holding the tray with the ball in front of their body. Instructions were given by the researcher before initiation of testing and also when switching from one task to another as a reminder. A gait belt was placed on the
participants before testing began and participants were spotted by a researcher during the entire testing protocol.

The four task conditions were presented in a random order for each participant and three trials were conducted for each task. If the Mobility Lab software did not recognize the movement and therefore did not validate a trial, the subject was asked to repeat the trial. A break was provided in between each task to explain the next task. Data were collected from all four sensors simultaneously via a wireless access point with Mobility Lab software at 128 Hz. Results reported from the Mobility Lab protocol for the iTUG test are broken into four separate categories: total duration, sit-to-stand, turn, and stand-to-sit. Specific parameters within those categories include: total duration, sit-to-stand duration, sit-to-stand lean angle, stand-to-sit duration, stand-to-sit lean angle, turn angle, turn duration, and turn peak velocity. IBM SPSS statistical software (Armonk, NY, USA) was used to perform a one-way multivariate analysis of variance (p≤0.05) to determine the effect of the type of task (Traditional, Manual, Cognitive, Cognitive+Manual) and faller group (Faller and Non-faller) on the iTUG outcome measures. Post-hoc analysis was performed on the main effect of task and faller group.

Results

148 participants participated in the study. Subject characteristics are seen below in Table 3.1 for the pooled populations as well as by fallers (n=59) and non-fallers (n=88). Significant differences were found between the faller and non-faller groups for age, height and gender. The faller group had a mean fall incidence of 2.27 ± 3.17 (range=1-24) over the previous 12 months.
<table>
<thead>
<tr>
<th></th>
<th>Sample Size</th>
<th>Age</th>
<th>Weight (N)</th>
<th>Height (cm)</th>
<th>M/F</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Non-faller Group</strong></td>
<td>89</td>
<td>74.24 (9.00)</td>
<td>764.65 (148.31)</td>
<td>170.11 (10.83)</td>
<td>47 M/ 42 F</td>
</tr>
<tr>
<td><strong>Faller Group</strong></td>
<td>59</td>
<td>77.17 (8.17)</td>
<td>743.39 (166.76)</td>
<td>164.41 (8.21)</td>
<td>15 M/ 44 F</td>
</tr>
<tr>
<td><strong>Total Group</strong></td>
<td>148</td>
<td>75.12 (8.77)</td>
<td>756.18 (155.72)</td>
<td>167.67 (10.21)</td>
<td>62 M/ 86 F</td>
</tr>
</tbody>
</table>

Results for the interaction of Group*Task showed no statistically significant interactions between factors for any of the ten iTUG transitional movements. Because there were no significant interactions for Group*Task, Group and Task could then be analyzed separately. The main effect of Task (Traditional, Cognitive, Manual, Cognitive+Manual) was statistically significant (p<0.05) for six of the eight outcome parameters, as seen in Table 3.2. Post-hoc analysis was performed on the main effect of Task to determine which task comparisons showed statistical significance. This is denoted in superscript in Table 3.2.
### Table 3.2. iTUG Outcome Measures Mean (SD) By Task for All Older Adults

<table>
<thead>
<tr>
<th>ITUG TRANSITION</th>
<th>TRADITIONAL</th>
<th>COGNITIVE</th>
<th>COGNITIVE+MANUAL</th>
<th>MANUAL</th>
<th>P-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTAL DURATION (SEC)</td>
<td>13.15 (2.93)</td>
<td>14.85 (4.01)</td>
<td>16.36 (5.49)</td>
<td>14.13 (3.19)</td>
<td>*0.000&lt;sup&gt;bdf&lt;/sup&gt;</td>
</tr>
<tr>
<td>SIT-TO-STAND</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>1.17 (0.17)</td>
<td>1.23 (0.21)</td>
<td>1.26 (0.20)</td>
<td>1.24 (0.25)</td>
<td>*0.013&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>LEAN ANGLE (DEG)</td>
<td>25.99 (8.44)</td>
<td>25.84 (7.67)</td>
<td>22.96 (6.87)</td>
<td>22.32 (7.60)</td>
<td>*0.001&lt;sup&gt;b&lt;/sup&gt;&lt;sup&gt;bcdef&lt;/sup&gt;</td>
</tr>
<tr>
<td>STAND-TO-SIT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>1.12 (0.23)</td>
<td>1.13 (0.22)</td>
<td>1.15 (0.23)</td>
<td>1.15 (0.20)</td>
<td>0.780</td>
</tr>
<tr>
<td>LEAN ANGLE (DEG)</td>
<td>24.32 (8.90)</td>
<td>25.39 (9.56)</td>
<td>21.59 (8.28)</td>
<td>20.77 (8.19)</td>
<td>*0.000&lt;sup&gt;b&lt;/sup&gt;&lt;sup&gt;bcde&lt;/sup&gt;</td>
</tr>
<tr>
<td>TURN</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANGLE (DEG)</td>
<td>179.05 (5.10)</td>
<td>178.87 (7.12)</td>
<td>177.33 (8.45)</td>
<td>178.49 (4.85)</td>
<td>0.271</td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>2.32 (0.38)</td>
<td>2.36 (0.38)</td>
<td>2.65 (0.39)</td>
<td>2.57 (0.36)</td>
<td>*0.000&lt;sup&gt;b&lt;/sup&gt;&lt;sup&gt;bcde&lt;/sup&gt;</td>
</tr>
<tr>
<td>PEAK VELOCITY (DEG/SEC)</td>
<td>173.32 (35.56)</td>
<td>165.59 (33.36)</td>
<td>141.79 (29.25)</td>
<td>148.76 (25.18)</td>
<td>*0.000&lt;sup&gt;b&lt;/sup&gt;&lt;sup&gt;bcde&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

*<sup>p</sup><0.05, main effect significant difference between tasks
<sup>a</sup> Statistical significance (<sup>p</sup><0.05) seen between Traditional and Cognitive
<sup>b</sup> Statistical significance (<sup>p</sup><0.05) seen between Traditional and Cognitive+Manual
<sup>c</sup> Statistical significance (<sup>p</sup><0.05) seen between Traditional and Manual
<sup>d</sup> Statistical significance (<sup>p</sup><0.05) seen between Cognitive and Cognitive+Manual
<sup>e</sup> Statistical significance (<sup>p</sup><0.05) seen between Cognitive and Manual
<sup>f</sup> Statistical significance (<sup>p</sup><0.05) seen between Cognitive+Manual and Manual

The main effect of Group, considering all of the testing conditions pooled together, (faller or non-faller) was statistically significant (<sup>p</sup><0.05) for three of the eight transition outcome parameters, as seen in Table 3.3 below. For all significant parameters, the faller group demonstrated longer total time duration, sit-to-stand duration, and greater sit-to-stand lean angle.
**Table 3.3. iTUG Outcome Measures Mean (SD) By Fall Status, For All Task Conditions**

<table>
<thead>
<tr>
<th>ITUG TRANSITION</th>
<th>FALLER</th>
<th>NON-FALLER</th>
<th>P-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTAL DURATION (SEC)</td>
<td>15.23 (5.05)</td>
<td>14.21 (3.49)</td>
<td>*0.006</td>
</tr>
<tr>
<td><strong>SIT-TO-STAND</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>1.27 (0.25)</td>
<td>1.20 (0.18)</td>
<td>*0.000</td>
</tr>
<tr>
<td>LEAN ANGLE (DEG)</td>
<td>25.48 (8.79)</td>
<td>23.70 (7.19)</td>
<td>*0.017</td>
</tr>
<tr>
<td><strong>STAND-TO-SIT</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>1.15 (0.24)</td>
<td>1.13 (0.20)</td>
<td>0.242</td>
</tr>
<tr>
<td>LEAN ANGLE (DEG)</td>
<td>24.08 (9.64)</td>
<td>22.52 (8.49)</td>
<td>0.057</td>
</tr>
<tr>
<td><strong>TURN</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANGLE (DEG)</td>
<td>178.04 (7.54)</td>
<td>178.71 (5.85)</td>
<td>0.295</td>
</tr>
<tr>
<td>DURATION (SEC)</td>
<td>2.50 (0.42)</td>
<td>2.45 (0.39)</td>
<td>0.210</td>
</tr>
<tr>
<td>PEAK VELOCITY (DEG/SEC)</td>
<td>156.81 (34.63)</td>
<td>158.59 (33.07)</td>
<td>0.478</td>
</tr>
</tbody>
</table>

*p<0.05, main effect significant difference between groups

**Discussion**

One of the two main objectives of this study was to evaluate the effect of dual-tasks on iTUG performance, specifically examining how different outcome parameters are affected. A secondary objective was to identify which of the iTUG subcomponents seemed most promising in differentiating between fallers and non-fallers. This study is the first to provide an in-depth analysis of the effect of dual-tasks while performing the iTUG assessment in older adults. Multiple types of dual-task conditions and outcome parameters exist. Identifying which testing conditions results in significantly different performance than others is important because it provides insight into understanding an individual’s abilities under more realistic everyday challenges, in minimizing testing conditions to include only the most discriminative tasks, and therefore reducing time required for clinicians to administer the test. It may also improve testing procedures for future studies and clinical evaluations with a high performing older adult population who only exhibit subtle deficits when maximally challenged.
Dual-tasks were used in this study to place an attentional demand on the subjects. This demand distracts the subject, and generally negatively affects performance. Dual-tasks also represent common multitasking events humans experience in everyday life. It is necessary to ascertain which dual-tasks provide enough challenge in order to highlight subtle differences in performance throughout the TUG test. The traditional and cognitive tests indicated individuals performed better than they did during the cognitive+manual dual-task for five of the six iTUG movements that showed statistically significant differences between testing conditions. Individuals performing the traditional task assessment demonstrated significantly better performance than when performing the manual task condition in four of the six outcome measures. Results showed that individuals performed significantly worse, demonstrated through longer time and greater lean angle, when performing the cognitive+manual condition compared to the majority of other test conditions. In particular, total time duration – the only outcome measure reported from the traditional TUG – showed significantly longer duration values for the cognitive and cognitive+manual task conditions as compared to the traditional task. Furthermore, the cognitive+manual task resulted in significantly longer performance in total time duration (worse performance) compared to the cognitive or manual tasks. Additionally, total time duration and sit-to-stand lean angle show significantly larger values in the cognitive+manual dual-task over the manual dual-task. This suggests that the combination of two dual-tasks can be beneficial in providing a greater difficulty to the task than the manual task, cognitive task alone or the traditional task. These results imply that utilizing the cognitive+manual dual-task for older adults performing the iTUG may provide a greater challenge to older adults, under the most realistic conditions.
The above results suggest that the cognitive+manual task may affect iTUG performance the most. It is possible that adding the cognitive+manual task not only provides a real-life task to the iTUG, but may also provide a means in which an appropriate amount of attention is diverted from the primary task at hand. Introducing an attentional demand, such as the cognitive+manual dual-task, requires individuals to rely on their innate executive function to complete daily independent activities. Executive function was not measured in this case, but generally executive function declines with age and even more so in balance impairment populations, such as older adults at risk of falls. With limited research on the use of a dual-task protocol during the iTUG test, there are few comparisons to be made with regard to the iTUG results among older adults. Although the cognitive+manual dual-task is not commonly performed, the current results suggest that it should be implemented for examination in future research and would be non-redundant to other TUG assessments. The cognitive+manual dual-task could be used either in isolation or in conjunction with other clinical evaluations to provide a sufficient difficulty level for the task at hand. This may lead to participants relying more heavily on inherent ability during the assessment.

The second main objective of this study was more exploratory and it was to identify the outcome parameters within the iTUG that best demonstrates differences between the faller and non-faller population. While the primary objective of this work was to explore the effect of testing condition, since work of this kind had not previously been conducted, it is also beneficial to consider which iTUG outcome measures may be most appropriate for differentiating between fallers and non-fallers. While this work looked specifically at the effect of fall status as pooled over all the testing conditions,
these findings provide guidance for future work. Study results indicate that time alone, the normal TUG outcome parameter, did show significant differences between fallers and non-fallers, as other studies have also reported. However, by using the iTUG to analyze the sub-components of the test, it became clear that the sit-to-stand movement may be insightful for identifying differences between fallers and non-fallers. The sit-to-stand movement was the only portion of the iTUG where both measurements displayed statistically significant differences between fallers and non-fallers. Other commonly used clinical assessments attempt to identify balance disorders through the sit-to-stand movement. The Five-Times-Sit-To-Stand Test (FTSST) and the BESTest evaluate the sit-to-stand movement, yet their sole outcome measure is time, rather than specific parameters of the transitions within the sit-to-stand movement itself. Although these clinical tests can be quick and insightful, instrumenting the iTUG to include movements, such as the sit-to-stand, gives more information about the movements involved than simply the duration it takes to complete the task. In particular, the sit-to-stand outcome parameters showed significant differences between fallers and non-fallers. The larger sit-to-stand durations for the faller group compared to the non-faller group suggests the faller group may have had more trouble, and possibly less mobility or strength, to complete the sit-to-stand movement. Although research has shown that force exertion during the sit-to-stand movement is related to fall risk in the elderly, Schlicht et al. suggested that strength training alone does not enhance sit-to-stand performance in older adults. The current study shows the sit-to-stand trunk lean angle as one measurement that demonstrates differences between fallers and non-fallers. Trunk lean angle plays an important role in the sit-to-stand movement in order to maintain equilibrium. Results
shown here also suggest that an increase in sit-to-stand lean angle relates to an increase in fall risk. The sit-to-stand movement is one that may require attention during rehabilitation or training methods in order to improve functionality of the sit-to-stand movement in fall-risk populations. Utilizing the iTUG to provide a more extensive look at the mechanisms involved in the sit-to-stand movement can help identify movements where an individual has more difficulty. With this specific transition information, clinicians may be able to direct therapy interventions to the explicit sit-to-stand deficit (such as the lean angle).

With the identification of the cognitive+manual dual task as a beneficial addition to the iTUG protocol, comes a need to further refine the tasks chosen. This study suggests that the tasks chosen were successful in providing an appropriate difficulty level to older adults. Although the cognitive task – counting backward by 3’s – has commonly been used as an attentional demand, there is little existing literature for comparing manual dual-task conditions. Further research should include the manual task chosen here – carrying a clear tray with a ball - to compare it to other manual dual-tasks in existing literature. Continued research with this manual task can help identify additional benefits of its inclusion in other iTUG protocols. The secondary goal of identifying which subcomponents of the iTUG appear to capture differences in performance between fallers and non-fallers provides insight for the future. Future work will be necessary to extend these findings to the individual dual-tasking scenarios to determine whether differences are observed.

One of the limitations of this study was the unexpected challenge of the cognitive counting task. Each participant was asked to count backward by 3’s, yet some individuals did not feel comfortable or were unable to count backward by 3’s. In this case, the
participants were allowed to count backward by 2’s. Although consistency within the cognitive task was desired, allowing individuals to count backward by 2’s provided similar difficulty levels to all individuals. Additionally, although a clear plastic tray was chosen for the manual task in order to minimize the obstruction of view during the iTUG, this tray and ball may have slightly obstructed the visual field during the iTUG task. Although participants were instructed to look straight ahead during the task, it was observed that many participants tended to glance down towards the tray and ball during the trial.

The results of this study suggest that these four task conditions (traditional, cognitive, manual, and cognitive+manual) may require different levels of attentional demand. The findings suggest that the cognitive+manual dual task provided the most challenge in most aspects of the iTUG task and additionally may help provide insight into the sub-components of the iTUG and the potential relationship to fall risk. Additionally, the sit-to-stand movement was found as the sub-component of the iTUG that appeared most promising in identifying differences between fallers and non-fallers. The utilization of wearable sensors gives researchers an understanding of the transitional movements that otherwise cannot be obtained from a traditional TUG assessment.
CHAPTER IV
IDENTIFICATION OF KEY OUTCOME MEASURES WHEN USING POSTUROGRAPHY AND/OR THE INSTRUMENTED TIMED UP AND GO FOR FALL SCREENING

Abstract

The Timed Up and Go (TUG) test has been used as a fall risk assessment, yet there is room for improvement. The instrumented Timed Up and Go (iTUG) test builds upon the traditional TUG test by adding wearable sensors to capture movements within the TUG assessment. The iTUG and posturography tests have been used as fall risk differentiation tools, yet varying parameters are reported, depending on the nature of the study. This study builds off previous work and uses stepwise logistic regression models to determine the effectiveness of the TUG, iTUG and posturography in differentiating fallers from non-fallers based on identified key outcome measures. One hundred and fifty participants completed the iTUG and posturography protocols. The iTUG movement measures were calculated utilizing the Mobility Lab software. Traditional and non-linear measures were calculated from the posturography center of pressure data. Logistic regression was performed to determine the model for each assessment that best discriminated between fallers and non-fallers. The key outcome measures incorporated in the iTUG assessment model resulted in a model sensitivity of 51.1% and max re-scaled
R\(^2\) value of 0.2580. This was a higher sensitivity, indicating better differentiating, compared to when only the total time duration (traditional TUG) model was considered, which had a sensitivity of 18.2% and max re-scaled R\(^2\) value of 0.0497. When the key outcome measures of the iTUG and the posturography assessments were combined into a single model, the sensitivity was about the same as the iTUG model but the measures included were different: height, stand-to-sit duration, sit-to-stand displacement, and anterior/posterior sway range. This work supports that the iTUG demonstrates more sensitivity than the TUG and that considering multiple outcome measures together can provide additional insight when differentiating between fallers and non-fallers.

**Introduction**

Identifying older adults at risk of falls is extremely important. One in three older adults over the age of 65 fall each year.\(^9\) Factors that contribute to a fall include: reduced static and dynamic balance, poor mobility, gait disorders, acute or chronic illness, polypharmacy, and external or environmental factors.\(^2,5,7,47\) Due to the multifaceted nature of fall risk, several different assessments are often used when trying to evaluate differences between fallers and non-fallers.\(^7\) Because of the multiple factors that contribute to falls, it is difficult to identify an assessment that alone can be used as a sensitive screening tool for fall-risk in older adults. A more sensitive screening tool for fall risk may help identify fall risk earlier and prevent future falls. There are many pitfalls associated with these current assessment tools, however, including: time consuming data analysis, subjective qualitative measures, and lack of discrimination.\(^7\) Identifying a fall risk assessment that overcomes these pitfalls and can identify deficits earlier could lead to more effective fall
prevention interventions, training programs, and individualized therapies. Identifying fall risk can help reduce falls in the future.\textsuperscript{7,91}

One of the quantitative assessments that has been shown to discriminate between healthy and impaired populations is the Timed Up and Go (TUG) test.\textsuperscript{11,17} The TUG test is a commonly used assessment of mobility that involves transitions that examines how balance and gait maneuvers contribute to functional mobility.\textsuperscript{22} The TUG test requires the individual to start seated in a chair, wait for the cue to stand, stand from the chair (preferably without use of arms of the chair), walk a path, turn around and walk back to the chair, turn around and sit down to a fully seated position in the chair.\textsuperscript{20} The sole outcome measure of the TUG test, the total completion time, has been shown to be able to differentiate fallers from non-fallers.\textsuperscript{6,21,71} One potential weakness with the TUG test, however, is the fact that its single outcome measure may not be able to detect subtle changes between fallers and non-fallers. Even a subtle balance deficit could lead to a fall. Therefore, improving the differentiation in this screening tool could lead to better differentiation in clinical evaluations.

In an effort to improve the TUG as a fall risk assessment, researchers introduced the instrumented Timed Up and Go (iTUG) test which enhances the original TUG test by incorporating wearable inertial measurement units (IMU).\textsuperscript{23} Adding IMUs to the TUG test allows researchers to evaluate transitional movements including sit-to-stand, turns, and stand-to-sit along with their associated accelerations and velocities during these movements. With knowledge of the movements within the test, the iTUG allows researchers to identify specific deficits within the complex movements that may be indicative of fall-risk.\textsuperscript{81} Examining the potential value of the iTUG test over the TUG test
could help demonstrate whether these additional parameters add benefit to fall risk differentiation in older adults.

In order to provide the most accurate fall risk model, The Guideline for the Prevention of Falls in Older Persons recommends a fall risk screening tool that encompasses multiple facets of fall risk factors, such as balance, gait, and functional movements. The iTUG assessment allows researchers to gain information concerning transitional movements, but an individual’s balance is also an important aspect of fall risk. While balance is intertwined into the iTUG assessment, a more specific assessment may be needed. An individual with a balance deficit is up to 5.4 times more likely to fall than a healthy counterpart. Posturography testing is one method of measuring an individual’s balance while standing in the upright position. Posturography testing involves using a force-measuring platform to measure individuals’ center of pressure (COP), which is related to the center of gravity of the individual, as they are standing on the force plate. Traditional posturography has had success in identifying differences in postural control that are indicative of balance impairments between individuals who have fallen and those who have not fallen. Researchers have modified the traditional posturography test to provide increased differentiation or cater the protocol to a certain subset of the population, such as adding foam to the testing surface and eyes open/closed methodologies. Possibly by incorporating two different types of assessments, iTUG and static posturography, a fall screening tool could be improved by creating a better fall risk model.

Although these clinical tests have been identified independently as tools that can differentiate older adult fallers and non-fallers, there is no current holistic picture of what
fall-risk identification could look like in a short, easy to administer, clinical screening tool that incorporates static and dynamic physiological aspects. Work completed by Bigelow et al. established a fall screening protocol including only posturography measures. Bigelow et al. found that combining traditional sway parameters, fractal measures and subject characteristics provided the best fall risk screening model. This work builds off work by Bigelow et al. by incorporating posturography and iTUG in tandem so that it may be possible to find which assessments are most sensitive to fall-risk differences. Due to the variety of outcome parameters and protocol modifications, researchers tend to report varying outcome measures, depending on the focus of the study. One issue of combining the posturography test with the iTUG test is the wide number of outcome parameters can make it difficult to isolate the best parameters for differentiation between fallers and non-fallers. Other issues that arise when combining both assessments include longer testing time and increased data processing. In order to develop a feasible fall risk screening tool, this study seeks to develop a fall risk algorithm which can provide clinicians with a definitive set of outcome parameters yielding the best differentiation model. Identifying outcome parameters that best describe fall risk may also eliminate the number of outcome parameters needed. This algorithm can describe how much benefit is added to the model with the addition of wearable sensors to the iTUG protocol. The resulting fall risk screening models can also tell us if a combination of posturography and iTUG assessments improve the fall risk screening model. This will enable clinicians to facilitate only the most indicative assessments and reduce data processing time.
The first objective of this study was to determine the ability of the identified outcome measures of the iTUG test to differentiate fallers versus non-fallers over the TUG test with the sole outcome measure of total time duration. The second objective of this study was to determine which combination of iTUG and posturography outcome measures best differentiated fallers from non-fallers. To determine which combination of parameters best differentiated between the two populations, stepwise logistic regression models were compared using max-rescaled $R^2$ values, sensitivity, and specificity. The outcome of this study will help determine which protocol clinicians should utilize to increase the likelihood of predicting an older adult’s fall risk. We hypothesized that the iTUG would show greater differentiation over the TUG test with a higher sensitivity. We also hypothesized that a combination of iTUG and posturography parameters would generate the fall risk screening model with the best differentiation between fallers and non-fallers.

**Methods**

150 participants, ages 60 years and older, were recruited for this study. Individuals were recruited from local retirement communities, senior centers, various interest groups, community exercise classes, and through word of mouth from other participants. Individuals with balance or mobility deficits, those with a lower limb brace such as a prosthetic limb or ankle foot orthosis, those with the inability to stand unassisted for 5 minutes, or the inability to walk 50 feet without assistance or pain were excluded from the study. Exclusion criteria were kept to a minimum in order to have a sample size representing the typical older population with a wide range of health and activity levels. This study was approved by the University of Dayton Institutional Review
Board and all participants gave written, informed consent before data collection began. The protocol described here was part of a larger study protocol.

Information on age, height, weight, health history, and fall history was collected before testing began. In order to determine if participants were classified as a faller or non-faller, participants were asked if they had fallen in the past twelve months. A fall was defined as “any time you come to rest on the ground or a lower surface unintentionally”.

For the posturography testing protocol, study participants were asked to stand with their feet approximately shoulder width apart on a force plate (Model 5046, Bertec Corporation, Worthington, Ohio). For all trials, study participants were asked to stand still, look straight ahead, and not talk during the duration of the trial. Participants wore a gait belt and were spotted by a researcher during data collection. For traditional posturography parameters the force plate center of pressure (COP) data were collected at 1000 Hz, downsampled to 100 Hz and filtered utilizing a 4th order butterworth filter with a 5 Hz cutoff for a duration of 60 seconds per trial. The following traditional linear parameters were calculated: anterior/posterior (A/P) sway range, medial/lateral (M/L) sway range, ML velocity, mean velocity, 95% confidence ellipse area (95% CEA).

Further, the following non-linear analysis measures were calculated from downsampled data prior to filtering: M/L and A/P α-scaling exponent (detrended fluctuation analysis) and M/L and A/P sample entropy. Traditional outcome measures were chosen from the 80+ posturography outcome parameters due to their recognition as parameters that have showed differentiation between fallers and non-fallers in an older adult population.
Due to recent insight into variability analysis, non-linear analysis parameters were chosen and calculated according to published literature.\textsuperscript{44,59}

For the iTUG testing protocol, four inertial measurement units (Model: OPAL, APDM, Inc, Portland, Oregon) consisting of tri-axial accelerometers, tri-axial gyroscopes, and tri-axial magnetometers were used. Test directions for participants, sensor placement, and walking distance were conducted according to the APDM Mobility Lab User Guide. The sensors were placed on the participant’s chest, lower back, and each foot. Participants were instructed to sit in the chair with their arms at their sides and to refrain from using their arms for assistance when standing from the chair. When instructed, participants stood from the chair, walked forward three meters to a taped line on the floor, crossed the taped line and turned around, walked three meters back to the chair, turned to sit, then sat down in the chair, without using assistance from their arms if possible. The test was completed when the participant was fully seated. The participant was asked to complete the assessment at a comfortable, self-selected speed. The participant wore a gait belt while a researcher walked slightly behind them to act as a spotter if necessary. All data were collected for the four sensors simultaneously through the APDM Mobility Lab software via a wireless access point at 1280 Hz. The following outcome parameters for the iTUG test were reported from the APDM Mobility Lab software: Total time duration, sit-to-stand duration, sit-to-stand lean angle, stand-to-sit duration, stand-to-sit lean angle, turn angle, turn peak velocity, and turn duration.

A stepwise logistic regression was performed in SAS version 9.4 (SAS Institute Inc, Cary, North Carolina) for the following conditions: 1) TUG, 2) iTUG, 3) Posturography, and 4) iTUG and posturography (Combined). For each model, age,
gender, height, weight, and all of the respective outcome measures for that assessment were included as variables. Multi-collinearity was checked between all outcome measure pairs by utilizing the Pearson correlation coefficients. The significance chosen for variables to enter the model was $\alpha = 0.15$, significance chosen for variables to stay in the model was $\alpha = 0.20$, and all variables not meeting these significances were removed from the model. For each model, the level of fit was determined by the max-rescaled $R^2$ value. The sensitivity and specificity were calculated for each model with a cut value of 0.5.

Results

A group of 150 participants participated in the study, with 148 participants completing the consent form process, the iTUG testing protocol, and the posturography protocol. Subject characteristics are seen below in Table 4.1 for both groups, 59 fallers and 91 non-fallers. Significant differences were found between the faller and non-faller groups for age, gender, and height. The faller group experienced between 1 and 24 falls over the past 12 months, with a mean fall incidence of $2.27 +/- 3.17$ falls.

Table 4.1. Faller and Non-faller Group Subject Characteristics, Mean (SD)

<table>
<thead>
<tr>
<th></th>
<th>Sample Size</th>
<th>Average Age (St. Dev.)</th>
<th>Average Weight (N) (St. Dev.)</th>
<th>Average Height (cm) (St. Dev.)</th>
<th>Male/Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-faller Group</td>
<td>91</td>
<td>74.35 (9.00)</td>
<td>764.65 (148.31)</td>
<td>169.81 (10.91)</td>
<td>47 Male/44 Female</td>
</tr>
<tr>
<td>Faller Group</td>
<td>59</td>
<td>77.17 (8.17)</td>
<td>743.39 (166.76)</td>
<td>164.41 (8.21)</td>
<td>15 Male/44 Female</td>
</tr>
</tbody>
</table>

Table 4.2 summarizes the results of the fall risk model only containing the iTUG duration, the sole outcome parameter of the traditional TUG test compared to the iTUG
model including all the parameters chosen for the iTUG model. Through the inclusion
height and sit-to-stand lean angle in the iTUG model, the max re-scaled $R^2$ increased
from 0.0497 to 0.1910, the sensitivity increased from 18.2% to 48.1%, and the specificity
decreased from 93.1% to 82.1%. The odds ratio is denoted by OR in tables 4.2 and 4.3
below.

Table 4.2. iTUG Duration Only Fall Risk Model Compared to
All iTUG Parameter Model

<table>
<thead>
<tr>
<th>iTUG DURATION Only</th>
<th>iTUG All Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max re-scaled $R^2=0.0497$</td>
<td>Max re-scaled $R^2=0.1910$</td>
</tr>
<tr>
<td>Sensitivity = 18.2%</td>
<td>Sensitivity = 48.1%</td>
</tr>
<tr>
<td>Specificity = 93.1%</td>
<td>Specificity = 82.1%</td>
</tr>
<tr>
<td>Parameters</td>
<td>Significance</td>
</tr>
<tr>
<td>iTUG Duration</td>
<td>0.0280</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3 summarizes the results of the stepwise logistic regression fall risk
models: iTUG parameters, posturography parameters, iTUG and posturography
parameters together. The posturography model included height, 95% CEA, and M/L
velocity with a max re-scaled $R^2$ value of 0.1679, sensitivity of 37.3%, and specificity of
79.5%. The combination model includes height, sit-to-stand duration, stand-to-sit
duration, turn peak velocity and A/P sway range. The combined model increased max re-
scaled $R^2$ value to 0.3244, increased sensitivity to 54.3%, and increased specificity to
82.7% over the iTUG and posturography models alone.
Table 4.3. Stepwise Logistic Regression Models by Test Considering All Variables

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sig.</th>
<th>OR Exp(B)</th>
<th>Parameter</th>
<th>Sig.</th>
<th>OR Exp(B)</th>
<th>Parameter</th>
<th>Sig.</th>
<th>OR Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>iTUG</td>
<td></td>
<td></td>
<td>Posturography</td>
<td></td>
<td></td>
<td>iTUG + Posturography</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max re-scaled $R^2$</td>
<td>0.1910</td>
<td></td>
<td>Max re-scaled $R^2$</td>
<td>0.1679</td>
<td></td>
<td>Max re-scaled $R^2$</td>
<td>0.3244</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>48.1%</td>
<td></td>
<td>Sensitivity</td>
<td>37.3%</td>
<td></td>
<td>Sensitivity</td>
<td>54.3%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>82.1%</td>
<td></td>
<td>Specificity</td>
<td>79.5%</td>
<td></td>
<td>Specificity</td>
<td>82.7%</td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Sig.</td>
<td>OR</td>
<td>Parameter</td>
<td>Sig.</td>
<td>OR</td>
<td>Parameter</td>
<td>Sig.</td>
<td>OR</td>
</tr>
<tr>
<td>Height</td>
<td>0.0003</td>
<td>0.918</td>
<td>Height</td>
<td>0.0011</td>
<td>0.937</td>
<td>Height</td>
<td>&lt;0.0001</td>
<td>0.869</td>
</tr>
<tr>
<td>Sit-to-Stand Lean Angle</td>
<td>0.0319</td>
<td>14.205</td>
<td>95% CEA</td>
<td>0.0309</td>
<td>1.003</td>
<td>Sit-to-Stand Duration</td>
<td>0.0332</td>
<td>24.020</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ML Velocity</td>
<td>0.0751</td>
<td>0.893</td>
<td>Stand-to-Sit Duration</td>
<td>0.0203</td>
<td>13.521</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Turn Peak Velocity</td>
<td>0.0496</td>
<td>1.015</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>AP Sway Range</td>
<td>0.0310</td>
<td>1.047</td>
</tr>
</tbody>
</table>

The best resulting fall risk screening equation, as described by the highest $R^2$, sensitivity, and specificity, that signifies the probability of correctly identifying an individual at risk of falls is the combined iTUG and posturography model. The model can be represented by the following: \( \text{Logit}(p) = \ln[p/(1-p)] = 11.9834 - 0.1401(\text{Height}) + 3.1789(\text{Sit-to-Stand Duration}) + 2.6042(\text{Stand-to-Sit Duration}) + 0.0149(\text{Turn Peak Velocity}) + 0.0462(\text{AP Sway Range}) \).

**Discussion**

There are a number of assessments that can be used to identify older adults at risk of falls. Even choosing two of the commonly used assessments, posturography and iTUG, there are over one hundred outcome parameters that could be investigated. This study performed posturography and iTUG testing and utilized stepwise logistic regression to identify the combination of outcome parameters that together are best able to identify fallers from non-fallers. This is important in order to recognize fall risk earlier and reduce future falls. Of all of the possible combinations, four models were examined: TUG, iTUG parameters, posturography parameters, and a combination of posturography and iTUG.
parameters. Results indicate the iTUG test shows clear improvement in fall risk discrimination over the TUG fall risk screening model only including total time duration. Although showing only slight improvements in fall risk identification, results indicate there is a need to further examine a combined iTUG and posturography fall risk screening model to best identify an individual at risk of falls.

The results of this study allowed a direct comparison of the TUG total time duration to the iTUG parameters. Comparing a stepwise logistic regression model including only the traditional TUG duration to a model containing all iTUG parameters, we were able to directly relate the fit of each model. The model that included all iTUG movements yielded a max re-scaled re-scaled $R^2$ values of 0.258, as opposed to a value of 0.0498 for the model with the TUG duration as the only variable. In addition, the sensitivity values were 51.1% and 18.2% respectively. Both models had similar specificities. Although the traditional TUG test has shown to differentiate fallers and non-fallers, our results show the direct benefit of simply instrumenting individuals, the iTUG test.$^{20,22}$

Analyzing movements within the iTUG test did allow for the iTUG model to show that the sit-to-stand movement contributes valuable information to fall risk screening. The parameter included in the iTUG regression model, sit-to-stand lean angle, represents the sit-to-stand movement within the iTUG test. This movement requires strength and coordination that individuals with fall risk may lack. Results of the iTUG models are in accordance with Salarian et al. and Mancini et al. who found that implementing wearable sensors to clinical assessments, such as the iTUG test, provided greater sensitivity and reliability over the original assessment, the TUG test.$^{23,81}$ Results
here expand upon those results which focused on individuals with Parkinson’s disease, by implementing the iTUG in a faller and non-faller population. The increases shown in model fit statistics (max re-scaled $R^2$ and sensitivity) for the iTUG model further reinforces that greater differentiation can be achieved when wearable sensors are used to perform the iTUG test, as compared to the total time duration alone.

The posturography fall screening model had the lowest sensitivity and max re-scaled $R^2$ compared to the iTUG and the combined model, suggesting it did not differentiate between fallers and non-fallers as well as the other assessments. The two parameters identified in the posturography model suggest that M/L sway velocity and 95% CEA are identifiers of fall risk when examining posturography alone, although with a low sensitivity. An increase in the 95% CEA can be an indication of a decrease in stability, which suggests an increase in this parameter would contribute to an individuals’ fall risk, as described by Bigelow et al. Bigelow et al. also found similar results to this study with M/L sway velocity as the single most identifying parameter for fall risk, yet with a much higher sensitivity and specificity than results here. In addition, Melzer et al. and Maki et al. also suggested that an increase in M/L sway velocity contributes to an inability to control velocity lead to a greater instability. Bigelow et al. identified fallers as those with two or more falls in the past year, therefore the greater sensitivity and specificity may be attributed to the type of faller used in the model. Fall risk increases after an individual experience just one fall. Therefore, classification for this study for a faller was an individual that had fallen at least once. Although the parameters included in the model help identify fall risk, statistical results suggest the posturography model alone
is not an adequate model to be used for a fall risk assessment screening, justifying the need for a combination of multiple assessments.

The combination of the posturography parameters with the iTUG parameters did slightly improve over the posturography model alone and over the iTUG model alone, shown by an increase in sensitivity. One notable difference for the combined model are the parameters included in the model. Rather than M/L Velocity and 95% CEA, the posturography parameter included in the combined model is the A/P Sway Range. This is surprising as M/L, not A/P, COP parameters are more often linked to showing differences between fall risk individuals. For the iTUG parameters included in each model, the sit-to-stand movement remained the same from the iTUG model to the combined model, in addition to the stand-to-sit and the turning movement. This is important to note as it demonstrates how analyzing movements within the iTUG allows those movements to be highlighted as notable contributions to two different fall screening assessments.

One benefit of the combined model is the ability to include two types of fall screening assessments, as each of the assessments have the ability to examine different facets of fall risk. The posturography assessment was developed to use subtle movements within the individuals’ COP to identify balance deficits recognizable even when the individual is standing in an upright position. The iTUG test is able to identify differences exhibited when the individual is performing common movements that can lead to falls. An individual may have trouble in one area more than the other, where a single assessment may not pick up on the deficit. The combination suggests that there is promise in utilizing two assessments that when combined into one fall risk screening tool, may be able to identify deficits in two facets of fall risk. This is all in line with
Tiedemann et al.’s suggestion that there is an increased risk of multiple falls if deficits are seen in two different mobility assessments, with a cumulative effect on their fall risk.\textsuperscript{93}

One descriptor included in all three models was height. Initial statistics demonstrated that the faller group was significantly shorter than the non-faller group and that there was a higher percentage of women participants in the faller group than the non-faller group. These significant differences in height demographics may explain height’s inclusion in the model as women tend to be shorter than men and height tends to decrease as age increases. There was also a significant difference in age between the two groups, with the faller group being significantly older than the non-faller group. This may suggest that the participants in this study are an accurate depiction of the sample population in regard to more falls occurring as individuals age and women exhibiting a higher percentage of previous falls.\textsuperscript{69,70}

One limitation of the study was the sample size. This may have contributed to the low sensitivity and $R^2$ values for each of the models. With a larger sample size and more homogenous groups of fallers and non-fallers (with regards to age, height, gender), it may be possible to produce a model with a higher sensitivity. Another limitation to the study is the classification of fallers. In this case, those individuals that incurred at least one fall in the past twelve months were classified as fallers. While some of the individuals in the faller group fell multiple times, many of the individuals fell only once in the past twelve months. Falls were reported for various reasons therefore it could not be determined that all fallers incurred a fall due to physiological fall risk factors. Additionally for the classification of fallers, the individuals in the faller group were classified as fallers based on retrospective data. While ultimately prospective would be important, since it is known
that past falls lead to future falls, retrospective fall data can be used to classify faller groups. A third limitation to this study was that there were not sufficient study participants to build the model with one large pool of individuals and then validate it with a separate, independent group. With more participants, it would have been possible to develop the model with one subset of the participants and use the second subset of the participants to cross-validate the model.

The current work suggests a fall screening assessment should incorporate the iTUG test as well as a posturography assessment. However, if time is at a premium, then the iTUG should be used over posturography alone. As the combined model demonstrated only slightly increased differentiation over the single assessment models, the combined model has the ability to evaluate two different types of balance assessments. By examining the combined assessment in the future, it will have the ability to identify deficits seen in either of the assessments, demonstrating the possibility of a balance disorder not displayed through one assessment alone. Future work may be necessary to validate the model with a second population of older adult fallers at risk of falls. Additionally, future work should evaluate whether one-time fallers is the appropriate population to utilize for a fall-screening assessment model.
CHAPTER V

CONCLUSION

Determining fall risk in older adults is an important step in reducing future falls and helping older adults sustain healthy lifestyles. There is evidence that posturography and iTUG assessments used for fall risk differentiation can be enhanced through a variety of methods. Not only can dual-tasks be added to posturography and iTUG protocols, but different methods of analysis can be applied to the data to achieve different goals. The overall aims of this study were to determine: how postural sway and iTUG parameters are affected under standard and three different dual-task conditions, how different dual-tasks affect different characteristics of sway, how iTUG subcomponents are affected by different dual-task conditions, and which combination of traditional posturography and iTUG parameters best differentiate fallers from non-fallers utilizing a stepwise logistic regression model. The work done on dual-tasking incorporated in this study supported the theory that postural control is not automatic, but requires attention that is affected with the addition of a dual-task. The level of attention required during a dual-task depends on the type of dual-task as well as the innate executive function of the individual. Although the TUG test is a common clinical assessment, this study suggests that a wealth of knowledge can be gained from the movements within the iTUG assessment, rather than just the time to complete the test. This conclusion chapter will first summarize each of the
Manual and Cognitive Dual-Tasks Contribute to Fall-Risk Differentiation in Posturography Measures

The first aim of this work sought to examine various dual-tasks during posturography through a means of traditional linear and nonlinear analyses. When examining the traditional measures of sway, M/L sway range and 95% confidence ellipse area, demonstrated significantly greater values in the faller group than non-faller group. Both of these measures include medial/lateral sway components, just as previous studies also found these measures to be promising indications of fall risk\textsuperscript{12,26}. Traditional posturography measures the amount of sway, with larger values indicating greater postural instability and poorer balance. These differences were seen not only in the traditional task, but also various dual-task conditions. The manual and cognitive+manual dual-task conditions showed the largest differences between fallers and non-fallers with the largest effect sizes, although they did not show the greatest amount of sway. These results suggest that identifying conditions that elicit a difference between fallers and non-fallers does not always translate to the greatest amount of sway. Rather, learning more about how performance are affected by these conditions in different fall-risk populations can identify differences in their performance. As traditional measures seek to describe the amount of sway, it makes sense that the manual dual-task and cognitive+manual dual task would demonstrate the largest differences in groups during tasks where individuals are
physically holding a tray, due to holding the tray likely changing the mechanics of overall sway, best be characterized by traditional measures.

Contrary to the traditional outcome measures, the nonlinear analyses showed that the faller group demonstrated a higher M/L $\alpha$-scaling exponent in the cognitive and cognitive+manual task. This would suggest fallers show a more persistent pattern, whereas the non-faller group showed an anti-persistent pattern where a drift away from equilibrium was followed by a shift back to equilibrium in a corrective pattern. The fallers also demonstrated lower M/L SampEn values during the cognitive dual-tasks, indicating more predictability and less ability to adapt to surroundings. As nonlinear analyses describe sway movement over time, with multiple regions of the brain involved in maintaining stability, it makes sense that the cognitive tasks have a greater effect on the nonlinear analyses. Further research into attentional demands is necessary to understand the resources utilized during each of the dual-tasks and how they affect a primary task such as posturography.

**Sit-to-Stand iTUG Transition Contributes to Fall-Risk Differentiation in Older Adults**

Just as the results of the posturography protocol evaluated the effects of dual-tasks on balance, the iTUG assessment also observed the effects of dual-tasks on the subcomponents of the iTUG test. Results show that iTUG parameters were most affected by the cognitive+manual dual-task. This suggests that the cognitive+manual dual-task is useful for providing the most challenging condition for older adults. Additionally, the total time duration, the one outcome parameter of the traditional TUG test, did not show
significance between fallers and non-fallers, as other studies have shown. However, by utilizing movement sensors for the iTUG assessment, the sit-to-stand movement proved to be insightful for identifying differences between fallers and non-fallers. Other clinical assessments utilize the sit-to-stand movement as an attempt to identify balance disorders. Sit-to-stand trunk lean angle was identified here as one parameter with a significant increase in the faller group over the non-faller group. Guimaraes et al. also suggested that an increase in sit-to-stand lean angle relates to an increase in fall risk, as results show here\textsuperscript{89}. With the ability to identify deficits particular to certain movements within the iTUG test, clinicians may be able to cater therapy protocols to best address individual patients’ needs.

**Posturography and iTUG Assessments Contribute to a Fall-Risk Screening Model**

The posturography and iTUG measures showed promise in showing differences between fall risk groups and that the chosen dual-tasks provided an appropriate attentional demand for these assessments. The aim of the final study was to determine the amount of differentiation each assessment could provide, independently as well as through a combined model. As this aim was exploring the benefit of combing two different types of assessments for a fall screening tool, only the traditional task condition were included. Although the sole measure of total time duration of the iTUG test has shown to discriminate between fallers and non-fallers, the iTUG regression model suggests that by also including analysis for the movements done during the iTUG test, greater differentiation is achieved. The first two aims of this dissertation examined posturography and iTUG independently. The combination of these two assessments into a fall screening model provides the ability to assess two different facets of fall risk,
standing balance and balance during movements and transitions. Results indicated that fall differentiation is better for iTUG than posturography models, but when both are done together a slight increase in insight is gained.

**Study Themes**

Based on the results of the three studies included in this work, incorporating dual-tasking methodologies as well as instrumenting the Timed Up and Go test have contributed to developing improved fall risk screening tools. One aim of this study was to identify the dual-task which provides the biggest difference between fallers and non-fallers, in order to improve fall risk differentiation screening between these two populations. Results suggest that not just one dual-task excelled over the other dual-tasks in all types of assessments. All three of the dual-tasks studied showed promise in providing differences in three different types of analyses. To increase differentiation when using traditional posturography analyses, it is recommended to use the manual dual-task to show larger differences between fall risk groups. When using non-linear analyses in posturography to identify differences in fall risk populations the cognitive dual-task should be utilized. When assessing fall risk using the iTUG assessment the cognitive+manual dual-task provided most difficulty during the iTUG assessment. Another aim was to quantify the improvement of the iTUG test as a screening tool over the traditional TUG assessment. Results showed that the iTUG test improved sensitivity of discrimination between fallers and non-fallers by more than double over the traditional TUG assessment. Additionally, this study sought to determine how fall risk screening tools improve when combining two assessments that look at two different facets of fall risk. The logistic regression fall screening model combining the two assessments showed
minor improvements over the independent posturography and iTUG assessment regression models, warranting further investigation of combining two facets of fall risk into one screening tool.

**Study Limitations**

One limitation of this work was the unexpected difficulty of the counting task for many of the participants. The task of counting backward by 3’s was chosen as the cognitive task due to its inclusion in existing posturography and iTUG literature. Although each participant was asked to count backward by 3’s, many participants did not feel comfortable doing so. In this case, participants were allowed to count backward by 2’s. Regardless of what number the participants chose to count backward by, they were provided an equal challenge according to their abilities. Although this is a limitation and preferably all participants would count backward by the same number, this actually helped provide a similar challenge to each individual.

In addition to the cognitive task, the manual task also presents a limitation to the work. As posturography has shown to be affected by visual or proprioceptive feedback, the manual task of holding a tray with a ball may have contributed to the overall sway of the individual. A clear tray was chosen in order to minimize the obstruction of view during the iTUG test. Regardless, holding the tray in their arms while performing the iTUG test may have affected their visual field. In addition to the tray, a ball was placed on the tray that moved slightly as the participants moved. Participants were instructed to simply keep the ball on the tray during testing, but it appeared as though some participants wanted to keep the ball in the center of the tray. Although participants were
instructed to look straight ahead during testing, some participants tended to glance down at the ball, especially during the iTUG test. It is unknown how these factors may have contributed to the attentional demand of the manual task and how the participants prioritized the tasks they were presented.

A third limitation to this work is the retrospective nature of classifying fallers and non-fallers. Through a questionnaire, participants self-reported if they had fallen in the past twelve months. In addition to simply the number of falls in the past twelve months, participants were also asked to describe how the fall occurred and if they were injured as a result of the fall. Some falls occurred due to the participant being extremely active, other falls occurred due to limited and/or impaired mobility. This method of classifying fallers and non-fallers relied on the participants’ memory to recall the past twelve months and whether or not a fall occurred. Not only was this based on the participants’ memory of the past twelve months, but also does not necessarily translate to future falls.

**Future Work**

Based on the results of the overarching study, future work will include refining the incorporation of dual-task in posturography assessments in an older adult population. The manual and cognitive dual-tasks showed promise in posturography testing, yet this was just the first step in recognizing how different dual-tasks affect different aspects of sway. Future research will involve one large study that addresses three different aims.

The first aim of future research would be to examine the effect of the manual dual-task on posturography. This study suggests that the manual task and cognitive+manual task chosen for this study provided an appropriate attentional demand,
however including the manual task in further research allows the opportunity to compare the manual task chosen here – carrying a clear tray with a ball – to other manual dual-tasks in existing literature. Initially, it was expected that incorporating the manual task would demonstrate greater sway, but results show that participants demonstrated less sway. Despite demonstrating less sway, the manual condition was more effective in differentiating between fallers and non-fallers. The lesser degree of sway indicates that individuals were restricting movement. This may be due to the fact that individuals were concentrating on keeping the ball from moving too much on the tray. Future work would examine if the effects of the manual dual-task of carrying a tray with a ball on it, translate to other manual dual-tasks, such as carrying a tray with a cup of water. The addition of the manual task of a tray with a cup on it also allows for further examination of the effects of a manual dual-task. In comparing two different manual dual-tasks to the traditional task of posturography without a dual-task, we can determine whether the restricted movement is due to participants restricting movement of the ball on the tray, or the aid of touch to benefit balance as previous literature as reported, such as the aid of a finger touch to enhance stability. This would help improve standardization of the manual for future testing conditions.

Another aim of this work would be to determine the dual-task that provides the “best” fall risk differentiation. In order to provide better fall-risk differentiation, an additional piece of work would examine why fallers and non-fallers are affected differently by different dual-tasks. This could be accomplished through examining the effect of cognitive and physical load on individuals during various dual-tasks. Understanding how dual-tasks affect fallers and non-fallers different would allow allow
standardization of dual-task methodologies and may lead to eliminating un-needed testing conditions and therefore reducing testing time. Reducing testing time could help lead to a short, easy-to-administer, clinical fall risk screening tool.

Other areas of future research that can be incorporated into any of the three above aims would be to include an examination of the characterization of the faller and non-faller groups. Results showed that classification of the faller group, incurring at least one fall in the past twelve months, provided significant differences between fallers and non-fallers. The fall history questionnaire not only asked if the participant had fallen in the past twelve months, but also how many falls, the type of fall, and any injuries incurred from the fall. Future work could include characterizing the faller group according to type of fall, recurrent fallers rather than one-time fallers, or severity of fall injuries. With this information, this would allow researchers to report fall risk data to more specific at risk groups.

Finally, an independent study for future work should involve a prospective fall risk study. The present study examined individuals who had fallen in the past year, yet past falls do not translate to future falls. Therefore, through the collection of contact information from individuals that consented to a follow-up period, prospective fall data can be collected. With a follow-up period of one year after data collection, prospective fall data can be used to classify individuals differently, this time as a prospective faller or non-faller. Relating the data collected to the prospective fall risk, we can identify which outcome parameters and dual-tasks best identified future fall risk. This work would allow for a new logistic regression model for actual fall-risk.
Conclusion

It was the overall aim of this study to identify posturography and iTUG conditions that provide promise in identifying differences between faller and non-faller groups. Posturography results indicate that one method of analysis is not better than the other, but rather traditional linear and non-linear parameters measure different aspects of sway. Therefore, they should be used for different types of dual-tasks, depending on the type of attentional demand shown. The iTUG test results suggest that by instrumenting the movements within the iTUG test, researchers can identify the specific deficits within the assessment focusing on sit-to-stand. Through the combination of posturography and iTUG assessments, fall risk screening tools can examine two different facets of fall risk. This may enable researchers to more easily identify two different types of balance deficits and improve fall risk screening.
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APPENDIX A:

Traditional Posturography Analysis

All posturography data were collected via force plate (Model 5046, Bertec Corporation, Worthington, Ohio). Force plate center of pressure (COP) data were collected at 1000 Hz, as is standard on this model of force plate. In order to begin data processing, it was necessary to determine at which frequency to down-sample the raw data. To determine the rate at which to down-sample, a frequency domain analysis must be performed. The rate at which down-sampling biological data typically occurs at five to ten times the highest frequency in the signal. To determine the highest frequency in the signal, a Fast Fourier transform was performed. In the majority of trials, the highest frequency was approximately 10 Hz, therefore data should be down-sampled to 100 Hz. One example of this procedure can be seen in Figure A.1.
Figure A.1 Example of Power Spectral Density plot from the Fast Fourier Transform

Based on the Power Spectral Density plot, posturography raw data were downsampled to 100 Hz. Figure A.2 demonstrates an example of the down-sampled data.

Figure A.2 Example of Down-sampled posturography data
In order to simplify further calculations, the raw COP data were transformed with respect to the mean location of the COP using equations A.1 and A.2.

\[ y_n = y_i - \bar{y} \quad \text{for } i = 1 \ldots N \] [A.1]

\[ x_n = x_i - \bar{x} \quad \text{for } i = 1 \ldots N \] [A.2]

where: \( \bar{y} \) is the average of the A/P COP data set, \( \bar{x} \) is the average of the M/L COP data set, and \( N \) is the total length of the data set.

The next step of data processing was to smooth the data using a digital filter. The filter chosen was a 4th order low pass Butterworth filter with a 5 Hz cut-off, as is customary to use with this type of biological data. Figure A.3 is an example of a posturography data after filtering.

![Figure A.3 Example of Down-sampled and filtered posturography data](image-url)
After the raw data has been down-sampled, transformed and filtered, the linear posturography measures were calculated. A/P and M/L Sway Range were calculated according to equations A.3 and A.4. A/P and M/L Sway Range calculates the minimum and maximum peak amplitude range in the COP in the A/P and M/L directions respectively.

\[
A/P \text{ Sway Range} = |(y_n)_{\text{max}} - (y_n)_{\text{min}}| \quad [A.3]
\]

\[
M/L \text{ Sway Range} = |(x_n)_{\text{max}} - (x_n)_{\text{min}}| \quad [A.4]
\]

where: \((y_n)_{\text{max}}\) represents the maximum A/P data point, \((y_n)_{\text{min}}\) represents the minimum AP data point, \((x_n)_{\text{max}}\) represents the maximum M/L data point, and \((x_n)_{\text{min}}\) represents the minimum M/L data point.

The Mean Velocity is the average speed that the COP traveled, calculated by the total distance that the COP traveled divided by the total time of the trial. The Mean Velocity was calculated according to equation A.5.

\[
\text{Mean Velocity} = \frac{\sum_{n=1}^{N-1} \sqrt{(y_n + y_{n+1})^2 + (x_n + x_{n+1})^2}}{T} \quad [A.5]
\]

where: \(N = \) length of the data set, \(n = \) the data point of interest, \(y = \) A/P data, \(x = \) M/L data, and \(T = \) total time of the trial.

The M/L Mean Velocity is the average speed that the M/L component of the COP traveled during the trial. The M/L Mean Velocity is calculated by determining the total distance that the M/L component of the COP traveled during the trial. The total distance
of the M/L component of the COP is divided by the total duration of the trial, according
to equation A.6.

\[
M/L \text{ Mean Velocity} = \frac{\sum_{n=1}^{N-1} \sqrt{(x_{n+1}-x_n)^2}}{T} \quad [A.6]
\]

The final parameter for the traditional posturography analysis is the 95% Confidence Ellipse Area (95% CEA). The 95% CEA is another way to describe the area of the sway pattern during the trial. The 95% CEA fits the primary direction of sway to the major axis, then fits an ellipse to the data. There is thought to be 95% confidence that the ellipse encapsulates the center of pressure data for the trial. The first calculation that needs to be determined are the standard deviations of the COP data in the longitudinal and lateral axes, called the sigma values, \( \sigma_y, \sigma_x \) and \( \sigma_{xy} \). The standard deviations are used to calculate the area of the ellipse, as seen in equations A.7, A.8, and A.9.

\[
\sigma_y = \sqrt{\frac{\sum_{n=1}^{N} y_n^2}{N}} \quad [A.7]
\]

\[
\sigma_x = \sqrt{\frac{\sum_{n=1}^{N} x_n^2}{N}} \quad [A.8]
\]

\[
\sigma_{xy} = \sqrt{\frac{\sum_{n=1}^{N} (x_n y_n)}{N}} \quad [A.9]
\]

The first step to determining the major and minor axes of the ellipse is to create a covariance matrix (equation A.10) with the standard deviations calculated in equations A.7, A.8, and A.9.

\[
\text{CoVa} = \begin{bmatrix}
\sigma_x^2 & \sigma_{xy} \\
\sigma_{xy} & \sigma_y^2
\end{bmatrix} \quad [A.10]
\]
Eigen values ($\lambda_1$ and $\lambda_2$) were created to determine the major ($a$) and minor ($b$) axes of the ellipse, using the MATLAB function, \texttt{eig}. A 1.96 value was used in equations A.11 and A.12 to determine the 95\% confidence.

\begin{align*}
  a &= 1.96 \times \sqrt{\lambda_1} \quad \text{[A.11]} \\
  b &= 1.96 \times \sqrt{\lambda_2} \quad \text{[A.12]}
\end{align*}

The final step in calculating the 95\% Confidence Ellipse Area is calculated in equation A.13 using the area of an ellipse formula, using the major and minor axes calculated from the eigen values.

\[ \text{Area of 95\% Confidence Ellipse} = \pi \times a \times b \quad \text{[A.13]} \]

A custom MATLAB code performing the calculations demonstrated above can be found in Appendix E.
APPENDIX B:

Detrended Fluctuation Analysis of Posturography Data

Detrended Fluctuation Analysis (DFA) determines a fractal scaling exponent and describes the structure within the data series and the degree of patterns and persistence present in a set of data. The DFA process includes integrating a time series, then repeatedly dividing the integrated time series into equal-length windows. The average fluctuation of the data and the window size are determined by de-trending each of the windows for a variety of window sizes. The output measure of DFA is an $\alpha$-scaling exponent related to the linear portion of the double log plot. The $\alpha$-scaling exponent describes the pattern of sway as either persistent, $\alpha > 1.5$, (i.e. forward movements are followed by additional forward movements) or anti-persistent, $\alpha < 1.5$, (i.e. forward movements are followed by backward movements). All center of pressure (COP) data used for DFA analysis was collected via force plate (Model 5046, Bertec Corporation, Worthington, Ohio). Force plate COP data was collected at 1000 Hz, the standard on this model of force plate, and recommended as the frequency at which force plate data should be collected for non-linear analysis.

In order to run the DFA analysis, a window size must be chosen that is appropriate for this specific time series data set. The first step is to determine a
preliminary alpha based on each data set in order to determine which type of noise should be used to determine the appropriate window sizes for this time series, using initiate_DFA.m without knowing window sizes. The preliminary alpha corresponds to the scaling region that spans the entire range of window sizes. Once a preliminary alpha is determined, the next step is to proceed with the initiate_FindWindow.m process. To find the appropriate window size, the length of the data set and the preliminary alpha determined from the data set are input into the function. Depending on the preliminary alpha, GenerateNoise.m creates a data set the same length of the original data set of brown noise, pink noise or white noise, all of which have a known value of alpha (1.5, 1.0, and 0.5 respectively). Next, the findWindow.m function is called and the log10n (log of window sizes) and log10F (log of the fluctuation of the integrated and detrended time series) are calculated and used in conjunction with the type of noise to determine a DFA plot. Next, the findSlope.m and CheckSD functions are called and the researcher is asked to hand select two points (minimum and maximum window sizes) to chose the most appropriate slope of the data set. A region in the middle of the slope should be selected in order to reduce variance. Selection of the region should exclude the lower portion of the plot where the standard deviations of the windows contain very few points. The upper region of the plot should also be excluded to reduce variability. The DFA plot in Figure B.1 demonstrates these regions, with the red line indicating selected middle region.
To determine if the selected slope is appropriate, 100 theoretical noise data sets will be created using the same noise type and length of original data set. The hand-selected region will also be applied to these 100 theoretical data sets to determine 100 theoretical alpha values. The initial alpha is then statistically compared to the 100 theoretical alphas. The code determines if the hand selected window sizes are appropriate if the initial alpha is contained within the 95% confidence interval of the 100 theoretical alphas. If the initial alpha is contained within this confidence interval, the window sizes are appropriate and the code outputs the value of the window sizes. If the initial alpha is not contained within the 95% confidence interval of the 100 theoretical alphas the window size is not appropriate. The above process would then be repeated by hand choosing a different window size.

The window sizes for this study were determined in a pilot study of six individuals. Window sizes were found for each trial of each individual. One window size was chosen for Medial/Lateral (M/L) sway parameters and a separate window size was
determined for Anterior/Posterior (A/P) sway parameters. Table B.1 shows the window sizes for all six pilot study subjects, with the suggested window sizes for moving forward with the full study analysis. The suggested window size was contained within the window sizes for all six pilot study subjects for each medial/lateral and anterior/posterior separately. The suggested window size for M/L is 33 to 73 and the suggested window size for A/P is 27 to 71.

Table B.1 Window Size Estimation for DFA Analysis

<table>
<thead>
<tr>
<th>Subject</th>
<th>Medial/Lateral Window Size</th>
<th>Anterior/Posterior Window Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>RP1 – Faller</td>
<td>31 – 73</td>
<td>27 – 85</td>
</tr>
<tr>
<td>RP2 – Faller</td>
<td>26 – 76</td>
<td>22 – 71</td>
</tr>
<tr>
<td>RP3 – Non-Faller</td>
<td>33 – 81</td>
<td>22 – 73</td>
</tr>
<tr>
<td>RP4 – Faller</td>
<td>25 – 78</td>
<td>23 – 81</td>
</tr>
<tr>
<td>RP5 – Non-Faller</td>
<td>29 – 78</td>
<td>27 – 85</td>
</tr>
<tr>
<td>RP6 – Non-Faller</td>
<td>27 – 81</td>
<td>27 – 92</td>
</tr>
<tr>
<td>Suggested</td>
<td>33 – 73</td>
<td>27 – 71</td>
</tr>
</tbody>
</table>

Now that window sizes were determined for each type of data set, the DFA analysis calculated the alpha of the time series for the specified window, using initiate_DFA, with the determined window sizes as the inputs. The first step is to integrate the time series of length, $N$, as seen in equation B.1.

$$y(k) = \sum_{i=1}^{k}[B(i) - B_{ave}] \quad [B.1]$$

Then, the integrated time series is divided into boxes of equal length (window size), $n$. A least squares line is fit to the data in each box of length, $n$. The integrated time series, $y(k)$, is then detrended by subtracting the local trend, $y_n(k)$. The root-mean-square fluctuation of this integrated and detrended time series is calculated by equation B.2.
\[ F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2} \]  

[B.2]

This is repeated over all window sizes to provide a relationship between \( F(n) \), the average fluctuation as a function of box size and the box size, \( n \). In order to plot the time series, the log is taken of \( F(n) \) and \( n \) to create \( \log F(n) \) and \( \log(n) \), respectively. The scaling exponent, \( \alpha \), is the slope of the line relating to \( \log F(n) \) and \( \log(n) \).

Custom MATLAB code was used to run all DFA analyses, which can be found in Appendix F.
Sample Entropy Analysis of Posturography Data

Sample Entropy (SampEn) is a means of nonlinear analysis that describes the degree in which complexity is present. SampEn has been used to describe changes in postural control by evaluating the probability that an inherent pattern will be repeated. SampEn has been shown to reliable with shorter data sets. The SampEn output value ranges between 0 (indicating rigidity and the inability to adapt) and 1.5 (erratic and chaotic).

The medial/lateral (M/L) and anterior/poster (A/P) data sets are run independently to obtain an A/P SampEn and M/L SampEn. The first step is to downsample the data from 1000 Hz to 100 Hz for further analysis. The identification of the downsampling rate follows the same steps outlined in Appendix A. To calculate the SampEn value for each data set, two initial values must be set, \( m \) and \( r \). The vector size, \( m \), was set at 2 and the tolerance level, \( r \), was set at 0.2, per recommendation for clinical data. The final tolerance ends up being \( r \times \) standard deviation of the entire data set. Once vectors of length \( m \) are established, the algorithm looks for matches for vectors of length \( m \). Then using the set tolerance, the algorithm counts the vector matches that are within the tolerance, not counting self-matches (i.e. the vector itself). Once this is done, this process is repeated.
with vectors of length $m+1$. Next, the conditional probability is calculated by dividing the number of matches by the total number of comparisons, as seen in Equation C.1 and Equation C.2.

\[
C_i^m = \frac{\text{Vectors of } m \text{ within the tolerance } r}{\text{Total vectors compared}} \quad [C.1]
\]

\[
C_i^{m+1} = \frac{\text{Vectors of } m+1 \text{ within the tolerance } r}{\text{Total vectors compared}} \quad [C.2]
\]

Next, the averages of the conditional probability vectors are calculated, as seen in Equation C.3 and Equation C.4.

\[
B^m(r) = \frac{C_1^m + C_2^m + C_3^m + \ldots + C_N^{m-m}}{N \times m} \quad [C.3]
\]

\[
A^m(r) = \frac{C_1^{m+1} + C_2^{m+1} + C_3^{m+1} + \ldots + C_N^{m+1}}{N \times m} \quad [C.4]
\]

Next, to calculate the total number of template matches in an $m$-dimensional phase space within tolerance $r$, equations C.5 and C.6 are performed.

\[
B(r) = \frac{1}{2} (N - m - 1)(N - m)B^m(r) \quad [C.5]
\]

\[
A(r) = \frac{1}{2} (N - m - 1)(N - m)A^m(r) \quad [C.6]
\]

Finally, SampEn is calculated in equation C.7.

\[
\text{SampEn}(m, r, N) = -\log \left( \frac{A(r)}{B(r)} \right) \quad [C.7]
\]

After SampEn values were established, a surrogate analysis was required to test validity of the analysis and to verify the existence of patterns and to show that they were not random noise. The surrogation process randomized and scrambled each data set 19 different times, creating 19 sets of surrogated data. The SampEn value of the original data set was compared to the SampEn values of the 19 altered data sets. Validity to use
SampEn as a non-linear tool requires SampEn values to be significantly different than the SampEn values of the surrogate data sets. A t-test was run to determine that the values were significantly different from each other. This suggests that the original data has a degree of complexity and not random noise data.

The Sample Entropy and Surrogation Analysis MATLAB files are found in Appendix G.
APPENDIX D:

Mobility Lab and Accelerometry Analysis

APDM Inc. has become a popular company for both researchers and clinicians seeking to use wearable sensors, inertial measurement units (IMUs) to capture human movements to evaluate clinical populations. APDM offers packages of instrumented versions of common clinical assessments. The instrumented Timed Up and Go (iTUG) is a modification of the Timed Up and Go (TUG) assessment which is used to collect data about the movements within the assessments (sit-to-stand, turn, stand-to-sit, etc.) rather than simply measure the time it takes to complete the test. APDM offers Mobility Lab software that is used in conjunction with their wearable sensors that makes it easier for clinicians to collect, store and analysis outcome measures for various standardized tests such as the iTUG. Mobility Lab outputs individual outcome measures and offers normative values as comparison. The hardware and software package provides a sensitive way to quantitatively measure and compare performance over time. This can be used to monitor decline or gauge rehabilitation progress. There are multiple components to the Mobility Lab set-up for the iTUG assessment. Each physical component will be described below in more detail.
The OPAL measurement units collect kinematic data through a tri-axial accelerometer, gyroscope and magnetometer. Each OPAL consists of a 9-axis IMU containing a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. The accelerometer is used to measure linear acceleration, G-forces on three axes proportional to each other. The gyroscope detects and measures rotational accelerations on three axes, known as pitch, roll, and yaw. The magnetometer measures magnetic field strength at a point in space and assists calibration against orientation drift. The OPAL measures to be 48.4 mm in length, 36.1 mm in width and 13.4 mm in height. The OPAL has an internal storage of 8 Gb, sampling rate of 1280 Hz, and adjustable output rate of 20 to 128 Hz. The OPALs are used in tandem to collect and analyze data for segments of the body or the body as a whole. Four OPALs were used in this assessment for the iTUG test: one on the chest, one on the lower back, one on the left foot, and one on the right foot. The configuration of sensors can be seen in Figure D.1

Figure D.1 Configuration of the 4 OPAL sensors
A docking station is used to configure the sensors as well as charge the sensors. Four sensors were used for this assessment, therefore four docking stations were chained together as a single unit. An access point was used to allow for wireless communication and data transmission between the OPALs and the host computer. The access point also synchronizes the four independent OPAL sensors. Mobility Lab uses the raw signals and internal automatic analysis algorithms to quantify gait and balance parameters.

Mobility Lab assessed movements within the iTUG assessment for the total time duration, sit-to-stand, turn, and stand-to-sit. Measurements for each movement are detailed in Table D.1.

<table>
<thead>
<tr>
<th>Table D.1 Mobility Lab Measurements for the iTUG Assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>iTUG</strong></td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td><strong>Sit-to-Stand</strong></td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Lean Angle</td>
</tr>
<tr>
<td><strong>Turn</strong></td>
</tr>
<tr>
<td>Angle</td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Velocity</td>
</tr>
<tr>
<td><strong>Stand-to-Sit</strong></td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Lean Angle</td>
</tr>
</tbody>
</table>
APPENDIX E:

Fast Fourier Transform MATLAB Code

Traditional Posturography MATLAB Code

%Original Code by Dr. Nick Stergiou's Lab, modified by Renee Sample

%%Fourier Transform
close all;clc;clear;

%Get the data from the file and subtract the mean
[filename,path]=uigetfile('*.*','Pick a Text file');

%data=dlmread([path filename]);
directory_name=uigetdir(pwd,'Select data directory');
directory_name=(['directory_name '/'']);
data= csvread([directory_name filename],0,0);
use_data=data(:,11);

%Set the sampling frequency of the data
Fs = 1000;

%Calculate the FFT
T = 1/Fs;
L = length(use_data);
t = (0:L-1)*T;
NFFT = 2^nextpow2(L);
Spect = fft(use_data,NFFT)/L;
f = Fs/2*linspace(0,1,NFFT/2+1);
data2=2*abs(Spect(1:NFFT/2+1));

% Plot Power Spectrum
bar(f,data2)
axis([0 20 0 (max(abs(data2)))]
title('Power Spectra using fft function')
xlabel('Frequency (Hz)')
ylabel('Power')
%Batch Balance Plate Posturography Data Analysis Created by Renee Sample
clc; close all; clear all;

% Initialisation of POI Libs
% Add Java POI Libs to matlab javapath
javaaddpath('poi_library/poi-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-schemas-3.8-20120326.jar');
javaaddpath('poi_library/xmlbeans-2.3.0.jar');
javaaddpath('poi_library/dom4j-1.6.1.jar');
javaaddpath('poi_library/stax-api-1.0.1.jar');

%Name the Subject and Name for Excel Spreadsheet
PathName = 'Pilot_RP150.xlsx'; %This needs to be changed for each subject

%Bring in Data
%Need multiselect for batch processing
Data_file=uigetfile('*.txt','Select the File to Display',
'Multiselect','on'); %change depending on txt or csv
[~,numFiles]=size(Data_file);
TrialNames=cell(1,numFiles);

for f=1:numFiles
%Read the file
balance_data=csvread(Data_file{f},0,0);

%Assign variables to each column of data
Time1=balance_data(:,1);
Fz1=balance_data(:,8);
Mx1 = balance_data(:,9);
My1 = balance_data(:,10);
COPx1 = balance_data(:,11);
COPy1 = balance_data(:,12);

Time = downsample(Time1,10);
Fz = downsample(Fz1, 10);
Mx = downsample(Mx1, 10);
My = downsample(My1, 10);
COPx = downsample(COPx1, 10);
COPy = downsample(COPy1, 10);

%Pre-processing Data
N = length(COPy);
y_bar = (1/N)*sum(COPy);
for ii = 1:N
    yn(ii) = COPy(ii) - y_bar;
end

x_bar = (1/N)*sum(COPx);
for iii = 1:N
    xn(iii) = COPx(iii) - x_bar;
end

%Apply 4th order butterworth filter
Fs = 100; %Hz
Cutoff = 5; % Hz cutoff
[b,a] = butter(2,2*Cutoff/Fs);
yn_filt=filtfilt(b,a, yn);
[b,a] = butter(2,2*Cutoff/Fs);
xn_filt=filtfilt(b,a, xn);

% Calculate the nine primary sway parameters
% A) & B) A/P and M/L Sway Range (mm)
yn_filt_min = min(yn_filt);
yn_filt_max = max(yn_filt);
APsway(f) = abs(yn_filt_max - yn_filt_min)*1000; % converts to mm
xn_filt_min = min(xn_filt);
xn_filt_max = max(xn_filt);
MLsway(f) = abs(xn_filt_max - xn_filt_min)*1000; % converts to mm

% Mean Velocity
Mean_Vel = 0;
for jj = 1:N-1
    Mean_Vel = Mean_Vel + (sqrt((yn_filt(jj+1)-yn_filt(jj))^2 +
                                (xn_filt(jj+1)-xn_filt(jj))^2));
end
Mean_Velocity(f) = Mean_Vel*1000/(max(Time)-min(Time));

% M/L Mean Velocity
ML_Mean_Vel_loop = 0;
for ii = 1:N-1
    ML_Mean_Vel_loop = (ML_Mean_Vel_loop + sqrt((xn_filt(ii+1)-...
                                     xn_filt(ii))^2));
end
ML_Mean_Velocity(f) = ML_Mean_Vel_loop*1000/(max(Time)-min(Time));

% % f) 95% Confidence Ellipse Sway Area (mm^2)
xn = xn_filt*1000;
yn = yn_filt*1000;
Sigma_X = 0; Sigma_Y = 0; Sigma_XY = 0;
for iv = 1:N
    Sigma_X = Sigma_X + (xn(iv)^2)/N;
    Sigma_Y = Sigma_Y + (yn(iv)^2)/N;
    Sigma_XY = Sigma_XY + (xn(iv)*yn(iv));
end
Sigma_x = sqrt(Sigma_X);
Sigma_y = sqrt(Sigma_Y);
Sigma_xy = Sigma_XY/N;
clear Sigma_X; clear Sigma_Y; clear Sigma_XY;
CoVar_Matrix = [Sigma_x^2 Sigma_xy; Sigma_xy Sigma_y^2];
[EigV,Eig] = eig(CoVar_Matrix);
% [Vec, Val] = eig(CoVar_Matrix);
% Lam1 = abs(Val(1,1));
% Lam2 = abs(Val(2,2));
a = 1.96*sqrt(Eig(1,1));
b = 1.96*sqrt(Eig(2,2));
Confidence_Interval(f) = pi*a*b; % 95% Confidence Ellipse Area

% Assign outputs to the matrix
OutputCell(f+1,2:6) = {APsway(f), MLsway(f), Mean_Velocity(f),
                        ML_Mean_Velocity(f), Confidence_Interval(f)};
% Assign trial names to the matrix rows
OutputCell(f+1,1) = {Data_file(f)};
figure(f)
plot(xn_filt, yn_filt, 'b');
title(Data_file(f));
xlabel('COPx')
ylabel('COPy')
end

%Assign headings to first row of the outputcell
OutputCell(1,1:6) = {PathName, 'A/P Sway Range', 'M/L Sway Range', 'Mean Velocity', 'ML_Mean_Velocity', 'Area of 95% Confidence Ellipse'};

xlwrite(PathName, OutputCell, 1, 'A1');


APPENDIX F:

Detrended Fluctuation Analysis Posturography MATLAB Code

Includes:
initiate_DFA.m
DFA.m
initiate_FindWindow.m
findWindow.m
findSlope.m
StatsAlpha.m
CheckSD.m
GenerateNoise.m
brownNoise.m
pinkNoise.m
whiteNoise.m

%initiate_DFA Obtained from Dr. Nick Stergiou’s Lab, Modified by Renee Sample and Melissa Taylor

clear all; clc

% Select the directory to get the files from
directory_name=uigetdir(pwd,'Select data directory');
directory_name=(directory_name '/');

% Grabs all text files in the selected directory
files=dir([directory_name,'*txt']);

% Returns an error if there aren't any text files in the selected directory
if isempty(files)
    msgbox('No raw files in this directory');
end

% Select the directory to save any outputs
saving_directory_name=uigetdir(directory_name,'Select saving directory');
saving_directory_name=(saving_directory_name '/');

% Choose whether to analyze AP Sway or ML Sway
prompt1='Do you want to analyze AP or ML Sway?';
answer1=questdlg(prompt1,'',ML','AP','ML');

% Choose whether you know the min and max window sizes to compute alpha
prompt2='Do you know nmin and nmax for your data?';
answer2=questdlg(prompt2, ['','Yes','No','Yes']);
if strcmp(answer2,'Yes')
prompt3={'Enter nmin:','Enter nmax: '};
answer3=inputdlg(prompt3);
nmin=str2double(cell2mat(answer3(1)));
nmax=str2double(cell2mat(answer3(2)));
OptionDFA=1;
else
    OptionDFA=0;
end

% Open each file in the selected directory, chooses correct column of
data% based on selected of AP or ML Sway, passes data and min and max
window sizes
% (if applicable) into the DFA function, and outputs alpha after
calling% the DFA function
ALPHA=[];
for i_files=1:length(files);
    filename=files(i_files).name;
    opendata=fopen([directory_name filename]);
    all_data=fscanf(opendata,'%f',[16,inf]); % the 6 will need to be
changed to number of columns for new balance plate
    fclose(opendata);
    all_data=transpose(all_data);
    % if you need to downsample
    m=10;
    all_data=downsample(all_data,m);
    if strcmp(answer1,'ML')
        data=all_data(:,15); % change this for new plate
    elseif strcmp(answer1,'AP')
        data=all_data(:,16); % change this for new plate
    else
        msgbox('Invalid input, start again')
    end
    if OptionDFA==1
        [s_s,log10n,log10F]=DFA(data,nmin,nmax,filename(1:end-4),1);
        alpha=s_s;
    else
        [s_s,log10n,log10F]=DFA(data);
        alpha=s_s;
    end
    ALPHA=[ALPHA;str2num(alpha)];
end
function [s_s,log10n,log10F]=DFA(data,nmin,nmax,filename,plotOption)
% DFA Calculation File, Obtained from Dr. Nick Stergiou's Lab, Modified
% by Renee Sample and Melissa Taylor

% Defines increment in which boxes will be created
step_n=2;

[r c]=size(data);
if r >1
    data=data';
end

% This ensures that the data set will have an even number of data points
if mod(length(data),2)==0
    data=data;
else
    data=data(1:length(data)-1);
end

N=length(data);

% Defines min and max box sizes
min_n = 2;
max_n = N;

% This section is the bulk of the DFA calculation
fcount = 1;
for n=min_n:step_n:max_n
    clear B yn y X Y slopeintercept
    numberboxes = floor(N/n); % Determines the integer number of boxes
    B = data(1:numberboxes*n); % Creates the data set including only the data points in the box size being calculated in this iteration
    Bave = mean(B); % Average of the entire data set being analyzed
    y = cumsum(B-Bave); % Integrates the time series

    % This loop calculates the local trend (yn(X)) in each box
    for count = 0:numberboxes-1
        X = n*count+1:n*count+n;
        Y = y(X);
        A=[X' ones(length(X),1)];
        B=Y';
        slopeintercept= A\B;
        % Does the same thing as the polyval command, but faster
        yn(X) = slopeintercept(1,1)*X+slopeintercept(2,1);
    end

    % Calculates the RMS fluctuation of the integrated and detrended time series
    f(fcount) = sqrt(mean((y-yn).^2)); % (y-yn) detrends the integrated time series
    fcount = fcount + 1;
end

% Eliminate log of zero from the computations
step = 1;
for n=1:length(f)

    s_s = s_s + log10n;
    log10n = log10n + log10F;
    log10F = log10F + f(n);
end

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flag = 0;
if f(n) > 0.00000001
    F(step) = f(n);
    t(step) = n;
    step = step + 1;
end
end

% Takes log of data to be plotted
logn = log10(t);
logF = log10(F);

% Chooses how much data will be used to calculate alpha based on whether
% min and max window sizes were originally passed into this function
if nargin < 2
    log10n=logn;
    log10F=logF;
else
    log10n=logn(nmin:nmax);
    log10F=logF(nmin:nmax);
end

% Calculates alpha and fits a line to the data
alpha = polyfit(log10n, log10F, 1);
s_s = num2str(alpha(1));
fittedline = polyval(alpha,log10n);

% If min and max window sizes were not passed into this function
% originally, the plot will not be generated
if nargin < 4
    plotOption = 0;
end

% Generates the DFA plot
if plotOption==1
    clf
    F=figure;
    plot(logn,logF, '.','MarkerSize',10);
    hold on
    plot(log10n,fittedline,'r')
    legend('logF/logn','\alpha = ' num2str(s_s), 'Location', 'SouthEast')
    outputfile=filename;
    saveas(F,outputfile,'jpg')
    close
end
%This program is to find window size for the computation of alpha value
%(DFA) based on theoretical noise. Obtained from Dr. Nick Stergiou’s
% Lab, Modified by Renee Sample and Melissa Taylor

clear all
clc

% 1 is to plot and save. 0 is not to save.
plotOption = 0;

% Sets the number of theoretical time series that will be generated
NumOfIterations=100; %100

% Defines the length of the data set being analyzed so that that the
% theoretical noise generated is of the same length
prompt1='Enter data length.';
answer1=inputdlg(prompt1);
N=str2double(cell2mat(answer1));

% Defines the type of noise associated with the data set being analyzed
% based on the preliminary alpha calculated from the preliminary
% alpha calculated from DFA code
prompt2='Enter preliminary alpha calculated from DFA code.';
answer2=inputdlg(prompt2);
prelim_alpha=str2double(cell2mat(answer2));
if 0.25<=prelim_alpha && prelim_alpha<=0.75
    noise='White noise';
elseif 0.75<prelim_alpha && prelim_alpha<=1.25
    noise='Pink noise';
elseif 1.25<prelim_alpha && prelim_alpha<=1.75
    noise='Brown noise';
else
    msgbox('Preliminary alpha is not appropriate to correspond to
noise.');
end

% Calls the GenerateNoise function to create theoretical noise with a
% known
% alpha according the the type of noise specified from the preliminary
% alpha.
data=GenerateNoise(noise,N);

% Calls the findWindow function to determine the appropriate window
% size
% for the theoretical noise with known alpha.
[nmin, nmax]=findWindow(data,noise);
pause(1)
close

%Generates theoretical noise for NumOfIterations and computes alpha for
%each.
ALPHA=[];
for i=1:NumOfIterations
    data=GenerateNoise(noise,N);
    alpha=DFA(data,nmin,nmax,num2str(i),plotOption);
    ALPHA=[ALPHA,str2num(alpha)];
pause(1)
i
end
% Calls the StatsAlpha function to determine if the alphas calculated in
% the above loop are realistic for the theoretical noise. This is to
% determine if the window size chosen is acceptable.
StatsAlpha(ALPHA,nmin,nmax,noise);

% Outputs the min and max window sizes that should be used.
disp(['You have used nmin =', num2str(nmin), ' and nmax = ',
num2str(nmax)])
function [nmin,nmax]=findWindow(data,noise)
% Function to determine window size, Obtained from Dr. Nick Stergiou’s
% Lab, Modified by Renee Sample and Melissa Taylor

% Calls DFA function to get log10n and log10F to input into findSlope.
[~,log10n,log10F]=DFA(data);

% Calls find slope function to calculate min and max window sizes.
[nmin,nmax]=findSlope(log10n,log10F,noise);

% Check to determine if you accept the slope generated. If not, reruns
% findSlope.
button2=questdlg('Do you accept the slope? ','slope for
alpha','Yes','No','Yes');
while strcmp(button2,'No')
    hold off
    [nmin,nmax]=findSlope(log10n,log10F,noise);
    button2=questdlg('Do you accept the slope? ','slope for
alpha','Yes','No','Yes');
end
function [nmin,nmax]=findSlope(log10n,log10F,noise)
% Function to find the slope, Obtained from Dr. Nick Stergiou’s Lab,
% Modified by Renee Sample and Melissa Sample

% Initiates plots
subplot(2,1,1)
plot(log10n,log10F, '.', 'MarkerSize',10);
title('Select a slope')
subplot(2,1,2)
% Calls CheckSD function
SD=CheckSD(log10F);
hold on

% Pick up the points that are clicked on the plot to create the slope.
[xi,yi]=ginput(2);

% Find nmin and nmax from the points clicked on the plot to create a window
i_x=intersect(find(log10n >= xi(1)), find(log10n <= xi(2)));
nmin=i_x(1);
nmax=i_x(end);

% Find the best fit line for the data within the window selected
alpha = polyfit(log10n(nmin:nmax), log10F(nmin:nmax), 1);
s_s = num2str(alpha(1));
fittedline = polyval(alpha,log10n(nmin:nmax));

% Defines the alpha value of the theoretical noise
switch(noise)
    case 'Pink noise'
        theoreticalA = 1;
    case 'White noise'
        theoreticalA = 0.5;
    case 'Brown noise'
        theoreticalA = 1.5;
end

% Plotting commands
subplot(2,1,1)
plot(log10n,log10F, '.', 'MarkerSize',10);
hold on
plot(xi,yi,'ro')
hold on
plot(log10n(nmin:nmax),fittedline,'r')
title(['Theoretical alpha value = ', num2str(theoreticalA)])
legend(['logF/logn', ['\alpha = ',num2str(s_s)],'Location','SouthEast'])
subplot(2,1,2)
plot(nmin,SD(nmin),'ro')
hold on
plot(nmax,SD(nmax),'ro')
xlim([nmin-4 nmax+5])
title(['You have selected window size of ',
        num2str(length(nmin:nmax))])
xlabel(['Mean SD = ',num2str(mean(SD(nmin:nmax))), ', (StDev of SD = ',
        num2str(std(SD(nmin:nmax))),'])
function StatsAlpha(ALPHA,nmin,nmax,noise)
% Determines stats for the found Alpha, Obtained from modified by Renee
% Sample and Melissa Sample

AlpMean=mean(ALPHA);
AlpStd=std(ALPHA);

% Calculates 95% CI
UpperBounds=AlpMean+ 1.96* AlpStd/sqrt(length(ALPHA));
LowerBounds=AlpMean- 1.96* AlpStd/sqrt(length(ALPHA));

% Displays mean, SD, and 95% CI
disp(['Mean alpha = ', num2str(AlpMean)])
disp(['SD alpha = ', num2str(AlpStd)])
disp(['95% CI is [', num2str(LowerBounds), ',', num2str(UpperBounds), ']'])

% Sets the theoretical alpha based on the type of noise input.
switch (noise)
    case 'Pink noise'
        theoreticalA=1;
    case 'White noise'
        theoreticalA=0.5;
    case 'Brown noise'
        theoreticalA=1.5;
end

% Checks to see if the 95% CI is reasonable and contains the theoretical
% alpha.
if (theoreticalA < UpperBounds)&&(theoreticalA > LowerBounds)
    disp('According to the results, nmin and nmax seems to be a
    reasonable choice to determine the window size.')
    disp([ 'nmin: ', num2str(nmin)])
    disp([ 'nmax: ', num2str(nmax)])
else
    disp('Theoretical alpha value should be close to
    ',num2str(theoreticalA))
    disp('The window size you selected (nmin and nmax) did not create
    a slope for a corresponding theoretical alpha value to be in 95%CI.')
    disp('However, it may be very difficult to obtain a corresponding
    theoretical alpha value due to the limited amount of data points.')
    disp('Therefore, check to see if mean alpha is close enough to a
    theoretical alpha value.')
    disp('Otherwise, try to find another set of nmin and nmax.')
end
clf
% Plots a histogram of the mean alpha
hist(ALPHA)
xlabel([ 'Mean alpha = ',num2str(AlpMean)])
function SD=CheckSD(log10F)

% This function checks the standard deviation of the log of the RMS
% fluctuation, Obtained from Dr. Nick Stergiou’s Lab, Modified by Renee
% Sample and Melissa Taylor

Interval=1:length(log10F);
for i=1:length(Interval)-1
    SD(i)=std(log10F(Interval(i):Interval(i+1)));
end

plot(SD)
ylim([0 max(SD)])
xlabel(['Interval'])
ylabel('SD')
function data=GenerateNoise(noise,N)
% Generate the type of noise

switch noise
    case 'Pink noise'
        data=pinkNoise(N);
    case 'White noise'
        data=rand(1,N);
    case 'Brown noise'
        data=brownNoise(N);
end
function sig = brownNoise(iterations,d,T,plotFlag)
% sig = brownNoise(iterations,d,T);
% Brownian motion in d-dimensions
% G. Clifford 2004 gari AT mit DOT edu, Modified by Renee Sample

if nargin<4
plotFlag=0;
end

if nargin<3
T=1;
end
if nargin<2
d=1;
end
if nargin<1
iterations=1000;
end

x0=0;
dt=T/iterations;

sig=zeros(iterations,d);
for (j=1:d)
    for (i=2:iterations);
        ds = sqrt(dt)*randn;
        sig(i,j)= sig(i-1,j)+ds;
    end
end

% just plotting the result ...
if plotFlag>1
    if(d==1)
        subplot(2,1,1)
        plot(sig(:,1),'+-');
        axis([0 length(sig) min(sig)-(abs(min(sig))/20)
             max(sig)+(abs(max(sig))/20) ]);  
        title('1-D Brownian motion');
        grid on;
    end
    if(d==2)
        subplot(2,1,1)
        plot(sig(:,1),sig(:,2),'+-');
        title('2-D Brownian motion');
        grid on;
    end
    if(d>2)
        subplot(2,1,1)
        plot3(sig(:,1),sig(:,2),sig(:,3),'+-');
        title('3-D Brownian motion');
        grid on;
    end
end

subplot(2,1,2)
psd(sig(:,1))

end
function pink = pinkNoise(iterations, economy, plotFlag)
% sig = pinkNoise(iterations);  
% Pink noise generator, Modified by Renee Sample
% G. Clifford 2004 gari AT mit DOT edu adapted from
%     paul.kellett AT maxim.abel.co.uk
%
if nargin<1
    iterations=1000;
end
if nargin<2
    economy=0;
end
if nargin<3
    plotFlag=0;
end

% intialise
white = rand(1,iterations); white=white-mean(white);
pink  = zeros(1,iterations);

if economy==0; % slow & accurate version

    b0=0;b1=0;b2=0;b3=0;b4=0;b5=0;b6=0;
    for i=1:length(white) % loop over each element to create a new one
        b0 = 0.99886 * b0 + white(i) * 0.0555179;
        b1 = 0.99332 * b1 + white(i) * 0.0750759;
        b2 = 0.96900 * b2 + white(i) * 0.1538520;
        b3 = 0.86650 * b3 + white(i) * 0.3104856;
        b4 = 0.55000 * b4 + white(i) * 0.5329522;
        b5 = -0.7616 * b5 - white(i) * 0.0168980;
        pink(i) = b0 + b1 + b2 + b3 + b4 + b5 + b6 + white(i) * 0.5362;
        b6 = white(i) * 0.115926;
    end

end

if economy==1

    b0 = 0.99765 * b0 + white(i) * 0.0990460;
    b1 = 0.96300 * b1 + white(i) * 0.2965164;
    b2 = 0.57000 * b2 + white(i) * 1.0526913;
    pink(i) = b0 + b1 + b2 + white(i) * 0.1848;
end

end

if economy>1
% These have approximately equiripple error in decibels from 20hz to 
% 20khz at a 44.1khz sampling rate.

%1st order, ~ +/- 3 dB error (not recommended!)
num = [0.05338071119116 -0.03752455712906]
den = [1.00000000000000 -0.97712493947102]

% 2nd order, ~ +/- 0.9 dB error
num = [ 0.04957526213389 -0.06305581334498 0.01483220320740 ];
den = [ 1.00000000000000 -1.80116083982126 0.80257737639225 ];
pink = filtfilt(den,num,white);
end

% just plotting the data
if plotFlag>0

figure;
subplot(2,1,1)
plot(pink,'+---');
axis([0 length(pink) min(pink)-(abs(min(pink))/20)
max(pink)+(abs(max(pink))/20)])
title('Pink Noise');
grid on;
subplot(2,1,2)
psd(pink)

end
function sig = whiteNoise(len,plotFlag)
% sig = whiteNoise(length);
% White Noise with plots, Modified by Renee Sample
% % G. Clifford 2004 gari AT mit DOT edu

if nargin<1
    len=1000;
end
if nargin<2
    plotFlag=0;
end

sig = randn(1,len);
sig = sig/max(sig); % scale it to be unit height

if plotFlag>0 % plot the data
    subplot(2,1,1)
    plot(sig,.--');
    axis([0 length(sig) min(sig)-(abs(min(sig))/20) max(sig)+(abs(max(sig))/20)])
    title('White Noise');
    grid on;
    subplot(2,1,1)
    xlabel('time')
    subplot(2,1,2)
    psd(sig)
end
APPENDIX G:

Sample Entropy Analysis MATLAB Code

Includes:
surrogate11_renee.m
SampenDayton.m

% Program for producing Phase randomized surrogate time series.
% Obtained from Dr. Nick Stergiou’s Lab, Modified by Renee-May27th, 2015
clc; close all; clear all;

% Initialisation of POI Libs
% Add Java POI Libs to matlab javapath
javaaddpath('poi_library/poi-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-schemas-3.8-20120326.jar');
javaaddpath('poi_library/xmlbeans-2.3.0.jar');
javaaddpath('poi_library/dom4j-1.6.1.jar');
javaaddpath('poi_library/stax-api-1.0.1.jar');

% Select Folder where trials are saved as text files
directory_name=uigetdir(pwd,'Select data directory');
directory_name=[directory_name '/'];

Data_file=uigetfile('*.txt','Select the File to Display');
fid=fopen(Data_file, 'r'); % Open the file.
if fid == -1
    errordlg('File could not be opened, check name or path.', 'File Import Error')
end
% Assign variables to each column of data
balance_data=importdata(Data_file);

for f=1:19
    for j=1:2

        % Manually change the name of how you want your excell spreadsheet to save
        output_name=[Data_file '_Surg' num2str(f)];

        % Selects the COPx column on the first pass of the for loop, 
        % and the COPy column on the second pass of the for loop (j = 1:2)
        data=balance_data(:,j+10);
        % Downsamples data by a factor of 10%

    end
end
s=downsample(data,10);

%Length of data
N=length(s);
%Imaginary number
im=sqrt(-1);
%Define pi
twopi=2*pi;
%Round each element toward zero
half=fix((N+1.1)/2);

%Take the fast fourier transform of the original data
z=fft(s);
%Loop for half the data
for i=2:half;
    r=rand*twopi;
    z(i)=z(i)*(cos(r)+im*sin(r));
end
for i=2:half
    %Complex conjugate (3+4i = 3-4i)
    z(N+2-i)=conj(z(i));
end
zz=ifft(z);
%take the real part of a complex number for the series
output(:,j)=real(zz);
end

%output data in an excel file
outputname=strcat(Data_file,'_Surg',num2str(f),'.txt');
save (outputname, 'output','-ascii')
end
% SampEn Code
% Written by Allison Kinney, edited by Senia Reinert and Renee Sample (2015)
% This code will batch run COP data and is currently set up for text files
% where the 11 and 12 columns contain the COPx and COPy data respectively.

clear all
close all
clc

% Set m, vector size, and r factor, for tolerance size
m = 2;
rf = .2;

% Initialisation of POI Libs
% Add Java POI Libs to matlab javapath
javaaddpath('poi_library/poi-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-3.8-20120326.jar');
javaaddpath('poi_library/poi-ooxml-schemas-3.8-20120326.jar');
javaaddpath('poi_library/xmlbeans-2.3.0.jar');
javaaddpath('poi_library/dom4j-1.6.1.jar');
javaaddpath('poi_library/staxpi-1.0.1.jar');

% Manually change the name of how you want your excell spreadsheet to save
output_name = 'RD01_Sampen';

% Select Folder where trials are saved as text files
directory_name = uigetdir(pwd, 'Select data directory');
directory_name = {[directory_name '/']};
files = dir({directory_name,'*txt'});
if isempty(files)
    msgbox('No raw files in this directory')
end

% Batching
% build place holder matrix for all sampen values for batching
output = zeros(length(files), 2);
FileName = cell(length(files), 1);

for i = 1:length(files)
    % run a for loop for COPx and COPy vectors to get SampEn for both
    for j = 1:2
        filename = files(i).name;
data_all = load([directory_name filename]);
FileName{i, 1} = filename;
% Selects the COPx column on the first pass of the for loop, and the COPy column on the second pass of the for loop (j = 1:2)
data = data_all(:, 14 + j);
% Downsamples data by a factor of 10%
data = downsample(data, 10);
% Sets the tolerance, r (When r = 0.2, the tolerance level is
within %20% of the standard deviation of all step lengths within the entire %time series.)
\[ r = rf * \text{std}(data); \]
%N = number of data points in the set
\[ N = \text{length}(data); \]

%Initialize counters for m length vectors
\% originally was length(data)-m-1 to get the 25
%vectors but removed the '-1' to drop the last vector
count_m_vectors = zeros(length(data)-m,1);
vector_count = 1;
m_vectors = zeros(length(data)-m,m);

%Breaks COP data into vectors of length m.
%originally was vector_count <= length(data)-m-1 to get the 25
%vectors but removed the '-1' to drop the last vector
%want to have the same amount of comparisons
while vector_count <= length(data)-m
  m_vectors(vector_count,:) = data(vector_count:vector_count+m-1,1)';
  vector_count = vector_count + 1;
end

%Builds an empty matrix for the vectors that are matches
matched_vectors=zeros(N-m,1);%
%look for matches for vectors of length m
for vector_count = 1:length(m_vectors)
  %build a vector comprised entirely of the vector currently being matched
  vector_to_match=repmat(m_vectors(vector_count,:),length(m_vectors),1);
  %determine if corresponding elements of each vector are
  %tolerance, r
  comparisons =(abs(vector_to_match-m_vectors)<= r);
  matches = all(comparisons,2);
  % Subtract 1 from vector_count(s) to remove the self-match
  count(matched_vectors(vector_count,1) = sum(matches)-1;
end

% Initialize counters for m+1 length vectors
count_m_p1_vectors = zeros(length(data)-m,1);
vector_count_p1 = 1;
m_vectors_p1 = zeros(length(data)-m,m+1);

% Get vectors of length m+1
while vector_count_p1 <= length(data)-m
  m_vectors_p1(vector_count_p1,:) = data(vector_count_p1:vector_count_p1+m-1,1)';
  vector_count_p1 = vector_count_p1 + 1;
end

%look for matches for vectors of length m+1 (same logic as m
vector
%for loop above)
matched_vectors_p1=zeros(N-m,1);
for vector_count_p1 = 1:length(m_vectors_p1)
    vector_to_match_p1=repmat(m_vectors_p1(vector_count_p1,:),length(m_vectors_p1), 1);
    comparisons_p1 = (abs(vector_to_match_p1-m_vectors_p1)<= r);
    matches_p1 = all(comparisons_p1,2);
    matched_vectors_p1(vector_count_p1,1) = sum(matches_p1)-1;
end

% Calculate probabilities
prob_m_vectors = matched_vectors/(vector_count-1);
prob_m_p1_vectors = matched_vectors_p1/(vector_count_p1-1);

% Calculate A and B
B = sum(prob_m_vectors)/(N-m);
A = sum(prob_m_p1_vectors)/(N-m);

% be consistent with Ramdani
Br=(1/2)*(N-m-1)*(N-m)*B;
Ar=(1/2)*(N-m-1)*(N-m)*A;

SampEn = -log(Ar/Br);
output(i,j)=SampEn;
clearvars -except output i j m rf directory_name output_name
files FileName
    end
end

% output data in an excel file
header={'Filename' 'SampEn COPx' 'SampEn COPy'};
range=['A2:A',num2str(length(files)+1)];
xlwrite([directory_name output_name],header,'A1:C1')
xlwrite([directory_name output_name],FileName,range)
range2=['B2:C',num2str(length(files)+1)];
xlwrite([directory_name output_name],output,range2)
APPENDIX H:

Additional Tables

Table H.1 presents mean and standard deviation data for each component of the iTUG assessment during all dual-task conditions (Chapter 3). The participants were broken into two groups: those who experienced zero or one fall in the past twelve months (low faller) and those participants who experienced two or more falls in the past twelve months (multi-faller). No significant differences were found between the two groups.
Table H.1 iTUG Tasks Categorized by One-Time Faller vs. Recurrent Faller, Mean +/- St. Dev.

<table>
<thead>
<tr>
<th>Movement</th>
<th>LOW FALLER</th>
<th>MULTI-FALLER</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DURATION (s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>13.08 +/- 2.91</td>
<td>13.17 +/- 2.39</td>
<td>0.886</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>15.01 +/- 4.13</td>
<td>15.28 +/- 3.89</td>
<td>0.766</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>16.91 +/- 6.15</td>
<td>16.89 +/- 4.50</td>
<td>0.992</td>
</tr>
<tr>
<td>MANUAL</td>
<td>14.34 +/- 3.39</td>
<td>15.10 +/- 3.62</td>
<td>0.318</td>
</tr>
<tr>
<td><strong>SIT-TO-STAND DURATION (s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>1.16 +/- 0.14</td>
<td>1.23 +/- 0.23</td>
<td>0.059</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>1.22 +/- 0.21</td>
<td>1.19 +/- 0.37</td>
<td>0.603</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>1.35 +/- 1.07</td>
<td>1.27 +/- 0.19</td>
<td>0.752</td>
</tr>
<tr>
<td>MANUAL</td>
<td>1.22 +/- 0.24</td>
<td>1.30 +/- 0.26</td>
<td>0.159</td>
</tr>
<tr>
<td><strong>SIT-TO-STAND LEAN ANGLE (deg)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>26.48 +/- 8.94</td>
<td>26.44 +/- 7.86</td>
<td>0.983</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>26.09 +/- 8.20</td>
<td>24.91 +/- 10.04</td>
<td>0.554</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>23.09 +/- 7.56</td>
<td>22.79 +/- 8.41</td>
<td>0.869</td>
</tr>
<tr>
<td>MANUAL</td>
<td>23.01 +/- 7.86</td>
<td>23.58 +/- 9.51</td>
<td>0.764</td>
</tr>
<tr>
<td><strong>STAND-TO-SIT DURATION (s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>1.11 +/- 0.27</td>
<td>1.07 +/- 0.11</td>
<td>0.480</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>1.16 +/- 0.37</td>
<td>1.11 +/- 0.21</td>
<td>0.592</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>1.14 +/- 0.20</td>
<td>1.16 +/- 0.35</td>
<td>0.721</td>
</tr>
<tr>
<td>MANUAL</td>
<td>1.14 +/- 0.21</td>
<td>1.10 +/- 0.14</td>
<td>0.527</td>
</tr>
<tr>
<td><strong>STAND-TO-SIT LEAN ANGLE (deg)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>26.52 +/- 9.62</td>
<td>23.04 +/- 7.41</td>
<td>0.559</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>26.52 +/- 9.62</td>
<td>23.04 +/- 7.41</td>
<td>0.165</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>21.78 +/- 7.51</td>
<td>20.15 +/- 7.00</td>
<td>0.416</td>
</tr>
<tr>
<td>MANUAL</td>
<td>21.41 +/- 7.51</td>
<td>19.27 +/- 7.75</td>
<td>0.294</td>
</tr>
<tr>
<td><strong>TURN ANGLE (deg)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>178.54 +/- 7.11</td>
<td>178.72 +/- 6.88</td>
<td>0.349</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>178.55 +/- 7.11</td>
<td>178.72 +/- 6.88</td>
<td>0.914</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>176.32 +/- 8.76</td>
<td>179.10 +/- 6.22</td>
<td>0.135</td>
</tr>
<tr>
<td>MANUAL</td>
<td>176.58 +/- 16.99</td>
<td>175.92 +/- 7.66</td>
<td>0.850</td>
</tr>
<tr>
<td><strong>TURN DURATION (s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>2.31 +/- 0.38</td>
<td>2.34 +/- 0.34</td>
<td>0.742</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>2.39 +/- 0.40</td>
<td>2.41 +/- 0.32</td>
<td>0.741</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>2.66 +/- 0.41</td>
<td>2.74 +/- 0.31</td>
<td>0.351</td>
</tr>
<tr>
<td>MANUAL</td>
<td>3.43 +/- 0.38</td>
<td>2.56 +/- 0.32</td>
<td>0.640</td>
</tr>
<tr>
<td><strong>TURN PEAK VELOCITY (deg/s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>173.91 +/- 35.38</td>
<td>172.99 +/- 31.02</td>
<td>0.904</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>165.12 +/- 34.40</td>
<td>157.83 +/- 26.05</td>
<td>0.320</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>141.06 +/- 29.60</td>
<td>137.67 +/- 20.57</td>
<td>0.588</td>
</tr>
<tr>
<td>MANUAL</td>
<td>147.98 +/- 26.10</td>
<td>144.78 +/- 23.48</td>
<td>0.573</td>
</tr>
</tbody>
</table>

Table H.2 presents data for the movements within the iTUG assessment under all the dual-task conditions (Chapter 3). Mean and standard deviation data is presented for three different fall-risk groups: non-faller (no falls in the past twelve months), one-time faller (one fall in the past twelve months), and multiple faller (two or more falls in the
past twelve months). Significant differences were found during post-hoc analysis for the
traditional total time duration and cognitive+manual turn angle.

Table H.2 iTUG Tasks Categorized by Non-faller, One-Time Faller, and Recurrent Faller, Mean +/- St. Dev.

<table>
<thead>
<tr>
<th>DURATION (s)</th>
<th>NON-FALLER</th>
<th>ONE-TIME FALLER</th>
<th>MULTI FALLER</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRADITIONAL</td>
<td>12.66 +/- 2.13</td>
<td>14.31 +/- 4.30</td>
<td>13.17 +/- 2.39</td>
<td>0.021*</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>14.58 +/- 3.34</td>
<td>16.25 +/- 5.77</td>
<td>15.28 +/- 3.89</td>
<td>0.151</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>16.20 +/- 4.97</td>
<td>18.43 +/- 7.75</td>
<td>16.89 +/- 4.50</td>
<td>0.174</td>
</tr>
<tr>
<td>MANUAL</td>
<td>13.39 +/- 2.75</td>
<td>15.50 +/- 4.67</td>
<td>15.10 +/- 3.62</td>
<td>0.060</td>
</tr>
<tr>
<td>SIT-TO-STAND DURATION (s)</td>
<td>1.15 +/- 0.15</td>
<td>1.18 +/- 0.11</td>
<td>1.23 +/- 0.23</td>
<td>0.105</td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>25.74 +/- 7.93</td>
<td>28.91 +/- 11.51</td>
<td>26.44 +/- 7.86</td>
<td>0.286</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>25.61 +/- 7.81</td>
<td>27.69 +/- 9.39</td>
<td>24.91 +/- 10.04</td>
<td>0.477</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>22.26 +/- 7.20</td>
<td>25.79 +/- 8.21</td>
<td>22.79 +/- 8.41</td>
<td>0.130</td>
</tr>
<tr>
<td>MANUAL</td>
<td>22.44 +/- 7.58</td>
<td>24.87 +/- 8.63</td>
<td>23.58 +/- 9.51</td>
<td>0.410</td>
</tr>
<tr>
<td>SIT-TO-STAND Lean ANGLE(deg)</td>
<td>1.11 +/- 0.20</td>
<td>1.25 +/- 0.43</td>
<td>1.07 +/- 0.11</td>
<td>0.056</td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>25.40 +/- 9.01</td>
<td>24.98 +/- 8.01</td>
<td>23.04 +/- 7.41</td>
<td>0.832</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>25.85 +/- 9.27</td>
<td>29.14 +/- 10.83</td>
<td>23.04 +/- 7.41</td>
<td>0.181</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>21.32 +/- 7.04</td>
<td>23.59 +/- 9.19</td>
<td>20.15 +/- 7.00</td>
<td>0.412</td>
</tr>
<tr>
<td>MANUAL</td>
<td>21.14 +/- 7.51</td>
<td>22.46 +/- 7.67</td>
<td>19.27 +/- 7.75</td>
<td>0.483</td>
</tr>
<tr>
<td>STAND-TO-SIT DURATION (s)</td>
<td>1.12 +/- 0.20</td>
<td>1.25 +/- 0.43</td>
<td>1.07 +/- 0.11</td>
<td>0.056</td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>179.17 +/- 4.64</td>
<td>176.72 +/- 6.02</td>
<td>179.60 +/- 5.10</td>
<td>0.079</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>178.94 +/- 6.07</td>
<td>177.42 +/- 7.51</td>
<td>178.72 +/- 6.88</td>
<td>0.385</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>177.31 +/- 6.86</td>
<td>173.48 +/- 12.66</td>
<td>179.10 +/- 6.22</td>
<td>0.042*</td>
</tr>
<tr>
<td>MANUAL</td>
<td>178.37 +/- 4.56</td>
<td>177.23 +/- 6.39</td>
<td>175.92 +/- 7.66</td>
<td>0.143</td>
</tr>
<tr>
<td>TURN ANGLE (deg)</td>
<td>2.29 +/- 0.34</td>
<td>2.38 +/- 0.48</td>
<td>2.34 +/- 0.34</td>
<td>0.676</td>
</tr>
<tr>
<td>TRADITIONAL</td>
<td>175.36 +/- 3.33</td>
<td>169.59 +/- 40.71</td>
<td>172.99 +/- 31.02</td>
<td>0.736</td>
</tr>
<tr>
<td>COGNITIVE</td>
<td>166.43 +/- 3.27</td>
<td>161.24 +/- 37.91</td>
<td>157.83 +/- 26.05</td>
<td>0.468</td>
</tr>
<tr>
<td>COGNITIVE+MANUAL</td>
<td>143.37 +/- 29.89</td>
<td>134.21 +/- 28.10</td>
<td>137.67 +/- 20.57</td>
<td>0.276</td>
</tr>
<tr>
<td>MANUAL</td>
<td>148.61 +/- 25.87</td>
<td>146.12 +/- 27.15</td>
<td>144.78 +/- 23.48</td>
<td>0.771</td>
</tr>
</tbody>
</table>

The following tables, Table H.3 through Table H.13, present data for logistic regression models. Each model was created with a faller and non-faller population. The following tables also include statistics portraying how well the model fits the data.
Individual models were created for: all posturography parameters, single-most significant posturography parameter, all iTUG parameters, single-most significant iTUG parameter, all iTUG and posturography parameters, cognitive posturography parameters, cognitive+manual posturography parameters, manual posturography parameters, cognitive iTUG parameters, cognitive+manual iTUG parameters, and manual iTUG parameters. The model that produced the best fit and model statistics was the model that considered all parameters, posturography and iTUG during all four testing conditions. This model has a max re-scaled $R^2$ value of 0.6583, sensitivity of 63.3% and specificity of 83%. Although this model appears to be the best, it also includes the most testing conditions. Therefore, this model would be the most time intensive and does not help narrow down testing conditions to reduce testing and analysis time. For this reason, this model was not included in the final manuscript.

<table>
<thead>
<tr>
<th>Table H.3 All Posturography Parameters Fall-Risk Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Balance Only Fall-Risk Model</strong></td>
</tr>
<tr>
<td>Max-rescaled $R^2$=0.2386</td>
</tr>
<tr>
<td>Sensitivity = 51.7%</td>
</tr>
<tr>
<td>Specificity = 82.8%</td>
</tr>
<tr>
<td>Parameters</td>
</tr>
<tr>
<td>Height</td>
</tr>
<tr>
<td>95% CEA (Manual)</td>
</tr>
<tr>
<td>ML $\alpha$-scaling exponent (Cognitive)</td>
</tr>
<tr>
<td>Significance</td>
</tr>
<tr>
<td>0.0007</td>
</tr>
<tr>
<td>0.0126</td>
</tr>
<tr>
<td>0.0020</td>
</tr>
<tr>
<td>Odds Ratio</td>
</tr>
<tr>
<td>0.936</td>
</tr>
<tr>
<td>1.002</td>
</tr>
<tr>
<td>21.40</td>
</tr>
<tr>
<td>Logit($p$) = 5.2892 – 0.0664(Height) + 0.00236(Manual 95% CEA) + 3.0634(Cognitive ML $\alpha$-scaling exponent)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table H.4 Single Parameter Posturography Fall-Risk Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ONE Parameter Balance Only Fall-Risk Model</strong></td>
</tr>
<tr>
<td>Max-rescaled $R^2$=0.0988</td>
</tr>
<tr>
<td>Sensitivity = 32.8%</td>
</tr>
<tr>
<td>Specificity = 86.2%</td>
</tr>
<tr>
<td>Parameters</td>
</tr>
<tr>
<td>ML $\alpha$-scaling exponent (Cognitive)</td>
</tr>
<tr>
<td>Significance</td>
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<td>0.0031</td>
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<tr>
<td>Odds Ratio</td>
</tr>
<tr>
<td>43.156</td>
</tr>
<tr>
<td>Logit($p$) = -6.1668 + 3.7648(Cognitive ML $\alpha$-scaling exponent)</td>
</tr>
</tbody>
</table>
### Table H.5 All iTUG Parameters Fall-Risk Model

**iTUG Only Fall-Risk Model**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0096</td>
<td>0.876</td>
</tr>
<tr>
<td>Sit-to-Stand Duration (Manual)</td>
<td>0.0025</td>
<td>142.49</td>
</tr>
<tr>
<td>Stand-to-Sit Displacement (Traditional)</td>
<td>0.0159</td>
<td>&gt;999.99</td>
</tr>
<tr>
<td>Turn Angle (Cognitive+Manual)</td>
<td>0.1133</td>
<td>1.126</td>
</tr>
<tr>
<td>Stand-to-Sit Displacement (Cognitive+Manual)</td>
<td>0.1016</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Stand-to-Sit Duration (Cognitive+Manual)</td>
<td>0.1084</td>
<td>6.065</td>
</tr>
</tbody>
</table>

Logit($p$) = $-9.1013 - 0.132(Height) + 4.9592(Manual Sit-to-Stand Duration) - 17.7239(Cognitive+Manual Stand-to-Sit Displacement) + 21.5678(Traditional Stand-to-Sit Displacement) + 1.8026(Cognitive+Manual Stand-to-Sit Duration) + 0.1183(Cognitive+Manual Turn Angle)

### Table H.6 Single Parameter iTUG Fall-Risk Model

**ONE Parameter iTUG Only Fall-Risk Model**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sit-to-Stand Duration (Manual)</td>
<td>0.0386</td>
<td>5.352</td>
</tr>
</tbody>
</table>

Logit($p$) = $-2.5753 + 1.6774(Manual Sit-to-Stand Duration)

### Table H.7 All Parameter Fall-Risk Model

**All Parameters Fall-Risk Model**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0202</td>
<td>0.776</td>
</tr>
<tr>
<td>AP Sway Range (Manual)</td>
<td>0.0026</td>
<td>1.191</td>
</tr>
<tr>
<td>Stand-to-Sit Displacement (Cognitive+Manual)</td>
<td>0.0688</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Stand-to-Stand Displacement (Traditional)</td>
<td>0.0610</td>
<td>&gt;999.99</td>
</tr>
<tr>
<td>AP $\alpha$-scaling exponent (Cognitive)</td>
<td>0.0198</td>
<td>0.002</td>
</tr>
<tr>
<td>Turn Peak Velocity (Traditional)</td>
<td>0.0703</td>
<td>1.056</td>
</tr>
<tr>
<td>Total Duration (Manual)</td>
<td>0.0483</td>
<td>1.697</td>
</tr>
<tr>
<td>ML Sample Entropy (Traditional)</td>
<td>0.0932</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>ML Sway Range (Manual)</td>
<td>0.0954</td>
<td>0.896</td>
</tr>
<tr>
<td>Stand-to-Stand Displacement (Manual)</td>
<td>0.1218</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Logit($p$) = $27.8041 - 0.2540(Height) + 0.1746(Manual AP Sway Range) - 0.1093(Manual ML Sway Range) - 42.5806(Traditional ML Sample Entropy) - 5.9989(Cognitive AP -scaling exponent) + 0.5289(Manual Total Duration) - 37.3351(Manual Sit-to-Stand Displacement) + 93.3785(Traditional Sit-to-Stand Displacement) - 48.5140(Cognitive+Manual Stand-to-Sit Displacement) + 0.0541(Traditional Turn Peak Velocity)
### Table H.8 Cognitive Posturography Fall-Risk Model

**Cognitive Balance Task Fall-Risk Model**

Max re-scaled $R^2 = 0.1896$

- Sensitivity = 48.3%
- Specificity = 80.5%

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0007</td>
<td>0.940</td>
</tr>
<tr>
<td>Cognitive ML α-scaling exponent</td>
<td>0.0020</td>
<td>36.052</td>
</tr>
</tbody>
</table>

Logit($p$) = 4.4098 – 0.0616(Height) + 3.5850(Cognitive ML α-scaling exponent)

### Table H.9 Cognitive+Manual Posturography Fall-Risk Model

**Cognitive+Manual Balance Task Fall-Risk Model**

Max re-scaled $R^2 = 0.2201$

- Sensitivity = 48.3%
- Specificity = 85.2%

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0011</td>
<td>0.943</td>
</tr>
<tr>
<td>Cognitive+Manual 95% CEA</td>
<td>0.0071</td>
<td>1.002</td>
</tr>
<tr>
<td>Cognitive+Manual ML Velocity</td>
<td>0.0185</td>
<td>0.847</td>
</tr>
</tbody>
</table>

Logit($p$) = 9.1574 – 0.0584(Height) – 0.1664(Cognitive+Manual ML Velocity) + 0.00385(Cognitive+Manual 95% CEA)

### Table H.10 Manual Posturography Fall-Risk Model

**Manual Balance Task Fall-Risk Model**

Max re-scaled $R^2 = 0.1771$

- Sensitivity = 45.8%
- Specificity = 80.7%

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0011</td>
<td>0.939</td>
</tr>
<tr>
<td>Manual 95% CEA</td>
<td>0.0019</td>
<td>1.003</td>
</tr>
</tbody>
</table>

Logit($p$) = 9.3335 – 0.0634(Height) + 0.00278(Manual 95% CEA)

### Table H.11 Cognitive iTUG Fall-Risk Model

**Cognitive iTUG Fall-Risk Model**

Max re-scaled $R^2 = 0.1829$

- Sensitivity = 24.5%
- Specificity = 83.7%

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0048</td>
<td>0.876</td>
</tr>
<tr>
<td>Cognitive Sit-to-Stand Duration</td>
<td>0.0172</td>
<td>&gt;999.999</td>
</tr>
</tbody>
</table>

Logit($p$) = 14.9468 – 0.1329(Height) + 16.68(Cognitive Sit-to-Stand Duration)
### Table H.12 Cognitive+Manual Fall-Risk Model

**Cognitive+Manual Task iTUG Fall-Risk Model**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0026</td>
<td>0.918</td>
</tr>
<tr>
<td>Cognitive+Manual Turn Angle</td>
<td>0.0311</td>
<td>1.053</td>
</tr>
<tr>
<td>Cognitive+Manual Stand-to-Sit Lean Angle</td>
<td>0.1424</td>
<td>3.899</td>
</tr>
</tbody>
</table>

\[
\text{Logit}(p) = 11.1855 - 0.0854(\text{Height}) + 1.3608(\text{Cognitive+Manual Stand-to-Sit Lean Angle}) + 0.0512(\text{Cognitive+Manual Turn Angle})
\]

### Table H.13 Manual iTUG Fall-Risk Model

**Manual Task iTUG Fall-Risk Model**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significance</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>0.0046</td>
<td>0.926</td>
</tr>
<tr>
<td>Manual Sit-to-Stand Lean Angle</td>
<td>0.0035</td>
<td>11.176</td>
</tr>
</tbody>
</table>

\[
\text{Logit}(p) = 9.4028 - 0.077(\text{Height}) + 2.4137(\text{Manual Sit-to-Stand Lean Angle})
\]
APPENDIX I:

Data Collection Forms
   Includes:
      Consent Form
Fall Monitoring Preferred Correspondence
Fall History Questionnaire
Data Collection Form
   ABC Scale Form
UNIVERSITY OF DAYTON - CONSENT TO PARTICIPATE IN RESEARCH

TITLE OF STUDY: Examination of the Role of Dual Task in Postural Control and Gait Assessment to Best Determine Fall Risk: Full Scale Study – PHASE II

We are inviting you to be a part of a research study led by Renee Beach Sample at the University of Dayton. Your participation in this study is voluntary. Please review the information below to learn more about the study. Before participating, ask questions about anything you do not understand.

PURPOSE OF THE STUDY

The aim of this study is to identify a better way to assess individuals at a higher risk of falling.

PROCEDURES

If you decide to be a part of this study, you will:

1. Answer a few questions concerning your health.
2. Be asked questions about your history of falls and daily activity levels.
3. Fill out a form answering questions about how confident you are in your balance during tasks that you do every day.
4. Have your height, weight, and age recorded.
5. Step up onto a balance plate (similar in look and function to a bathroom scale) and have your balance measured while you stand as still as possible for 60 seconds. You will perform the balance task alone as well as while performing a second task: counting backward by 3, holding a tray with a ball, or these two tasks combined. You will perform 3 trials for each task for a total of 12 balance trials.
6. Perform the Timed Up and Go (TUG) test (from seated position, stand up, walk a path, turn around, walk back and sit down) while wearing four small sensors located on each ankle, around your waist, and around your chest. They will be attached by an elastic strap. You will perform the TUG task alone as well as while performing a second task: counting backward by 3, holding a tray with a ball, or these two tasks combined. You will perform 3 trials for each task for a total of 12 TUG trials.
7. We would like to follow-up with you monthly for the next 12 months to see if you have any falls. At the end of your test we will provide you an informational packet to ask your preferred method of communication (email, phone, or mail) for this follow-up. You would then monthly tell us if you have fallen, and if yes, the circumstances of that fall. You are able to opt out of follow-up participation if you chose to do so.

You can rest as much as you would like during testing. Testing will take approximately 30-45 minutes to complete.

In order to participate in this study, you must be over the age of 60. You must be able to walk by yourself for 50 feet without assistance, be able to stand without assistance for 5 minutes, and not require the use of a lower limb brace ankle/foot orthotic (AFO) or a lower limb prosthesis.

POTENTIAL RISKS AND DISCOMFORTS

There may be a risk of losing your balance or falling during testing. To lower this risk you will wear a gait belt that a researcher can use to help slow your fall. You will also be spotted by a researcher during each test.

There is also a risk you may become fatigued during this study. A break will be provided to you halfway through data collection, but additional breaks may be taken as needed. Please inform the researcher if you feel the need to take a break.

ANTICIPATED BENEFITS TO PARTICIPANTS

There are no direct benefits to you. It is hoped that the findings of this study will aid in the identification of risk of falls earlier to decrease falls in older adults.

PAYMENT FOR PARTICIPATION

There is no payment for participation in this study.

IN CASE OF RESEARCH RELATED INJURY

If you become ill or are injured as a result of this study, you should seek medical treatment through your doctor or treatment center of choice. You agree to promptly tell the Principal Investigator about any illness or injury: Renee Beach Sample at 937-305-6186. You do not waive any liability rights for personal injury by signing this form.

CONFIDENTIALITY

When the results of the research are published or discussed in conferences, no information will be included that would reveal your identity. Photographs may be taken during testing and used in presentations or publications about this research with your permission. We will make every effort to protect your identity using techniques such as blurring or blacking out any identifying features. Nevertheless, use of these recordings does increase the risk that your identity may be compromised. No records of helping in this research will be shared with others. Your personal information and results will also not be shared with others.
Depending on your preferred means of communication for the follow-up period, we may contact you by email, phone, or by mailing address. All data we collect during this period will only be marked with your subject number and never your name or other identifiable information.

**PARTICIPATION AND WITHDRAWAL**

Your participation in this research is voluntary. If you choose not to participate, that will not affect your relationship with The University of Dayton or other services to which you are otherwise entitled. If you decide to participate, you are free to withdraw your consent and discontinue participation at any time without prejudice or penalty. The investigator may withdraw you from participating in this research if circumstances arise which warrant doing so.

**IDENTIFICATION OF INVESTIGATORS**

Please contact one of the investigators listed below if you have any questions about this research.

Renee Beach Sample, Principal Investigator, University of Dayton, Mechanical and Aerospace Engineering Department, 937-305-6186, beachr1@udayton.edu.

Dr. Kimberly Bigelow, Faculty Advisor, University of Dayton, Mechanical and Aerospace Engineering Department, 937-229-2918, kbigelow1@udayton.edu.

**RIGHTS OF RESEARCH PARTICIPANTS**

You may contact the Chair of the Institutional Review Board (IRB) at the University of Dayton if you have questions about your rights as a research participant: Dr. Mary Connolly, (937) 229-3493, Mconnolly1@udayton.edu.

**SIGNATURE OF RESEARCH PARTICIPANT (or legal guardian)**

I have read the information above. I have had a chance to ask questions and all of my questions have been answered to my satisfaction. I have been given a copy of this form. **I certify that I am at least 18 years of age.**

Name of Participant (please print)____________________________________________________

Address _____________________________________________________________________________

Signature of Participant __________________________________________ Date __________
SIGNATURE OF WITNESS

My signature as witness certifies that the Participant signed this consent form in my presence.

Name of Witness (please print)____________________________________________

Signature of Witness____________________________________________________ Date_______

(Must be same as participant signature date)

CONSENT TO USE IMAGES OR RECORDINGS FROM RESEARCH

I consent and give permission for the researcher to use photographs taken during the course of this research. My identity will be protected or disguised by the researcher prior to publication or use in presentations of their results. By signing below, I confirm that I understand that these images may compromise the confidentiality of my participation in this research. You may still participate in this research if you do not allow the use of your photos.

Name of Participant (please print)____________________________________________

Address_________________________________________________________________

Signature of Participant_________________________________________ Date_______
TITLE OF STUDY: Examination of the Role of Dual Task in Postural Control and Gait Assessment to Best Determine Fall Risk: Phase II

This form, once completed, is to be kept locked in the file cabinet within the key card locked University of Dayton Engineering Wellness through Biomechanics Lab.

Name: ______________________________________

[Subject Code:________________________________ ]

Each month, for the next 12 months we will be contacting you to see if you have fallen and if so, what the circumstances of that fall were. We will provide you monthly calendars to help you keep track. All of the data we collect will be saved only with your subject ID code and not your name or other identifiable information.

How would you like us to contact you each month:

_______ Call you by phone

(Please provide your phone number:______________________________)

_______ Correspond by mail with pre-stamped envelopes

(Please provide your address:__________________________________________

_______________________________________

_______________________________________

_______ Be emailed a form to complete and return electronically

(Please provide your email:__________________________________________)

_______ I do not agree to participate in this follow-up period.
Subject Code: _____________________________

Age: _________________________________

Height: _______________________________

Gender: M  F

Testing Facility Name: _________________________________

Testing Facility Type: _______________________________________

Have you fallen in the past year, with a fall being defined as any time you come to rest on a lower surface unintentionally, including slips, trips, and falling down the stairs:  YES  NO

If yes, how many falls have you had in the past year?

If yes, did any of these falls occur in the past 6 months?

If yes, where did the fall(s) happen?

If yes, please describe the circumstances when the fall(s) occurred.

If yes, please describe any injuries you may have incurred.

Does you have any of the following? *(Check all that apply)*

___ 1. Any diagnosed balance disorders, such as inner ear problems, ear infections, crystals in your ears (BPPV), or vertigo

___ 2. Any known neurological disorders, such as Multiple Sclerosis or Parkinson’s Disease

___ 3. Any orthopedic disorders (such as arthritis) or muscle weakness that affects your balance or walking
__ 4. Balance problems when standing
__ 5. Balance problems when walking
__ 6. Seizures in the last year
__ 7. Fainting or persistent dizziness within the last year
__ 8. Dizziness when you stand up too quickly
__ 9. Visual problems other than need for glasses/contacts
__ 10. Numbness of the feet
__ 11. Any total joint replacements
__ 12. Any lower leg surgery that affected your balance or walking post-surgery
__ 13. Any lower leg surgery that still affects your balance or walking today
__ 14. A stroke
__ 15. Use a mobility aid (walker, cane, etc.)
__ 16. Taking 4 or more medications
__ 17. Do any of your medications come with a warning to avoid driving/operating heavy machinery after taking?
__ 18. Do any of these make you noticeably sleepy or dizzy?

Physical Activity Questions:

__ 19. Have you seen a PT in the last year that included a focus on improving balance or how you walk
__ 20. Have you participated in fall prevention training (i.e. Matter of Balance) during the last year
__ 21. Describe your weekly physical activities: NONE   LIGHT   MODERATE   INTENSE
__ 22. Days/minutes each week do you do these activities: ________/__________
__ 23. Do you do activities to increase muscle strength once a week or more:   YES   NO
__ 24. Do you do activities to increase flexibility once a week or more:   YES   NO
Participant Code:__________________________
Date:____________________________________

Circle One: NON-FALLER      FALLER

CHECK WHEN COMPLETE:

_____ 1. Consent Form

_____ 2. Fall History Survey

_____ 3. Activities Specific Balance Confidence Test

_____ 4. Height__________  Weight_____________  Age__________

**Balance Protocol**

<table>
<thead>
<tr>
<th>Random Order</th>
<th>Trial Name</th>
<th>Testing Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S__BN_1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S__BN_2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S__BN_3</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>S__BC_3</td>
<td></td>
</tr>
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iTUG Protocol

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