Age-Associated Mechanisms of Multisensory Interaction on Postural Dynamics

by

Marina Meyer Vega

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
Requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 08, 2026

Keywords: postural control, aging, stroke, multisensory interaction, fall risk, body composition, low-frequency oscillations, COP signal

Approved by

Harsimran S. Baweja, P.T., Ph.D., Chair, Associate Professor of Kinesiology
Matthew W. Miller, Professor and Director of the School of Kinesiology
Michael Roberts, Ph.D., Professor of Kinesiology
William Murrah, Ph.D., Associate Professor and Department Head of Educational Foundations, Leadership, and Technology

Abstract

Postural control is a complex behavior that depends on the dynamic integration of visual, vestibular, and proprioceptive inputs, the allocation of attentional resources, and the coordination of neuromuscular responses. Postural control decline is a leading contributor to falls and a major cause of injury-related death and disability in aging and neurological populations. Despite this, postural control is still commonly assessed using subjective, performance-based clinical tools that measure only behavioral outcomes rather than the underlying mechanisms that produce them. The objective of this dissertation was to examine postural control across the lifespan and in neurological disorders, and to determine whether low-frequency oscillations in the center of pressure (COP) signal provide a more sensitive and mechanistic biomarker of fall risk than traditional measures alone.

This dissertation comprises four studies. The first was a systematic review and meta-analysis evaluating the diagnostic accuracy of the two most commonly used clinical fall-risk assessments among stroke survivors. Following PRISMA guidelines, 13 studies (1,347 stroke survivors) were analyzed. We found that the Berg Balance Scale (BBS; OR = 5.13, 95% CI [3.27, 8.05]) and the Timed Up and Go (TUG; OR = 3.38, 95% CI [2.23, 5.14]) demonstrated significant discriminative ability to categorize fall risk in stroke survivors, with no superiority of one over the other. However, moderate heterogeneity across studies

and the absence of standardized cut-off values and assessment approaches indicated that neither tool is sufficient as a standalone screening measure.

The second and third studies were conducted in a sample of over 100 healthy younger and older adults. We examined how the underlying sensory reweighting mechanisms of postural control reorganize under dual-task conditions on a stable (Study 2) and an unstable (Study 3) surface. On both surfaces, older adults reduced postural sway under dual-task conditions but at the cost of cognitive accuracy, reflecting a reallocation of attentional resources toward postural control. Low-frequency oscillations of the COP signal revealed that sensory reweighting mechanisms were task- and direction-specific, and that age-associated differences became more pronounced on the unstable surface, where older adults relied more heavily on visual and vestibular inputs to compensate for challenged proprioception.

The fourth study examined whether fat mass index (FMI), fat-free mass index (FFMI), and the FM/FFM ratio predict COP sway and low-frequency oscillations in community-dwelling older and younger adults. We found that fat mass indices (FMI and the FM/FFM ratio) were significantly associated with postural sway and low-frequency oscillations exclusively in older adults, despite no significant differences in body composition between groups. Whereas FFMI showed no significant association in either group. This established adiposity as an independent, age-associated contributor to postural instability.

Collectively, this dissertation demonstrates that fall risk cannot be fully explained by behavioral outcomes alone. Across neurological disorders such as stroke, healthy aging, and body composition, low-frequency oscillations of the COP signal are able to capture the underlying sensory reweighting mechanisms of postural control. By distinguishing the quantity of postural sway from its quality, this work provides a mechanistic framework for understanding why individuals fall and supports the integration of objective, instrumented assessments into fall risk evaluation across aging and neurological populations.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, Grammarly Inc. and Claude AI were used for grammar and spelling verification and to assist in brevity for original writing for this dissertation. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain the scholarly integrity of this research.

Digital Accessibility Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure this document complies with federal requirements: Microsoft Word Accessibility Checker. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

Acknowledgments

I am immensely grateful to Dr. Baweja for giving me this opportunity, for believing in me, and for making me believe in myself and in my potential. You always pushed me to think outside the box and step outside my comfort zone, and because of that, I learned so much, not only academically but personally, about what I can achieve when I set my mind to it. I am also immensely grateful to the Presidential Graduate Research Fellowship and the Nix Graduate Fellowship for giving me the incredible and unique opportunity to pursue a PhD at Auburn University.

To my committee, Dr. Miller, Dr. Roberts, and Dr. Murrah, thank you. Each of you has contributed to my growth and to this work. I am grateful for your time, your thoughtful feedback, and the perspective you brought that strengthened this dissertation. It has been a privilege to work with all of you.

To the current and past SMART Lab members, I am extremely grateful for your friendship, the long days spent collecting data, and the memories we shared during my time at Auburn. I would also like to thank all the friends I made at Auburn, especially Breanna, Bahman, Tony, Derick, Keven, Busra, Raissa, Alex, Hope, Raul, Alejandra, Jaime, Gemma, Iñaki, and Gaby. From the very first day, you reached out to listen and guide me. Because of you, I never felt alone in this process. Far from family, you became my home here, and I never imagined I would meet so many of my best friends during this adventure. Thank you for celebrating every breakthrough with me.

Quisiera agradecer a mis papás, Marisa y Roberto, y a mi hermano Beto, por siempre permanecer a mi lado, queriéndome, apoyándome y acompañándome en las

buenas y en las malas. Siempre los llevo en mi corazón y en la persona que soy. No tengo palabras para agradecer todo lo que han hecho por mí ni el amor tan incondicional que me han dado a lo largo de toda mi vida. Son mi amor infinito y soy la persona más afortunada por tenerlos a mi lado.

And finally, the biggest thank you belongs to Gabo, my husband and best friend. Gracias por siempre estar y por tu apoyo infinito. Siempre has creído en mí, mucho antes de que yo creyera en mí misma. Me diste fuerzas para luchar por este sueño. Gracias por elegir estar cada día, por tu amor incondicional. No hay palabras para agradecerte lo suficiente por haber decidido acompañarme no solo en este proceso, sino también por haber elegido pasar toda la vida juntos.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

CPGs Clinical Practice Guidelines

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-analysis

OR Odds Ratio

logOR Logarithm of Odds Ratio

REML Restricted Maximum Likelihood

TUG Timed Up and Go

BBS Berg Balance Scale

BBT Better Balance Test

HVLT Hopkins Verbal Learning Test

COP Center of Pressure

ML Mediolateral

AP Anteroposterior

ST Single-task

DT Dual-task

BMI Body Composition Analysis

FM Fat Mass

FMi Fat Mass Index

FFM Fat-Free Mass

FFMi Fat-Free Mass Index

BIS Bioimpedance spectroscopy

Chapter 1: Are We Falling Short? Evaluating the Accuracy of Common Clinical Fall Risk Assessments in Stroke Survivors: A Systematic Review and Meta-Analysis

Abstract

Background: Stroke survivors experience significant fall risk, with 73% falling within the first year post-stroke. However, conflicting findings exist regarding the diagnostic accuracy of commonly used clinical assessment tools in correctly identifying those at risk of falling. This systematic review and meta-analysis evaluated the diagnostic accuracy of the Timed Up and Go (TUG) and the Berg Balance Scale (BBS) in stroke survivors. **Methods:** Web of Science, PubMed, SPORTDiscus, and Ovid MEDLINE databases were searched from inception to March 2025. **Results:** Thirteen studies comprising 1,347 stroke survivors were included. Stroke survivors classified as high fall risk by the BBS had a higher odds ratio (OR = 5.13, 95% CI [3.27, 8.05]; $p < 0.001$) of being true fallers compared to those classified as low fall risk. Similarly, those classified as high fall risk by the TUG had a higher odds ratio of being true fallers (OR = 3.38, 95% CI [2.23, 5.14]; $p < 0.001$). Moderate heterogeneity was observed for both assessments (BBS: $I^2 = 51.34\%$; TUG: $I^2 = 38.69\%$). The limited number of eligible studies precluded formal subgroup analyses by stroke chronicity and clinical setting, which may have contributed to the observed heterogeneity. **Conclusion:** Both the TUG and BBS demonstrate statistically significant discriminative ability for identifying fall risk in stroke survivors; however, the moderate heterogeneity observed across studies suggests that neither should be relied upon as a standalone fall risk screening tool. They

are best used as components of a broader, multifactorial fall risk assessment framework in stroke rehabilitation.

Funding: None declared.

Systematic Review Registration PROSPERO registration number CRD420251004460

1. Introduction

Stroke is a major global health concern, affecting approximately 15 million people worldwide each year (Chohan SA, 2019). In the United States alone, every 40 seconds, someone suffers from a stroke, making it one of the leading causes of death and long-term disability in the country (Benjamin EJ, 2017). The neurological damage from stroke often results in multiple stroke-related impairments that significantly contribute to reduced balance and fall risk, including neuromuscular weakness, lack of multisensory integration, reduced attention, and deficits in vision and spatial awareness (Denissen S, 2020; Smania N, 2008). Consequently, 7% of stroke survivors experience a fall in the first week and 73% in the first year post-stroke (Abdollahi M, 2022).

In light of the above, stroke survivors are three times more likely to experience a fall when compared with healthy individuals (Homann B, 2013). Falls can lead to serious consequences, including fractures, reduced quality of life, prolonged length of hospital stays, and a heavy financial burden (Chen K, 2024). Moreover, individuals with a history of falls are more susceptible to future falls and increased mortality (Khan F, 2021). This makes fall prevention a significant economic and healthcare priority in this population, highlighting the importance of clinical assessment tools and tests to specifically evaluate fall risk in stroke survivors, which are critical for high-quality, effective rehabilitation and preventing future falls (Abdollahi M, 2024; Dos Santos RB, 2023).

Clinical assessment tools have the purpose of providing objective and reproducible data that can inform diagnosis and treatment planning, predict outcomes and/or prognosis, and monitor individual progress over time (Dos Santos RB, 2023; Moore JL, 2018). Despite these clear objectives, clinicians currently use more than 27 different tests, tools, and instruments to assess fall risk in stroke survivors (Dos Santos RB, 2023). This overabundance and inconsistency present a challenge to correctly inform clinical practice guidelines (CPGs). It complicates decision-making when selecting appropriate assessment tools. Moreover, standardized assessments are an essential element of evidence-based rehabilitation (Agyenkwa SK, 2020). However, in this case, the lack of standardization across tests complicates the comparison of outcomes and the identification of the most effective intervention (Montero-Odasso M, 2022).

In 2023, Dos Santos et al. reviewed the most commonly used tools in current CPGs for stroke survivors worldwide (Dos Santos RB, 2023). Among the 19 CPGs included in the review, the most frequently used were the Timed Up and Go (80%), the Berg Balance Scale (90%), the 6-Minute Walk Test (80%), and the 10-Meter Walk Test (70%) (Dos Santos RB, 2023). However, some groups have raised concerns regarding the diagnostic accuracy of these tests, specifically their sensitivity and specificity in differentiating between fallers and non-fallers, suggesting that clinicians should exercise caution in their application (Barry E, 2014; Harris JE, 2005).

Findings suggest that common stroke assessment tools may overestimate or miscategorize fall risk (Barry E, 2014; Pimenta C, 2022). Categorizing patients as high fall risk when they are not at risk leads to unwarranted additional assessments and interventions (Lafontant K, 2024). Perhaps more concerning, misclassification can create an elevated fear of falling, potentially reducing their independence and discouraging them from engaging in activities they are fully capable of performing (Hauer K, 2020). In contrast, other groups have shown that common stroke assessment tools have excellent interrater reliability (Regan E, 2020). They are easy to administer and serve as an effective clinical tool for assessing functional mobility and balance (Maeda N, 2015). Given the conflicting findings on the sensitivity and specificity of the most commonly used fall risk assessment tools and their critical role in fall prevention strategies for stroke survivors, a more comprehensive evaluation of their diagnostic efficacy is necessary.

This systematic review and meta-analysis aim to evaluate the sensitivity and specificity of the most commonly used clinical assessment tools for identifying fall risk in stroke survivors. The findings of this study will: 1) inform current CPGs whether existing tests demonstrate sufficient diagnostic accuracy to predict fall risk and guide rehabilitation interventions and outcomes accurately; 2) determine which of these assessments tools demonstrate the highest sensitivity and specificity, potentially establishing it as a standard across CPGs; and 3) evaluate whether the observed diagnostic accuracy of these tools is sufficient and consistent enough to support their standardized clinical application across CPGs for stroke survivors, and if not, to identify the specific limitations that warrant the development of a more objective, stroke-specific fall risk assessment.

2. Methods

A systematic search was conducted in accordance with the updated Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines (Page MJ, 2021). The protocol was registered in the International Prospective Register of Systematic Reviews (https://www.crd.york.ac.uk/PROSPERO/; Unique identifier: CRD420251004460).

Search Strategy and Study Selection

An electronic search was conducted by the lead author (MMV) in several electronic databases, including Web of Science, PubMed, SportDiscuss, and Ovid MEDLINE from inception to March 2025. Additionally, the reference list of all eligible studies was manually searched to identify any additional relevant studies not captured by the electronic search. The search terms were prepared by the lead author (MMV) using Boolean operators in the following format: ((Stroke OR Cerebrovascular OR CVA) AND (Accidental fall* OR fall* OR fall risk OR fall prevention OR fall assessment*) AND (postural sway OR postural control OR postural balance OR dynamic balance OR static balance) AND (risk assessment OR balance test OR balance assessment OR balance measure OR clinical measure* OR Timed Up and Go OR TUG OR Berg Balance OR BBS OR 6 Minute Walk Test OR 6MWT OR 10 Meter Walk Test or 10MWT) AND (sensitivity OR specificity OR measurement properties OR psychometric OR predictive value OR multivariate analysis)).

Two reviewers independently screened the titles and abstracts of all remaining studies to determine their eligibility. After removing studies irrelevant to the research questions, full-text articles of potentially eligible studies underwent a second independent screening. Any disagreements between reviewers were resolved through discussion and consensus. This systematic review and meta-analysis included studies that met the following criteria.

Inclusion and Exclusion Criteria

Studies were included if they (a) were articles published in English or Spanish; (b) participants with a medical diagnosis of stroke without any other neurological or musculoskeletal condition; (c) included the outcome of at least one of the following tests: (1) Timed Up and Go; (2) Berg Balance Scale; (3) 10-Meter Walk Test; (4) 6-Minute Walk Test; and (d) provided sufficient data to calculate effect size (e.g., number of true fallers, number of true non-fallers, sensitivity and specificity of the test). Studies classified as case reports, articles presented at conferences, systematic reviews, or meta-analyses were excluded from the analysis.

Data extraction

The lead author (MMV) systematically extracted relevant information from all included studies using Microsoft Excel (Microsoft Corporation, Redmond, WA, USA, version 16.88). The data extracted included authors, year of publication, study design, sample size (total fallers and non-fallers), diagnostic performance metrics (sensitivity and specificity, true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)), and participants' demographics (e.g., affected side, sex, and age).

For studies that did not directly report the contingency table values (TP, TN, FP, FN), we derived these values from the reported sensitivity and specificity, and the known number of true fallers and non-fallers. TP were calculated as the product of sensitivity and the total number of fallers. TN were calculated as the product of specificity and the total number of non-fallers. FP were derived by multiplying the complement of specificity (1-specificity) by the total number of non-fallers. Finally, FN were calculated by subtracting the TP from the total number of fallers (Parikh R, 2008).

Statistical analysis

The effect size for each study was calculated using the natural logarithm of odds ratio (logOR), along with its variance using the following formulas:

$$\text{logOR} = \ln (a*d / b*c) \qquad \text{Equation 1}$$

$$\text{logOR variance} = 1/a + 1/b + 1/c + 1/d \qquad \text{Equation 2}$$

Where a represents the number of true positives, b represents the number of false positives, c represents the number of false negatives, and d represents the number of true negatives. To facilitate the interpretation of the results, logOR and its confidence intervals were back-transformed into OR for all interpretations using the following formulas (Higgins JPT, 2008):

$$\text{OR} = \exp^{(\text{logOR})} \qquad \text{Equation 3}$$

$$\text{OR 95\% CI} = \exp^{(\text{CI lower bound})} \text{ and } \exp^{(\text{CI upper bound})} \qquad \text{Equation 4}$$

An OR greater than 1 indicates that the clinical tests effectively discriminate between falls and non-fallers, with higher values reflecting stronger discriminative ability. To address the statistical non-independence of effect size from studies contributing to both tests, separate random-effects meta-analyses were conducted for the BBS (10 studies) and TUG (8 studies). For Fiedorová et al. (2022), who reported two optimal BBS cut-off values, the cut-off of 42 points was selected as it most closely approximates the standard clinical BSS threshold reported across the included studies.

Both meta-analyses used a weighted random-effects model with the restricted maximum likelihood estimator (REML) (Higgins JP, 2003). The heterogeneity across included studies was quantified using the estimated tau-squared (τ^2) value, representing the variance of the true effect sizes (Deeks JJ, 2019). The I^2 statistic was also calculated to determine the percentage of total variability attributable to heterogeneity (Ariel de Lima D, 2022; Deeks JJ, 2019). A Q-test was conducted to assess the presence of heterogeneity, with its associated p-value indicating whether the observed heterogeneity was statistically significant (Ariel de Lima D, 2022; Deeks JJ, 2019). Additionally, a between-group heterogeneity test was performed to evaluate whether the pooled diagnostic accuracy differed significantly between the BBS and TUG. Meta-regression analyses examined whether cut-off values significantly moderated diagnostic accuracy for each test separately. The model results were reported as the estimated effect size (OR), standard error (SE), z-value, and p-value. The 95% confidence interval (CI) for the effect size was calculated to provide a range of plausible values. All statistical analyses were performed in R (version 4.4.2) using the metafor package.

Sensitivity Analysis and Risk of Bias

We evaluated publication bias using Egger's weighted regression test. Moreover, funnel plot asymmetry was assessed through a rank correlation test. To determine the robustness of the results, we conducted a leave-one-out sensitivity analysis by systematically removing each study individually from repeated meta-analyses to evaluate its impact on the overall findings.

Quality Assessment

Methodology quality of the included studies was assessed by the lead author (MMV) using the QUADAS-2 tool (Quality Assessment of Diagnostic Accuracy Studies, version 2) (Whiting PF, 2011).

3. Results

Search Results

Our search strategy identified 815 studies across Web of Science, PubMed, SPORTDiscus, and Ovid MEDLINE. Additionally, reference lists of all full-text articles reviewed for eligibility were manually searched to identify studies not captured by the electronic database search, yielding an additional 84 records, for a total of 899 studies. Following the removal of 255 duplicates, 674 remained for title and abstract screening. Following title and abstract screening, 138 studies were selected for full-text review. Of the remaining studies, only 13 were eligible for data extraction, as detailed in Fig. 1. Two studies were excluded at the full-text review stage because they used functional ability rather than fall occurrence as the reference standard, which did not meet the pre-specified inclusion criteria: Lee et al. (2016) and Chinsongkram et al. (2014) (Chinsongkram B, 2014; Lee G, 2016). Of these 13 studies, five exclusively evaluated the Berg Balance Scale (Ashburn A, 2008; Beninato M, 2009; Fiedorová I, 2022; Maeda N, 2009; Sahin IE, 2019), three focused on the Timed Up and Go (Lee KB, 2021; Pinto EB, 2014; Yang L, 2016), and five examined both tests (Table 1) (Andersson AG, 2006; Jalayondeja C, 2014; Liu TW, 2019;

Persson CU, 2014; Tsang CS, 2013). Furthermore, our search identified only five studies examining the diagnostic accuracy of the 6-Minute and 10-Meter Walk Tests. Of these, two studies evaluated only the 6-Minute Walk Test, two evaluated only the 10-Meter Walk Test, and one evaluated both tests, resulting in three studies per test. All five studies met the inclusion criteria; however, a minimum of 5 studies is recommended to conduct a meta-analysis (Myung, 2023), and studies that used only these tests were excluded from the final analysis.

INSERT FIGURE 1

INSERT TABLE 1

Study Characteristics

This systematic review analyzed data from 1,347 stroke survivors across the 13 included studies (Table 2). The demographic and clinical characteristics presented are based solely on variables that were reported in the studies. Among participants, 33.9% experienced falls, and 66.1% were non-fallers. Participants had a mean age of 64 years, with 60.1% males and 39.9% females. Regarding stroke lateralization, 49.8% suffered a right hemisphere stroke, 49.3% had a left hemisphere stroke, and 0.9% presented bilateral or unspecified stroke side.

INSERT TABLE 2

Study designs varied across the included studies (Table 3). Six studies employed a prospective cohort design, while seven used a retrospective cross-sectional approach. Settings were predominantly community-based (n = 7) or inpatient rehabilitation units (n = 5), with one study conducted in an outpatient clinical setting. Follow-up duration ranged from none in cross-sectional studies relying on retrospective fall recall to 12 months in prospective studies. Fall definitions were inconsistent across studies: nine studies provided an explicit definition of a fall, whereas four did not formally define the outcome and relied instead on participant self-report. Fall ascertainment methods similarly varied, including prospective falls diaries, telephone follow-up, staff-reported incident documentation, and retrospective self-reported questionnaires.

INSERT TABLE 3

Meta-analysis

A separate weighted random-effects model using the REML method was fitted to estimate the pooled diagnostic accuracy of the TUG and BBS for correctly identifying fallers and non-fallers among stroke survivors. Studies contributing data for both assessments were analyzed independently within each model to preserve statistical independence of effect sizes.

The BBS analysis included 10 studies (Fig. 2). The overall effect indicated that stroke survivors classified as high fall risk by the BBS had higher odds (OR = 5.13, 95% CI [3.27, 8.05], $p < 0.001$) of being true fallers when compared with those classified as low fall risk. However, significant heterogeneity was observed across studies ($Q(9) = 18.10$, $p = 0.034$; $\tau^2 = 0.260$; $I^2 = 51.34\%$), indicating that approximately 51% of the variance in effect sizes was attributable to true heterogeneity rather than sampling variability.

INSERT FIGURE 2

The TUG analysis included 8 studies (Fig. 3). The overall effect similarly indicated that stroke survivors classified as high fall risk by the TUG had higher odds of being true fallers when compared with those classified as low fall risk (OR = 3.38, 95% CI [2.23, 5.14], $p < 0.001$). Heterogeneity across studies was not significant (Q (7) = 12.22, $p = 0.094$); however, the between-study variance estimate ($\tau^2 = 0.139$) and I^2 statistic (38.69%) indicated moderate heterogeneity across the included studies.

INSERT FIGURE 3

A between-subgroup heterogeneity test demonstrated no statistically significant difference in pooled diagnostic accuracy between the BBS and the TUG (Q_m (1) = 1.28, $p = 0.257$), indicating that neither assessment demonstrates superior discriminative ability over the other. Furthermore, a meta-regression analysis examining whether cut-off values significantly moderated diagnostic accuracy demonstrated no significant effect for either the BBS (Q_m (1) = 0.120, $p = 0.729$) or the TUG (Q_m (1) = 0.564, $p = 0.453$).

Sensitivity Analysis and Risk of Bias

Publication bias was assessed separately for each test. For the BBS, Egger's weighted test (t(8) = 1.467, $p = 0.181$) and the rank correlation test ($\tau = 0.244$, $p = 0.381$) indicated no significant funnel plot asymmetry (Fig. 4). Similarly, for the TUG, Egger's weighted test (t(6) = −0.269, $p = 0.797$) and the rank correlation test ($\tau = -0.143$, $p = 0.720$), indicated no significant funnel plot asymmetry (Fig. 5). These findings suggest the absence of publication bias in the analyzed studies. Sensitivity analysis, conducted through leave-one-out analysis, revealed that none of the studies had a significant influence on the pooled effect size for either BBS or the TUG.

INSERT FIGURE 4

INSERT FIGURE 5

Quality Assessment

Results of the QUADAS-2 assessment are presented in Figure 6. Risk of bias in the index test was the most prevalent concern, rated high in 11 of 13 studies (85%), primarily because cut-off values were not pre-specified but were derived from post hoc ROC analysis of the same dataset, and assessor blinding to fall status was rarely reported. Patient selection bias was high in 6 studies (46%) and low in the remaining 7 (54%). Risk of bias in the reference standard domain was high in 6 studies, unclear in 3 (23%), and low in 4 (31%). Flow and timing risk was unclear in 7 studies (54%). Applicability concerns were low across all three domains in nearly all included studies, except for Beninato et al. (2009), which received an unclear rating in the reference standard applicability domain.

INSERT FIGURE 6

4. Discussion

This systematic review and meta-analysis evaluated the diagnostic accuracy of the most commonly used clinical assessment tools— the Timed Up and Go test and Berg Balance Scale—for identifying fall risk among stroke survivors. Our key findings were: 1) over one-third (33.9%) of stroke survivors experience a fall; 2) both the Timed Up and Go and the Berg Balance Scale demonstrated statistically significant discriminative ability for identifying fall risk in stroke survivors; 3) moderate heterogeneity was observed across studies for both tests, which was not explained by variability in cut-off values and may instead be related to broader methodological differences in fall ascertainment methods, follow-up duration, and clinical setting across the included studies.

Demographic and Clinical Characteristics

We analyzed data from 13 papers with a total of 1,347 stroke survivors with a mean age of 64 ± 6 years (see Table 2). The sex distribution (60.1% male, 39.9% female) aligns with other findings, where men generally have a higher stroke incidence at young ages (45-74 years) (Ospel J, 2023). However, as age increases, the difference is inverted, with females experiencing a higher incidence and mortality rate above 74 years of age (Ospel J, 2023). The relatively balanced distribution of stroke lateralization (49.8% right hemisphere, 49.3% left hemisphere) reduces the overrepresentation of either hemisphere stroke. This is particularly important as hemispheric specialization influences balance and mobility. For example, a stroke in the right hemisphere often affects spatial awareness, left-sided neglect, and visual-spatial areas (Osawa A, 2021). In contrast, a stroke in the left hemisphere may have a greater impact on movement planning, sequencing, and language (Peters S, 2015). The fall incidence of 33.9% observed across studies is consistent with previous findings reporting fall rates between 25-44% during the first year post-stroke (Divani AA, 2009).

Study characteristics

The included studies spanned multiple phases of stroke recovery. Acute-phase studies were mostly conducted in inpatient settings shortly after stroke onset, while subacute and chronic studies included both inpatients and community-dwelling survivors at varying time points post-stroke (see Table 3). This variability in stroke chronicity and clinical settings should be considered when interpreting the pooled estimates, as the functional demands and fall risk profiles of stroke survivors differ substantially across recovery phases. Accordingly, acute stroke survivors tend to present with more severe postural control impairments when compared with those in the chronic phase (Khan F, 2021). Moreover, the rate of clinical recovery is considered relatively rapid during the first weeks post-stroke, but spontaneous recovery has substantially slowed by 3 to 6 months, with only minor, measurable improvements in motor function typically observed beyond this window (Lee KB, 2015). This progression in balance impairment severity across recovery phases means that the discriminative performance of the BBS and the TUG may differ substantially depending on when the assessments were administered. While a moderator or meta-regression analysis would have been useful for further identifying study grouping by stroke chronicity and clinical settings, we did not have enough studies to properly perform or interpret these tests (Higgins JPT, 2008).

The definition of a fall and the method of fall ascertainment also varied considerably across the included studies. While most studies defined a fall as *“an unintentional event resulting in coming to rest on the ground or a lower level, that was not the result of a seizure, stroke, or overwhelming external force”*, four studies did not provide an explicit fall definition. Fall ascertainment methods also ranged from prospective approaches such as falls diaries, staff observation, and telephone follow-up, to retrospective self-reported questionnaires. This methodological variability in how fallers were identified and classified across studies is important to consider when interpreting the reported sensitivity and specificity values, as differences in fall definitions and assessment methods may influence the proportion of participants classified as fallers within each study, thereby affecting the diagnostic accuracy estimates contributed to the pooled analysis.

Meta-analysis

Our meta-analysis found that both the BBS and the TUG demonstrated statistically significant discriminative ability for identifying fall risk in stroke survivors. Stroke survivors classified as high fall risk by the BBS had higher odds of being true fallers when compared with those classified as low fall risk (OR = 5.13, 95% CI [3.27, 8.05], $p < 0.001$). Similarly, stroke survivors classified as high fall risk by the TUG had higher odds of being true fallers when compared with those classified as low fall risk (OR = 3.38, 95% CI [2.23, 5.14], $p < 0.001$). Neither assessment demonstrated superior diagnostic accuracy over the other ($Q = 1.28$, $p = 0.257$). While these findings indicate that both assessments can meaningfully differentiate between fallers and non-fallers, statistical significance alone does not establish clinical sufficiency. The moderate heterogeneity observed across studies, combined with the limitations of these tools in capturing the full complexity of post-stroke balance impairments, suggests that neither assessment should be relied upon as a standalone fall risk screening tool in stroke rehabilitation. These findings support their continued use as part of a broader clinical assessment framework; however, their utility is substantially limited by inconsistent diagnostic accuracy across clinical settings, which was not explained by the cut-off thresholds and likely reflects broader methodological differences across the included studies, such as fall ascertainment methods, follow-up duration, stroke chronicity, and clinical setting.

It is important to note that neither the TUG nor the BBS was originally designed as a fall risk assessment tool. The BBS was developed as a measure of functional balance, and the TUG as a measure of functional mobility (Miranda N, 2023; Podsiadlo D, 1991). Moreover, these tests were not explicitly created for stroke survivors but were initially developed for older adults and later applied to the stroke population (Berg KO, 1992; Blum L, 2008). Even among older adults without diagnosed neurological disorders, the Timed Up and Go and the Berg Balance Scale demonstrate limited diagnostic accuracy as standalone fall risk assessments (Barry E, 2014; Lima CA, 2018). Their application to the stroke population introduces additional complexity, as balance impairment following stroke extends beyond motor dysfunction to include perceptual and cognitive impairments (VanGilder JL, 2020), which neither assessment was designed to capture. Furthermore, these tests do not address the underlying mechanisms necessary for maintaining balance (Rose DJ, 2006), specifically the contributions of the visual, vestibular, and proprioceptive systems (Chagdes JR, 2009). Stroke survivors experience damage to all three sensory systems, with proprioception being affected in 11-85% of the stroke patient population (Chae SH, 2017). The broad variability in reported proprioceptive impairments reflects differences in assessment methods, stroke severity, and time since stroke, underscoring the heterogeneity of sensory deficits in this population and the consequent difficulty of applying a single standardized threshold across studies. Without evaluating these distinct sensory systems, clinicians cannot identify the nature of the balance deficit or understand which specific postural control mechanism is compromised (Mancini M, 2010).

It is also important to consider that falls in stroke survivors are multifactorial in nature. While the present review focuses on balance and mobility assessments, the broader fall literature has long recognized that fall risk is influenced by a range of factors beyond motor and sensory impairment, including the degree of neurological deficit, mental status, environmental fall-related risk, and medication (Djurovic, 2021; Novitzke, 2008).

The TUG and BBS, as motor-functional assessments, do not capture this broad complexity, which may further limit their standalone utility as fall-risk screening tools in clinical practice. A comprehensive fall risk assessment in stroke survivors should therefore extend beyond performance-based balance and mobility measures to incorporate multifactorial screening approaches that address the full spectrum of contributing risk factors.

Our between-subgroup analysis found no statistically significant difference in diagnostic accuracy between the TUG and the BBS ($Q_m = 1.28$, $p = 0.257$), indicating that both assessments demonstrate comparable discriminative ability for identifying fall risk in stroke survivors, and that selecting one over the other is unlikely to meaningfully impact fall risk classification in clinical practice. Publication bias assessments using Egger's weighted regression test, and the rank correlation test indicated no significant funnel plot asymmetry for either the BBS or the TUG, suggesting that publication bias did not substantially influence the observed effect sizes. Additionally, our leave-one-out sensitivity analysis, which systematically removed each study individually to evaluate its impact on the overall results, confirmed that no single study had a significant influence on the pooled effect size for either the BBS or the TUG, further strengthening the robustness of our findings.

These findings collectively suggest that while the BBS and the TUG demonstrate meaningful discriminative ability for identifying fall risk in stroke survivors, they should not be used as standalone assessments in clinical practice. Rather, these assessments should be incorporated as screening components within a broader, multifactorial fall risk assessment framework that accounts for the neurologically complex nature of postural control deficits in this population. Emerging objective, technology-based approaches, including wearable inertial sensors, force plates, and machine learning, have shown promise for providing more complete and individualized fall-risk stratification in stroke survivors (Abdollahi M, 2022). Future research and CPGs should prioritize integrating these approaches with validated clinical assessments to improve fall-risk classification in stroke rehabilitation.

Despite our comprehensive search using multiple databases, we identified only 13 eligible studies, which may limit the generalizability of our findings. This relatively small number of studies available for each analysis restricted our ability to conduct formal subgroup or meta-regression analyses to further identify study groupings. The included studies spanned acute, subacute, and chronic stroke survivors, with several studies enrolling participants across multiple recovery phases or reporting mixed samples, further precluding clear categorization for subgroup analysis by stroke chronicity. Furthermore, four studies did not provide an explicit definition of fall, introducing additional inconsistency in outcome measurement across the included studies. Stroke lateralization was not reported in 4 of 13 studies, and sex distribution was not reported in 1 of 13 studies. This level of missing data is a significant limitation, hindering our ability to examine hemispheric lateralization as a potential moderator of diagnostic accuracy in this population. We were also unable to assess the diagnostic accuracy of the 6-Minute Walk Test and 10-Meter Walk Test due to an insufficient number of eligible studies; future research should prioritize examining these assessments in stroke survivors.

Conclusion

In summary, this systematic review and meta-analysis provide evidence that both the Timed Up and Go test and the Berg Balance Scale demonstrate statistically significant discriminative ability for identifying fall risk in stroke survivors. However, the moderate heterogeneity observed across studies, combined with the inherent limitations of these tools in capturing the full neurological complexity of post-stroke balance impairment, suggests that neither assessment should be relied upon as a standalone fall risk screening tool in clinical practice. Clinicians should use these assessments as part of a broader, multifactorial fall risk assessment framework that addresses the sensory, motor, and cognitive contributors to fall risk in this population. Future research should prioritize developing stroke-specific fall-risk assessment tools and integrating emerging technology-based approaches, including wearable sensors, force plates, and machine-learning models, alongside validated clinical assessments to improve fall-risk classification and prevention in stroke rehabilitation.

ACKNOWLEDGMENTS

The authors would like to thank Mr. Santamaria-Guzman for serving as the second reviewer during data screening and the Auburn University Librarians for their guidance throughout the comprehensive literature search.

CONFLICT OF INTEREST

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Chapter 2: Mechanisms of Multisensory Interaction During Dual-Task Postural Control in Aging: I. Stable Surface.

1. Introduction

Falls affect 36 million older adults each year in the United States, making them the leading cause of injury-related death and a significant predictor of disability (Giovannini S, 2022; Shankar KN, 2023). Falls also represent the largest category of preventable adverse events (Dykes PC, 2023). Many of these risks arise from age-associated declines in strength, mobility, and the efficiency of multisensory interaction, defined as the process by which the nervous system dynamically weights visual, vestibular, and proprioceptive inputs to adapt to task and environmental constraints (Awosika OO, 2023; Brech GC, 2022; de Barros GM, 2021; Huxhold O, 2006; Mahoney JR, 2019). Among these environmental factors, surface stability significantly impacts postural control (Promsri A, 2024). Stable surfaces provide consistent sensory feedback and require minimal neuromuscular effort, allowing postural control to be maintained through efficient stability mechanisms that primarily rely on proprioceptive (70%), visual (10%), and vestibular (20%) information (Horak, 2006; Horak FB, 1986). On the other hand, unstable surfaces require greater multisensory integration and neuromuscular adaptation, primarily by challenging proprioceptive input and increasing reliance on visual and vestibular information to maintain postural control (Horak, 2006; Promsri, 2023; Promsri A, 2020). These surface-dependent demands become particularly relevant when balance must be maintained while performing concurrent cognitive or motor tasks.

Traditionally, age-associated postural instability has been attributed to declines in sensory and motor function. However, deficits in attentional allocation may exacerbate these sensory-motor declines, further increasing the risk of falls in older adults (Woollacott M, 2002). This becomes particularly pronounced during everyday activities that involve dual-tasking, where competing attentional demands challenge the integration of multisensory information (Huxhold O, 2006; Woollacott M, 2002). Maintaining postural control is attentionally demanding, and these demands increase with the complexity of both the postural task and any concurrent tasks (Woollacott M, 2002). In younger adults, multisensory interaction during dual-tasking is largely automatic, allowing balance to be preserved with minimal conscious effort (de Barros GM, 2021; Wang J, 2024). In contrast, reduced postural automaticity in older adults results in greater attentional costs and limited cognitive resources when postural control must be maintained alongside a suprapostural task, defined as any attentionally demanding voluntary task performed while maintaining postural control (de Lima, 2010; Wang J, 2024). Suprapostural tasks can be categorized as cognitive, such as memory, reaction time, or mental tracking that redirect attention externally, allowing more automatic postural control (Polskaia N, 2015; Rafiee Manesh V, 2024), or motor, such as tasks that mechanically challenge a primary sensory input while simultaneously requiring the motor system for postural control (Weeks DL, 2003). While both tasks compete for attentional resources, they may challenge postural control through different mechanisms. Hence, the dual-task paradigm has been widely investigated as a potential biomarker for fall risk (Bayot M, 2020; Choi JH, 2015). Despite its clinical significance, research on dual-task effects on postural control has yielded conflicting findings (Woollacott M, 2002; Yu SH, 2017). Some groups report decreased postural control under dual-task conditions (Motealleh A, 2021; Shim S, 2012). While others find that postural control either improves or remains unperturbed (Ghai S, 2017; Salihu AT, 2022). Moreover, the specific sensory patterns that enable older adults to adapt or fail to adapt during dual-task conditions remain poorly understood.

Linear center of pressure (COP) measurements, while considered the gold standard for assessing fall risk (Goble & Baweja, 2018a), reduce a rich physiological signal to a single measure of total sway displacement (cm). This approach overlooks the signal's time-frequency structure and provides limited insights into which sensory systems contribute to postural control or how those contributions shift under specific task demands (Chagdes JR, 2009). Time-frequency analyses of the COP signal can differentiate task-, age-, and disease-associated differences in postural control, with most of the diagnostically meaningful information occurring below 4 Hz (Meyer Vega M, 2026; Meyer-Vega et al., 2025). Within this range, modulation of low-frequency oscillations is believed to reflect sensory reweighting among visual (0-0.1 Hz), vestibular (0.1-0.5 Hz), and proprioceptive (0.5-1 Hz) inputs (Baltich J, 2014; Cavanaugh JT, 2007; Chagdes JR, 2009; Jafari H, 2023; Redfern MS, 2001). An increase in power within a specific frequency band suggests greater reliance on the corresponding sensory system, while a decrease may reflect reduced contribution. For example, decreased power in the visual range (0-0.1 Hz) combined with increased power in the vestibular (0.1-0.5) and proprioceptive bands (0.5-1 Hz) may indicate a greater reliance on vestibular and proprioceptive inputs when vision is unavailable, consistent with the idea of sensory reweighting (Chagdes JR, 2009). Moreover, we have found that the functional relation between low-frequency oscillatory modulation and total COP sway displacement, referred to as oscillatory-sway coupling, provides a mechanistic index of whether low-frequency sensory corrections are effectively translated into organized postural output across aging and neurological populations (Meyer Vega M, 2026; Meyer-Vega et al., 2025).

Given the inconsistencies in the literature regarding the effects of dual-task demands on postural control in older adults, the purpose of this study was to characterize age-associated changes in sensory reweighting during dual-task conditions on a stable surface. Since stable surface standing primarily relies on proprioceptive input, we hypothesize that dual-task conditions would increase reliance on proprioceptive input, revealing age-associated differences in postural sway dynamics. Characterizing age-associated changes in multisensory interaction may improve the understanding of the mechanisms underlying postural control during everyday tasks and contribute to fall risk in older adults. These findings could inform the development of personalized rehabilitation strategies and clinical diagnostics to help maintain independence and quality of life in this population.

2. Methods

Participants

One hundred and two participants, 51 young adults (YA; 26 ± 6 years old) and 51 older adults (OA; 70 ± 7 years old), participated in this cross-sectional observational study (see Table 4). Inclusion criteria were as follows: 1) healthy young adults aged 18-35 or older adults aged 60+ years; 2) no diagnosed history of neurological or musculoskeletal conditions; 3) no acute injuries affecting their ability to stand within the last six months; and 4) ability to perform simple motor and cognitive tasks. Exclusion criteria included: 1) difficulty understanding or following simple verbal instructions; 2) inability to complete standing tasks safely; 3) any medical conditions that could compromise safety during the balance testing; and 4) current pregnancy.

This study was approved by the Auburn University Institutional Review Board (Protocol #STUDY00000880) and followed the latest revisions of the Declaration of Helsinki, except for being pre-registered as a clinical trial, given that this was a cross-sectional investigation. All participants provided written informed consent before participating in the study.

INSERT TABLE 4

Equipment

Postural sway was assessed using the Balance Tracking System BTrackS (Balance Tracking Systems, San Diego, CA, USA), which includes a force plate (BTrackS Balance Plate) and accompanying software. The BTrackS has been validated as a reliable tool for acquiring COP data related to postural sway (Goble et al., 2019; O'Connor et al., 2016;

Richmond et al., 2018). COP data were sampled at 25 Hz, as specified by the manufacturer, and stored on a local PC for offline analysis.

Experimental Protocol

All participants completed a single session lasting approximately 1 hour. Each participant began the session with an explanation, demonstration, and familiarization with the testing equipment and protocol. A 5-minute rest period was provided between conditions. Moreover, all participants performed two single-task and three dual-task conditions on a stable surface. Auditory tones marked the beginning and end of each task. Each participant completed a 20-second trial for each condition with their eyes open.

Single-task conditions: These control conditions established baseline performance for each task component, ensuring that the observed changes during dual-tasking reflect the interaction between postural control and secondary-task demands rather than limitations of the tasks themselves.

- **Balance single- task (Balance ST):** Participants were asked to stand as still as possible on the force plate with their hands on their hips, feet shoulder-width apart, and eyes directed straight ahead (Fig. 7.1).
- **Cognitive single-task (Cognitive ST):** Participants performed the verbal memory encoding and recall task while comfortably seated. During the first 10 seconds, participants memorized the first five words from one of the Hopkins Verbal Learning Test (HVLT; versions B, D, or F), followed by 10 seconds of silence (Fig. 7.2). At the end of the task, participants were asked to recall the words in the order presented. The HVLT is a brief, easy-to-administer instrument with established reliability and

discriminant validity, and is sensitive to age-associated declines in older adults (Brandt, 1991; Woods SP, 2005).

Dual-task conditions: These conditions were designed to assess the interaction between postural control and a secondary task simultaneously by requiring participants to maintain balance while performing a cognitive or motor task.

- **Cognitive dual-task (cognitive DT):** Participants were asked to stand as still as possible on the force plate while simultaneously completing a verbal memory encoding and recall task (Fig. 7.3). Participants heard the first five words from one of the HVLT versions (A, C, or E) (Brandt, 1991). The HVLT word list was presented during the first 10 seconds, followed by 10 seconds of silence for encoding. Immediately after the trial, participants were asked to recall the words in the order in which they were presented. We used a verbal memory encoding and recall task during the balance trial to negate the effects of vocal articulation on postural sway, as respiratory changes during vocalization have been shown to influence postural sway (Dault MC, 2003).
- **Proprioceptive (motor) dual-task (proprioceptive DT):** Participants were asked to stand as still as possible on the force plate while simultaneously performing the cervical joint-position task (AlDahas A, 2024). A lightweight headband with an attached laser pointer was placed on the participant’s head (Bae S, 2023). Participants were instructed to maintain the laser beam aligned with the center of the target throughout the trial (Fig. 7.4).

- **Multitask condition**: Participants were asked to stand as still as possible on the force plate while simultaneously performing both the verbal memory encoding and recall task and the cervical joint-position task (Fig. 7.5).

INSERT FIGURE 7

Data analysis

Data were acquired using the BTrackS Assess Balance software and analyzed offline using a custom-written MATLAB program (MathWorks™, Inc., Natick, MA, USA). The postural sway signal for each 20-second trial length was filtered using a 4^{th}-order Butterworth filter with a low cut-off of 4 Hz. The dependent variables were the anteroposterior, mediolateral, and total COP sway displacement (cm). Mediolateral (ML) and anteroposterior (AP) sway displacement were calculated using the following formulas (Goble & Baweja, 2018a):

ML = 24.25 ((TR+BR) – (TL+BL)) / (TL+TR+BL+BR) Equation 1

AP = 15.50 ((TL+TR) – (BL+BR)) / (TL+TR+BL+BR) Equation 2

Where TR, TL, BR, and BL are the sensor values from the top right, top left, bottom right, and bottom left corners of the force plate. The constant 24.25 represents half of the ML width of the BTrackS Balance Plate, while 15.50 represents half of the AP length. The total COP sway displacement is determined by the distance between successive registered COP locations according to the following formula:

Total sway displacement = $[(\mathrm{COP}_{x^2} - \mathrm{COP}_{x^1})^2 + (\mathrm{COP}_{y^2} + \mathrm{COP}_{y^1})^2]^{0.5}$ Equation 3

Where COP_{x2} and COP_{x1} are adjacent time points in the COP_x (mediolateral) time-series, and COP_{y2} and COP_{y1} are adjacent time points in the COP_y (anteroposterior) timeseries. The total COP sway displacement is then obtained by summing all these individual distances across the entire time series (Goble & Baweja, 2018a, 2018b).

In addition, continuous wavelet transform analyses were performed on the COP signal using a base MATLAB function developed by Torrence and Compo (available at: http://paos.colorado.edu/research/wavelets) (Torrence & Compo, 1998). As part of the analysis, the total COP was detrended using MATLAB's detrend function. The wavelet transform of the COP signal determines both the signal's amplitude-frequency characteristics and how its amplitude varies with time (Baweja et al., 2011). The wavelet represents a set of functions in the form of small waves created by dilations and translations from a simple generator function, which is called the mother wavelet: ψ *(t)* (Addison, 2002). To perform a wavelet transform, the Morlet mother wavelet was calculated according to the following formula (Torrence & Compo, 1998):

$$\Psi_0(t) = \pi^{-\frac{1}{4}} e^{i\omega o\eta} e^{\frac{-n^2}{2}} \qquad \text{Equation 4}$$

Where η dimensionless time and w_0 dimensionless frequency (in this study, we used w_0 = 6, as suggested by Grinsted and colleagues (Grinsted A, 2004). The Morlet wavelet (with w_0 = 6) is appropriate when performing wavelet analysis, since it provides a balance between time and frequency localization (Grinsted A, 2004). The wavelet transform applies the wavelet function as a band-pass filter to the time series. To modify its frequency content, the wavelet function is stretched in time by varying its scale(s) (dilation). For the Morlet wavelet used in this study, the wavelet scale is almost equal to the Fourier period (Fourier period = 1.03 s) and was calculated according to the following formula:

$$W(s,\tau)^X = \int X\,(t)\Psi^*_{s,\tau}(t)\;dt \qquad \text{Equation 5}$$

Where s represents the dilation parameter (scale shifting), τ represents the location parameter (time shifting), and the basic function $\Psi_{s,\tau}$ (t) is obtained by dilating and translating the mother wavelet Ψ_0 (t) (Addison, 2002). For statistical comparisons, the COP signal frequency data were first divided into 0-1, 1-2, and 2-4 Hz bands, and then into 0-0.1, 0.1-0.5, and 0.5-1 Hz bands. The dependent variable for the spectral analysis of the COP signal was the absolute peak wavelet power in the above bands (0-1, 1-2, and 2-4 Hz, and 0-1, 0.1-0.5, 0.5-1 Hz).

Statistical analysis

A two-way mixed ANOVA model (2 groups x 4 tasks) with repeated measures on all factors compared the mean differences from AP, ML, and total COP sway displacement. A three-way mixed ANOVA model (2 groups x 4 tasks x 3 frequency bands) compared the absolute wavelet power from 0 to 4 Hz. A similar model (2 groups x 4 tasks x 3 frequency bands) compared the absolute wavelet power from 0 to 1 Hz. Furthermore, a two-way ANOVA (2 groups x 3 tasks) compared the mean difference in cognitive task accuracy when the verbal memory task was administered while standing (on the stable force plate) during dual- and multitasking, and while sitting (off the force plate).

Any participant who exhibited values outside ±3 SD was excluded as an outlier (all participants in this manuscript exhibited values within ±3SD). All analyses were performed using IBM SPSS (SPSS Inc., version 29, Chicago, IL, USA), and graphs were created using SigmaPlot® (Inpixon Inc., version 15) and JMP® Statistical Discovery LLC. Appropriate post-hoc analyses were conducted to follow up on significant interactions from the ANOVA models. Multiple t-test comparisons were corrected using the Bonferroni corrections, and the alpha level for all statistical tests was at $p < 0.05$. Data are reported as mean ± SD in text and mean ± standard error of the mean (SEM) in the figures.

3. Results

Age-associated and task-dependent changes in postural sway

Anteroposterior sway displacement

The group main effect was significant (OA: 26.41 ± 5.86 cm, YA: 22.87 ± 1.58 cm; $F_{1,100} = 20.104$, $P < 0.001$, $\eta_p^2 = 0.167$), indicating that the OA group exhibited significantly greater AP sway displacement when compared with YA. The task main effect was significant (Balance ST: 25.53 ± 4.85 cm, Proprioceptive DT: 24.41 ± 5.02 cm, Cognitive DT: 24.67 ± 4.65 cm, Multitask: 23.94 ± 3.89 cm; $F_{3,300} = 13.579$, $P < 0.001$, $\eta_p^2 = 0.120$, Fig. 8A), indicating greater AP sway displacement in Balance ST when compared with all other tasks. Moreover, cognitive DT demonstrated greater AP sway displacement when compared with the multitask, whereas Proprioceptive and Cognitive DT did not differ from each other. All other main effects and interactions were not significant.

Mediolateral sway displacement

The task main effect was significant (Balance ST: 21.98 ± 1.3 cm, Proprioceptive DT: 21.57 ± 1.46 cm, Cognitive DT: 21.55 ± 1.32 cm, Multitask: 21.18 ± 1.06 cm; $F_{3,300} = 18.786$, $P < 0.001$, $\eta_p^2 = 0.158$; Fig. 8B), indicating greater ML sway displacement during Balance ST when compared with all other tasks. Similarly, proprioceptive DT and cognitive DT were significantly greater when compared with the multitask, whereas proprioceptive DT and cognitive DT did not differ from each other. The group x task interaction was significant

($F_{3,300}$ = 5.815, P <0.001, η_p^2 = 0.005). The OA group exhibited greater ML sway displacement in the multitask condition when compared with YA. All other main effects and interactions were not significant.

Total COP sway displacement

The group main effect was significant (OA: 16.89 ± 8.35 cm, YA: 11.81 ± 3.43 cm; $F_{1,100}$ = 19.596, P <0.001, η_p^2 = 0.164; Fig. 8C), indicating that the OA group exhibited significantly greater total COP sway displacement when compared with YA. The task main effect was significant (Balance ST: 16.17 ± 6.88 cm, Proprioceptive DT: 14.02 ± 7.32 cm, Cognitive DT: 14.36 ± 6.86 cm, Multitask: 12.83 ± 5.98 cm; $F_{3,300}$ = 24.514, P <0.001, η_p^2 = 0.197), indicating greater total COP sway displacement during Balance ST when compared with all other tasks. Similarly, proprioceptive DT and cognitive DT were both significantly greater when compared with the multitask, whereas proprioceptive DT and cognitive DT did not differ from each other. All other main effects and interactions were not significant.

INSERT FIGURE 8

Age-associated increases in low-frequency oscillations

<u>Wavelet power spectrum of the COP signal from 0-4 Hz</u>

Anteroposterior 0-4 Hz wavelet power

The task main effect was significant (Balance ST: 6.15 ± 15.92 cm^2, Proprioceptive DT: 10.51 ± 31.19 cm^2, Cognitive DT: 3.94 ± 9.83 cm^2, Multitask: 5.82 ± 14.6 cm^2; $F_{3,300}$ = 9.740, P <0.001, η_p^2 = 0.089; Fig. 9), indicating greater AP wavelet power in the proprioceptive DT when compared with all other tasks. The frequency main effect was significant (0-1 Hz: 19.03 ± 30.59 cm^2, 1-2 Hz: 0.56 ±0.73 cm^2, 2-4 Hz: 0.23 ± 0.36 cm^2; $F_{2,200}$

$= 102.023$, $P < 0.001$, $\eta_p^2 = 0.505$), indicating greater AP wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The task x frequency interaction was significant ($F_{6,600} = 10.350$, $P < 0.001$, $\eta_p^2 = 0.094$), indicating that while the 0-1 Hz band was significantly greater when compared with the 1-2 and 2-4 Hz bands across all task conditions, proprioceptive DT exhibited significant greater 0-1 Hz power when compared with all other tasks, whereas cognitive DT demonstrated the lowest 0-1 Hz power across all conditions. All other main effects and interactions were not significant.

INSERT FIGURE 9

Mediolateral 0-4 Hz wavelet power

The group main effect was significant (OA: 1.08 ± 3.01 cm^2, YA: 0.42 ± 1.14 cm^2; $F_{1,100} = 14.854$, $P < 0.001$, $\eta_p^2 = 0.129$; Fig. 10), indicating that the OA group exhibited significantly greater ML wavelet power when compared with YA. The task main effect was significant (Balance ST: 1.03 ± 3.05 cm^2, Proprioceptive DT: 0.72 ± 1.98 cm^2, Cognitive DT: 0.73 ± 1.94 cm^2, Multitask: 0.53 ± 2.02 cm^2; $F_{3,300} = 3.808$, $P = 0.011$, $\eta_p^2 = 0.037$), indicating greater ML wavelet power in the balance ST when compared with the multitask. The frequency main effect was significant (0-1 Hz: 2 ± 3.62 cm^2, 1-2 Hz: 0.18 ± 0.63 cm^2, 2-4 Hz: 0.07 ± 0.23 cm^2; $F_{2,200} = 64.198$, $P < 0.001$, $\eta_p^2 = 0.391$), indicating greater ML wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The group x frequency interaction was significant ($F_{2,200} = 13.270$, $P < 0.001$, $\eta_p^2 = 0.117$), indicating that OA demonstrated greater ML wavelet power in the 0-1 and 1-2 Hz bands when compared with YA. The task x frequency interaction was significant ($F_{6,600}$ = 3.681, P = 0.001, η_p^2 = 0.036), indicating that while the 0-1 Hz band was significantly greater when compared with the 1-2 and 2-4 Hz bands across all task conditions, this differences were most pronounced during the Balance ST, which exhibited the greatest 0-1 Hz power when compared with all other task, and smallest during the Multitask, which demonstrated the lowest 0-1 Hz power across all conditions. All other main effects and interactions were not significant.

INSERT FIGURE 10

Total COP 0-4 Hz wavelet power

The group main effect was significant (OA: 0.004 ± 0.008 cm^2, YA: 0.002 ± 0.003 cm^2; $F_{1,100}$ = 10.535, P = 0.002, η_p^2 = 0.095; Fig. 11), indicating that the OA group exhibited significantly greater total COP wavelet power when compared with YA. The task main effect was significant (Balance ST: 0.004 ± 0.006 cm^2, Proprioceptive DT: 0.003 ± 0.007 cm^2, Cognitive DT: 0.004 ± 0.008 cm^2, Multitask: 0.002 ± 0.004 cm^2; $F_{3,300}$ = 5.420, P = 0.001, η_p^2 = 0.051), indicating greater total COP wavelet power in the balance ST when compared with the proprioceptive DT and multitask. Similarly, cognitive DT demonstrated greater AP wavelet power when compared with the multitask, with no significant differences between the balance ST and cognitive DT. The frequency main effect was significant (0-1 Hz: 0.006 ± 0.009 cm^2, 1-2 Hz: 0.002 ± 0.003 cm^2, 2-4 Hz: 0.001 ± 0.002 cm^2; $F_{2,200}$ = 72.472, P <0.001, η_p^2 = 0.420), indicating greater total COP wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The group x frequency interaction was significant

($F_{2,200} = 7.871$, $P < 0.001$, $\eta_p^2 = 0.073$), indicating that OA demonstrated greater total COP wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0-1 Hz band. All other main effects and interactions were not significant.

INSERT FIGURE 11

Wavelet power spectrum of the COP signal from 0-1 Hz

Anteroposterior 0-1 Hz wavelet power

The group main effect was significant (OA: 13.13 ± 24.59 cm^2, YA: 9.26 ± 16.01 cm^2; $F_{1,100} = 20.104$, $P = 0.039$, $\eta_p^2 = 0.042$; Fig. 12), indicating that the OA group exhibited significantly greater AP wavelet power when compared with YA. The task main effect was significant (Balance ST: 10.93 ± 17.11 cm^2, Proprioceptive DT: 16.95 ± 32.75 cm^2, Cognitive DT: 7.19 ± 10.03 cm^2, Multitask: 9.70 ± 14.91 cm^2; $F_{3,300} = 9.539$, $P < 0.001$, $\eta_p^2 = 0.087$), indicating greater AP wavelet power during proprioceptive DT when compared with Cognitive DT and Multitask. Similarly, balance ST was significantly greater when compared with the cognitive DT. The frequency main effect was significant (0-0.1 Hz: 18.4 ± 30.71 cm^2, 0.1-0.5 Hz: 11.35 ± 15.09 cm^2, 0.5-1 Hz: 3.83 ± 5.2 cm^2; $F_{2,200} = 61.315$, $P < 0.001$, $\eta_p^2 = 0.380$), indicating greater AP wavelet power from 0 to 0.1 Hz when compared with 0.1-0.5 and 0.5-1 Hz bands. Additionally, wavelet power in the 0.1-0.5 Hz band was greater when compared with the 0.5-1 Hz band. The task x frequency interaction was significant ($F_{6,600} = 9.319$, $P < 0.001$, $\eta_p^2 = 0.085$). Across all task conditions, AP wavelet power was greater from 0 to 0.1 Hz and progressively decreased in the 0.1-0.5 and 0.5-1 Hz bands. Additionally, proprioceptive DT exhibited significantly greater AP wavelet power in the 0-0.1

Hz band when compared with all other tasks, while cognitive DT demonstrated significantly lower AP wavelet power in the 0-0.1 Hz band when compared with the balance ST and multitask. All other main effects and interactions were not significant.

INSERT FIGURE 12

Mediolateral 0-1 Hz wavelet power

The group main effect was significant (OA: 1.93 ± 4.09 cm^2, YA: 0.78 ± 1.31 cm^2; $F_{1,100}$ = 13.100, P < 0.001, η_p^2 = 0.116; Fig. 13), indicating that the OA group exhibited significantly greater ML wavelet power when compared with YA. The task main effect was significant (Balance ST: 1.75 ± 3.33 cm^2, Proprioceptive DT: 1.35 ± 3.62 cm^2, Cognitive DT: 1.35 ± 3.08 cm^2, Multitask: 0.85 ± 2.12 cm^2; $F_{3,300}$ = 3.674, P = 0.013, η_p^2 = 0.035), indicating greater ML wavelet power during the Balance ST when compared with the Multitask. The frequency main effect was significant (0-0.1 Hz: 1.93 ± 3.55 cm^2, 0.1-0.5 Hz: 1.16 ± 2.07 cm^2, 0.5-1 Hz: 0.89 ± 3.37 cm^2; $F_{2,200}$ = 20.322, P <0.001, η_p^2 = 0.169), indicating greater ML wavelet power from 0-0.1 Hz when compared with 0.1-0.5 and 0.5-1 Hz bands. The group x frequency interaction was significant ($F_{2,200}$ = 3.092, P = 0.048, η_p^2 = 0.030), indicating that OA demonstrated greater ML wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0-0.1 Hz band and progressively decreasing throughout the 0.1-0.5 and 0.5-1 Hz bands. All other main effects and interactions were not significant.

INSERT FIGURE 13

Total COP 0-1 Hz wavelet power

The group main effect was significant (OA: 0.10 $\pm$ 0.02 cm^2, YA: 0.005 $\pm$ 0.008 cm^2; $F_{1,100}$ = 8.556, P = 0.004, η_p^2 = 0.079; Fig. 14), indicating that the OA group exhibited significantly greater total COP wavelet power when compared with YA. The task main effect was significant (Balance ST: 0.10 $\pm$ 0.018 cm^2, Proprioceptive DT: 0.007 $\pm$ 0.014 cm^2, Cognitive DT: 0.009 $\pm$ 0.02 cm^2, Multitask: 0.006 $\pm$ 0.011 cm^2; $F_{3,300}$ = 2.827, P = 0.039, η_p^2 = 0.027), indicating greater total COP wavelet power during the Balance ST when compared with the Multitask. The frequency main effect was significant (0-0.1 Hz: 0.004 $\pm$ 0.008 cm^2, 0.1-0.5 Hz: 0.011 $\pm$ 0.016 cm^2, 0.5-1 Hz: 0.009 $\pm$ 0.02 cm^2; $F_{2,200}$ = 52.772, P <0.001, η_p^2 = 0.345), indicating greater total COP wavelet power from the 0.1-0.5 Hz band when compared with the 0-0.1 Hz band. Additionally, wavelet power in the 0.5-1 Hz band was greater when compared with the 0-0.1 Hz band. The group x frequency interaction was significant ($F_{2,200}$ = 4.782, P = 0.009, η_p^2 = 0.046), indicating that OA demonstrated greater total COP wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0.1-0.5 Hz band and the smallest at the 0-0.1 Hz band. Finally, the task x frequency interaction was significant ($F_{6,600}$ = 2.116, P = 0.050, η_p^2 = 0.021). Across the balance ST, cognitive DT, and multitask conditions, total COP wavelet power was significantly greater in the 0.1-0.5 Hz and 0.5-1 Hz bands compared with the 0-0.1 Hz band. Proprioceptive DT demonstrated a distinct pattern, with the greatest wavelet power in the 0.1-0.5 Hz when compared with both 0-0.1 Hz and 0.5-1 Hz bands. All other main effects and interactions were not significant.

INSERT FIGURE 14

Age-associated differences in dual-task cognitive accuracy

The group main effect was significant (OA: 4.51 $\pm$ 0.72 cm^2, YA: 4.77 $\pm$ 0.52 cm^2; $F_{1,100} = 8.730$, $P = 0.004$, $\eta_p^2 = 0.080$; Fig. 15), indicating that YA demonstrated significantly greater cognitive task accuracy when compared with OA. The cognitive task main effect was significant (Cognitive ST: 4.65 $\pm$ 0.62, Cognitive DT: 4.81 $\pm$ 0.42, Multitask: 4.45 $\pm$ 0.78; $F_{2,200} = 13.267$, $P < 0.001$, $\eta_p^2 = 0.117$), indicating that cognitive task accuracy was significantly greater during the cognitive DT when compared with the cognitive ST and multitask. Additionally, cognitive ST demonstrated greater cognitive accuracy when compared with the multitask. Finally, the cognitive task x group interaction was significant ($F_{2,200} = 3.326$, $P = 0.038$, $\eta_p^2 = 0.032$), indicating that YA demonstrated significantly greater cognitive task accuracy during the cognitive DT and multitask conditions when compared with the OA, with no significant group differences observed during the balance ST condition (while sitting).

INSERT FIGURE 15

4. Discussion

The purpose of this study was to characterize age-associated changes in sensory reweighting during dual-task conditions on a stable surface. Specifically, we found that: A) older adults exhibited greater postural sway when compared with younger adults across all tasks; B) older adults prioritized postural control over cognitive task performance to reduce the risk of falls; C) proprioceptive DT consistently resulted in the greatest low-frequency oscillatory reorganization across both groups; and D) cognitive DT facilitated more automatic postural regulation in both groups.

Age-associated and task-dependent changes in postural sway

Older adults exhibited greater postural sway when compared with YA (Fig. 8), consistent with well-documented age-associated deficits in sensory and motor function that collectively impair the ability to maintain upright stance (Woollacott M, 2002). These group differences were observed in AP and total COP sway displacement irrespective of task conditions. In the ML direction, OA exhibited significantly greater sway displacement in the multitask condition when compared with YA. Suprapostural task demands did not uniformly increase postural sway in older or younger adults. Balance ST produced the greatest sway displacement across all directions, with sway decreasing progressively as suprapostural task complexity increased. This pattern is consistent with the constrained action hypothesis, which proposes that directing conscious attention toward a highly automated behavior, such as postural control, interferes with the automatic processes that normally regulate it, resulting in greater postural instability (Wulf G, 2001; Yu SH, 2017). Although this sway reduction was observed in both groups, OA paid a greater cognitive price, as evidenced by differences in cognitive accuracy discussed below.

Age-associated differences in dual-task cognitive accuracy

Despite the reduced postural sway under dual-task conditions, OA showed significantly greater cognitive accuracy costs when compared with YA (Fig. 15). Importantly, group differences in cognitive accuracy were absent during the cognitive ST and emerged only when postural demands were added. These findings suggest that OA unconsciously prioritized postural control over suprapostural task performance to reduce the risk of falls (Brown LA, 2002; Yu SH, 2017). Rather than reflecting improved postural control, the sway reduction observed under dual-task conditions in OA appears to reflect a reallocation of cognitive resources towards postural control, at the expense of cognitive task accuracy. However, this strategy relies on attentional resources that may not be available when balance is unexpectedly challenged or externally imposed, circumstances in which most real-world falls occur (Brown LA, 2002; Schaefer, 2014).

Age-associated increases in low-frequency oscillations

Consistent with previous findings from our group, most diagnostically meaningful information in the COP signal was concentrated below 1 Hz (Fig. 9-11) (Meyer Vega M, 2026; Meyer-Vega et al., 2025). While linear measures captured overall group differences in sway magnitude, frequency-domain measures revealed that the patterns of low-frequency oscillatory power differed across task conditions and frequency bands, offering mechanistic insights beyond those provided by linear measures alone.

Specifically, OA exhibited greater wavelet power in the ML and total COP directions when compared with YA. Proprioceptive DT consistently demonstrated the greatest AP wavelet power in both groups (Fig. 12F). This finding suggests a hierarchy of suprapostural task demands, in which combining a mechanical proprioceptive challenge with concurrent standing induces greater sensory reorganization than either cognitive DT or multitask conditions. Although previous work has shown that simple motor tasks require fewer attentional resources than complex cognitive tasks (Stelmach GE, 1990; Woollacott M, 2002), the present findings suggest a different hierarchy: proprioceptive DT imposed greater low-frequency oscillatory demands when compared with cognitive DT, likely because it simultaneously disrupted a primary sensory input while requiring attentional resources for postural control. In contrast, cognitive DT produced the lowest AP wavelet power at the 0-0.1 Hz band when compared with the balance ST and multitask conditions in both groups (Fig. 12G). This aligns with the automatization of the sway hypothesis, which proposes that focusing attention on an external cue allows automatic postural processes to regulate sway more efficiently (Richer N, 2017). Conversely, directing attention internally toward movement production, as may occur during balance ST, disrupts these automatic processes and increases low-frequency oscillatory activity (Richer N, 2017). These findings suggest that cognitive dual-tasks can facilitate, rather than challenge, postural control by redirecting attention away from balance and allowing more automatic regulation, although this will come with a cognitive cost in older adults.

In both ML and total COP directions, the balance ST condition produced the greatest wavelet power, while the multitask condition produced the lowest. This pattern is consistent with the constrained action hypothesis and the automatization of sway argument discussed previously. Notably, proprioceptive DT showed a distinct frequency pattern across directions. In the AP direction, greater power was concentrated at the 0-0.1 Hz band (Fig. 12F), while in the total COP direction, greater power was observed at the 0.1-0.5 Hz band (Fig. 14F) (Assländer L, 2014; Redfern MS, 2001). Contrary to our hypothesis, these results suggest that mechanically challenging proprioceptive input triggers a shift in coordination toward greater reliance on visual and vestibular inputs (Horak, 2006; Redfern MS, 2001). However, these frequency bands likely reflect patterns of sensory interaction rather than isolated contributions of a single sensory system and should be interpreted in that context. Taken together, these findings demonstrate that sensory reorganization patterns underlying dual-task postural control are both task- and direction-specific.

Furthermore, these findings add to growing evidence from our group where the quantity and quality of the COP signal provide complementary information about postural control. The quantity, measured as sway displacement, reflects the behavioral outcome of postural control dynamics. while the quality, captured through low-frequency oscillations, reveals the underlying mechanisms of sensory reorganization that produce it (Meyer Vega M, 2026).

Limitations

There are several limitations to consider when interpreting these findings. First, the cross-sectional design of this study prevents causal inferences about age-associated changes in sensory reweighting; longitudinal studies are needed to determine whether the observed differences reflect true aging trajectories. Second, participants were tested in a controlled laboratory setting, which does not fully capture real-world conditions where balance challenges are unexpected and attentional demands are self-imposed. Third, the verbal memory task primarily engaged short-term memory, a cognitive domain that is weakly associated with postural control when compared with executive function (Meyer-Vega et al., 2025). Future studies should examine whether executive-function tasks produce greater dual-task interference and more pronounced sensory reorganization in older adults.

Conclusion

In summary, the decrease in postural sway observed in older adults under dual-task conditions does not reflect improved postural control. Rather, older adults have to prioritize balance at the expense of cognitive task accuracy, a strategy that younger adults do not need to adopt. This finding suggests that, as attentional resources become more limited with age, avoiding falls takes priority over concurrent task performance. Additionally, proprioceptive DT imposed the greatest demands on sensory reorganization across all dual-task conditions, suggesting that rehabilitation programs targeting fall prevention in older adults should incorporate proprioceptive challenges alongside concurrent cognitive demands. However, the extent to which these findings generalize to more ecologically valid conditions, such as unstable surfaces, remains unclear. This question is addressed in a companion study examining age-associated changes in sensory reweighting during dual-task conditions on an unstable surface.

Chapter 3: Mechanisms of Multisensory Interaction During Dual-Task Postural Control in Aging: II. Unstable Surface.

1. Introduction

Postural control relies on the dynamic integration of visual, vestibular, and proprioceptive inputs (Huxhold O, 2006; Redfern MS, 2001). On stable surfaces, consistent sensory feedback allows postural control to primarily rely on proprioceptive information (Horak, 2006; Horak FB, 1986). In contrast, unstable surfaces reduce the reliability of sensory information from plantar mechanoreceptors (Patel M, 2011; Perry SD, 2000), requiring greater integration of visual and vestibular inputs to maintain balance (Horak, 2006; Promsri, 2023; Promsri A, 2020). Aging significantly alters these sensory reweighting processes, as older adults demonstrate a reduced capacity to reweight sensory inputs in response to task or environmental conditions, primarily due to declines in proprioception and vestibular function (Gabriel GA, 2022; Liu Z, 2023). These declines lead to an increased reliance on visual information to maintain postural control. These age-associated deficits become particularly relevant on unstable surfaces, where proprioceptive reliability is further reduced.

Dual-task conditions create additional demands on postural control. Balance regulation is largely automatic in younger adults, allowing a secondary cognitive or motor task to be performed with minimal impact on postural control (de Barros GM, 2021; Wang J, 2024). However, older adults must consciously allocate limited attentional resources to maintain postural control, increasing their susceptibility to dual-task interference (Wang J, 2024). Suprapostural tasks can be categorized as cognitive, which redirect attention externally and allow more automatic postural control, or motor, which mechanically challenge a primary sensory input while simultaneously competing for attentional resources (Polskaia N, 2015; Rafiee Manesh V, 2024; Weeks DL, 2003). On an unstable surface, where proprioceptive reliability is already compromised, a motor dual-task may pose a disproportionate challenge by simultaneously disrupting proprioceptive input from multiple sources. This represents a critical gap, as older adults often encounter unstable or compliant surfaces while performing everyday cognitive and motor activities.

Linear Center of Pressure (COP) measurements are widely used to quantify the body's response to age-associated postural control demands (Lai QQ, 2022). However, they reduce a rich physiological signal to total sway displacement (cm), ignoring its time-frequency structure and offering limited insight into which sensory systems contribute to postural control or how their contributions shift under specific task and environmental demands (Meyer Vega M, 2026; Meyer-Vega et al., 2025). Time-frequency analysis addresses this limitation by decomposing the COP signal into specific frequency components and has demonstrated sensitivity to task-, age-, and disease-associated differences in postural control, with most diagnostically meaningful information concentrated below 4 Hz (Meyer Vega M, 2026; Meyer-Vega et al., 2025). Within this range, modulation of low-frequency oscillations reflects sensory reweighting among visual (0–0.1 Hz), vestibular (0.1–0.5 Hz), and proprioceptive (0.5–1 Hz) inputs (Baltich J, 2014; Jafari H, 2023; Redfern MS, 2001). An increase in power within a specific frequency suggests greater reliance on the corresponding sensory input, while a decrease may reflect reduced contribution (Chagdes JR, 2009). On an unstable surface, where plantar mechanoreceptor reliability is reduced, greater power in the vestibular (0.1-0.5 Hz) and visual (0-0.1 Hz) would reflect a compensatory shift away from proprioceptive input, consistent with the expected sensory reweighting response to foam surface standing.

Despite these age-associated declines in sensory reweighting and attentional resource allocation, the mechanisms by which surface instability and dual-task demands disrupt postural control in older adults remain poorly understood. Therefore, the purpose of this study was to characterize age-associated changes in sensory reweighting during dual-task conditions on an unstable surface. We hypothesized that older adults would exhibit greater postural sway and wavelet power during dual-task conditions when compared with younger adults, and older adults on unstable surfaces would increase reliance on visual and vestibular inputs to maintain postural control. Characterizing how surface instability affects age-associated deficits in multisensory interaction may improve our understanding of mechanisms contributing to fall risk in older adults and inform the development of targeted rehabilitation strategies that promote quality of life in this population.

2. Methods

Participants

Participants and eligibility criteria were identical to those described in the companion manuscript (Chapter 2). Briefly, 51 young adults (YA; 26 ± 6 years old) and 51 older adults (OA; 70 ± 7 years old) were recruited from the Auburn, Alabama, community (see Table 4). This study was approved by the Auburn University Institutional Review Board

(Protocol #STUDY00000880) and followed the latest revisions of the Declaration of Helsinki, except that it was not pre-registered as a clinical trial, given that this was a cross-sectional investigation. All participants provided written informed consent before participating in the study.

Equipment

Postural sway was assessed using the Balance Tracking System BTrackS (Balance Tracking Systems, San Diego, CA, USA), which includes a force plate (BTrackS Balance Plate) and accompanying software. The BTrackS has been validated as a reliable tool for acquiring COP data related to postural sway (Goble et al., 2019; O'Connor et al., 2016; Richmond et al., 2018). COP data were sampled at 25 Hz, as specified by the manufacturer, and stored on a local PC for offline analysis. Surface instability was induced using a foam pad placed directly on top of the force plate.

Experimental Protocol

All participants completed a single session lasting approximately 1 hour. Each participant began the session with an explanation, demonstration, and familiarization with the testing equipment and protocol. Throughout all conditions, participants stood on a foam surface placed on top of the force plate. A 5-minute rest period was provided between conditions. Moreover, all participants performed two single-task and three dual-task conditions on a firm surface. Auditory tones marked the beginning and end of each task. Each participant completed a 20-second trial for each condition with eyes open.

Single-task conditions: These control conditions established baseline performance for each task component, ensuring that the observed changes during dual-tasking reflect the interaction between postural control and secondary-task demands rather than limitations of the tasks themselves.

- **Balance single- task (ST):** Participants were asked to stand as still as possible on the force plate with their hands on their hips, feet shoulder-width apart, and eyes directed straight ahead (Fig. 16.1).
- **Cognitive single-task (ST):** Participants performed the verbal memory encoding and recall task while comfortably seated. During the first 10 seconds, participants memorized the first five words from one of the Hopkins Verbal Learning Test (HVLT; versions B, D, or F), followed by 10 seconds of silence (Fig. 16.2). At the end of the task, participants were asked to recall the words in the order presented. The HVLT is a brief, easy-to-administer instrument with established reliability and discriminant validity, sensitive to age-associated declines and easy to administer in older adults (Brandt, 1991; Woods SP, 2005).

Dual-task conditions: These conditions were designed to assess the interaction between postural control and a secondary task simultaneously by requiring participants to maintain balance while performing a cognitive or motor task.

- **Cognitive dual-task (DT):** Participants were asked to stand as still as possible on the force plate while simultaneously completing a verbal memory encoding and recall task (Fig. 16.3). Participants heard the first five words from one of the HVLT versions (A, C, or E) (Brandt, 1991). The HVLT word list was presented during the first 10 seconds, followed by 10 seconds of silence for encoding. Immediately after the trial, participants were asked to recall the words in the order in which they were presented.

We used a verbal memory encoding and recall task during the balance trial to negate the effects of vocal articulation on postural sway, as respiratory changes during vocalization have been shown to influence postural sway (Dault MC, 2003).

- **Proprioceptive (motor) dual-task (DT):** Participants were asked to stand as still as possible on the force plate while simultaneously performing the cervical joint-position task (AlDahas A, 2024). A lightweight headband with an attached laser pointer was placed on the participant's head (Bae S, 2023). Participants were instructed to maintain the laser beam aligned with the center of the target throughout the trial (Fig. 16.4).
- **Multitask condition**: Participants were asked to stand as still as possible on the force plate while simultaneously performing both the verbal memory encoding and recall task and the cervical joint-position task (Fig. 16.5).

INSERT FIGURE 16

Data analysis

Data processing and analysis procedures have been fully described in the companion manuscript (Chapter 2). Data were acquired using the BTrackS Assess Balance software and analyzed offline using a custom-written MATLAB program (MathWorks™, Inc., Natick, MA, USA). The postural sway signal was filtered using a 4th-order Butterworth filter with a low cut-off of 4 Hz. The dependent variables were anteroposterior, mediolateral, and total COP sway displacement (cm). Continuous wavelet transform analyses were performed on the COP signal using a base MATLAB function developed by Torrence and Compo (Torrence & Compo, 1998). The COP signal was divided into 0–1, 1–2, and 2–4 Hz bands, and further into 0–0.1, 0.1–0.5, and 0.5–1 Hz sub-bands. The dependent variable for spectral analysis was absolute peak wavelet power within each band.

Statistical analysis

A two-way mixed ANOVA model (2 groups x 4 tasks) with repeated measures on all factors compared the mean differences from AP, ML, and total COP sway displacement. A three-way mixed ANOVA model (2 groups x 4 tasks x 3 frequency bands) compared the absolute wavelet power from 0 to 4 Hz. A similar model (2 groups x 4 tasks x 3 frequency bands) compared the absolute wavelet power from 0 to 1 Hz. Furthermore, a two-way ANOVA (2 groups x 3 tasks) compared the mean difference in cognitive task accuracy when the verbal memory task was administered while standing (on the unstable force plate) during dual- and multitasking, and while sitting (off the force plate).

All analyses were performed using IBM SPSS (IBM SPSS version 29, SPSS Inc., Chicago, IL, USA), and graphs were created using SigmaPlot® (Inpixon Inc. version 15 for Windows) and JMP® Statistical Discovery LLC. Appropriate post-hoc analyses were conducted to follow up on significant interactions from the ANOVA models. For example, group-associated differences were followed by independent-sample t-tests. Multiple t-test comparisons were corrected using the Bonferroni corrections, and the alpha level for all statistical tests was 0.05. Data are reported as mean ± SD in text and mean ± standard error of the mean (SEM) in the figures. Only significant main effects and interactions are presented unless otherwise noted.

3. Results

Age-associated and task-dependent changes in postural sway

Anteroposterior sway displacement

The group main effect was significant (OA: 36.35 ± 11.10 cm, YA: 26.93 ± 2.89 cm; $F_{1,100}$ = 40.584, P <0.001, η_p^2 = 0.289; Fig. 17A), indicating that the OA group exhibited significantly greater AP sway displacement when compared with YA. All other main effects and interactions were not significant.

Mediolateral sway displacement

The group main effect was significant (OA: 25.99 ± 5.9 cm, YA: 22.63 ± 1.67 cm; $F_{1,100}$ = 17.020, P <0.001, η_p^2 = 0.145; Fig. 17B), indicating that the OA group exhibited significantly greater ML sway displacement when compared with YA. The task main effect was significant (Balance ST: 24.84 ± 5.34 cm, Proprioceptive DT: 24.10 ± 4.11 cm, Cognitive DT: 24.28 ± 4.5 cm, Multitask: 24.03 ± 4.6 cm; $F_{3,300}$ = 4.505, P = 0.004, η_p^2 = 0.043), indicating greater ML sway displacement during Balance ST when compared with the proprioceptive DT and multitask conditions. All other main effects and interactions were not significant.

Total COP sway displacement

The group main effect was significant (OA: 32.87 ± 15.26 cm, YA: 18.94 ± 5.06 cm; $F_{1,100}$ = 43.693, P <0.001, η_p^2 = 0.304; Fig. 17C), indicating that the OA group exhibited significantly greater total COP sway displacement when compared with YA. All other main effects and interactions were not significant.

INSERT FIGURE 17

Age-associated increases in low-frequency oscillations

<u>Wavelet power spectrum of the COP signal from 0-4 Hz</u>

Anteroposterior 0-4 Hz wavelet power

The group main effect was significant (OA: 19.16 ± 54.58 cm^2, YA: 13.05 ± 31.56 cm^2; $F_{1,100}$ = 5.216, P = 0.024, η_p^2 = 0.050; Fig. 18), indicating that the OA group exhibited significantly greater AP wavelet power when compared with YA. The task main effect was significant (Balance ST: 11.43 ± 27.73 cm^2, Proprioceptive DT: 28.83 ± 71.56 cm^2, Cognitive DT: 9.02 ± 20.2 cm^2, Multitask: 15.14 ± 38.31 cm^2; $F_{3,300}$ = 22.156, P <0.001, η_p^2 = 0.181), indicating greater AP wavelet power during proprioceptive DT when compared with all other tasks. Similarly, the multitask demonstrated greater AP wavelet power when compared with the cognitive DT. The frequency main effect was significant (0-1 Hz: 46 ± 68.12 cm^2, 1-2 Hz: 1.75 ± 2.31 cm^2, 2-4 Hz: 0.56 ± 0.83 cm^2; $F_{2,200}$ = 125.354, P <0.001, η_p^2 = 0.556), indicating greater AP wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The task x group interaction was significant ($F_{3,300}$ = 3.380, P = 0.019, η_p^2 = 0.033), indicating that OA demonstrated greater AP wavelet power in the proprioceptive DT when compared with YA. The frequency x group interaction was significant ($F_{2,200}$ = 3.934, P = 0.021, η_p^2 = 0.038), indicating that OA demonstrated greater AP wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0-1 Hz band. The task x frequency interaction was significant ($F_{6,600}$ = 22.634, P <0.001, η_p^2 = 0.185), indicating that while the 0-1 Hz band was significantly greater when compared with the 1-2 and 2-4 Hz bands across all task conditions, this difference was most pronounced during the proprioceptive DT, which exhibited the greatest 0-1 Hz power when compared with all other tasks, whereas cognitive DT demonstrated the lowest 0-1 Hz power across all task conditions. Finally, the task x frequency x group interaction was significant ($F_{6,600}$ = 3.543, *P* = 0.002, η_p^2 = 0.034), indicating that group differences in AP wavelet power across frequency bands were dependent on task condition. During balance ST, OA demonstrated significantly greater AP wavelet power when compared with YA at the 1-2 Hz band. During proprioceptive DT, age-associated differences emerged at the 0-1 Hz and 2-4 Hz bands. During cognitive DT and the multitask conditions, OA exhibited significantly greater AP wavelet power when compared with YA in the 1-2 and 2-4 Hz bands.

INSERT FIGURE 18

Mediolateral 0-4 Hz wavelet power

The group main effect was significant (OA: 5.54 ± 14.27 cm^2, YA: 2.33 ± 6.65 cm^2; $F_{1,100}$ = 18.074, *P* <0.001, η_p^2 = 0.153; Fig. 19), indicating that the OA group exhibited significantly greater ML wavelet power when compared with YA. The frequency main effect was significant (0-1 Hz: 11 ± 17.37 cm^2, 1-2 Hz: 0.67 ± 1.81 cm^2, 2-4 Hz: 0.16 ± 0.26 cm^2; $F_{2,200}$ = 100.006, *P* <0.001, η_p^2 = 0.500), indicating greater ML wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The frequency x group interaction was significant ($F_{2,200}$ = 16.769, *P* <0.001, η_p^2 = 0.144), indicating that OA demonstrated greater ML wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0-1 Hz band. The task x frequency interaction was significant ($F_{6,600}$ = 2.889, *P* = 0.009, η_p^2 = 0.028), indicating that ML wavelet power in the 0-1 Hz band was significantly greater when compared with the 1-2 and 2-4 Hz bands across all task conditions, this difference was most pronounced during the multitask condition, which exhibited the greatest power in the 0-1 Hz band when compared with all other tasks, whereas the cognitive DT demonstrated the lowest 0-1 Hz power across all conditions. All other main effects and interactions were not significant.

INSERT FIGURE 19

Total COP 0-4 Hz wavelet power

The group main effect was significant (OA: 0.02 ± 0.032 cm^2, YA: 0.01 ± 0.009 cm^2; $F_{1,100} = 20.828$, $P < 0.001$, $\eta_p^2 = 0.172$; Fig. 20), indicating that the OA group exhibited significantly greater total COP wavelet power when compared with YA. The frequency main effect was significant (0-1 Hz: 0.023 ± 0.037 cm^2, 1-2 Hz: 0.006 ± 0.009 cm^2, 2-4 Hz: 0.004 ± 0.008 cm^2; $F_{2,200} = 69.038$, $P < 0.001$, $\eta_p^2 = 0.408$), indicating greater total COP wavelet power from 0 to 1 Hz when compared with 1-2 and 2-4 Hz bands. Additionally, wavelet power in the 1-2 Hz band was greater when compared with the 2-4 Hz band. The frequency x group interaction was significant ($F_{2,200} = 13.060$, $P < 0.001$, $\eta_p^2 = 0.116$), indicating that OA demonstrated greater total COP wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0-1 Hz band. All other main effects and interactions were not significant.

INSERT FIGURE 20

<u>Wavelet power spectrum of the COP signal from 0-1 Hz</u>

Anteroposterior 0-1 Hz wavelet power

The group main effect was significant (OA: 32.38 ± 55.88 cm^2, YA: 21.71 ± 31.31 cm^2; $F_{1,100} = 8.297$, $P = 0.005$, $\eta_p^2 = 0.077$; Fig. 21), indicating that the OA group exhibited significantly greater AP wavelet power when compared with YA. The task main effect was significant (Balance ST: 20.53 $\pm$ 28.33 cm^2, Proprioceptive DT: 44 $\pm$ 71.49 cm^2, Cognitive DT: 18.32 $\pm$ 21.69 cm^2, Multitask: 25.33 $\pm$ 39.25 cm^2; $F_{3,300}$ = 20.450, P <0.001, η_p^2 = 0.170), indicating greater AP wavelet power during proprioceptive DT when compared with all other tasks. The frequency main effect was significant (0-0.1 Hz: 44.42 $\pm$ 68.73 cm^2, 0.1-0.5 Hz: 26.2 $\pm$ 28.41 cm^2, 0.5-1 Hz: 10.52 $\pm$ 11.74 cm^2; $F_{2,200}$ = 62.750, P <0.001, η_p^2 = 0.386), indicating greater AP wavelet power from 0 to 0.1 Hz when compared with 0.1-0.5 and 0.5-1 Hz bands. Additionally, wavelet power in the 0.1-0.5 Hz band was greater when compared with the 0.5-1 Hz band.

The task x group interaction was significant ($F_{3,300}$ = 3.230, P = 0.023, η_p^2 = 0.031), indicating that OA demonstrated greater AP wavelet power in the proprioceptive DT and multitask conditions when compared with YA. The task x frequency interaction was significant ($F_{6,600}$ = 19.822, P <0.001, η_p^2 = 0.165), indicating that while the 0-0.1 Hz band was significantly greater when compared with the 0.1-0.5 and 0.5-1 Hz bands across all task conditions, this difference was most pronounced during the proprioceptive DT, which exhibited the greater 0-1 Hz power when compared with all other tasks. Finally, the task x frequency x group interaction was significant ($F_{6,600}$ = 19.822, P = 0.007, η_p^2 = 0.029), indicating that group differences in AP wavelet power across frequency bands were dependent on task condition. During proprioceptive DT, OA exhibited significantly greater total AP wavelet power when compared with YA in the 0-0.1 and 0.1-0.5 Hz bands. During cognitive DT, age-associated differences emerged at the 0.5-1 Hz bands. During the multitask condition, OA exhibited significantly greater wavelet power when compared with

YA at the 0.1-0.5 and 0.5-1 Hz bands. All other main effects and interactions were not significant.

INSERT FIGURE 21

Mediolateral 0-1 Hz wavelet power

The group main effect was significant (OA: 12.59 $\pm$ 19.9 cm^2, YA: 4.55 $\pm$ 7.32 cm^2; $F_{1,100}$ = 23.801, P <0.001, η_p^2 = 0.192; Fig. 22), indicating that the OA group exhibited significantly greater ML wavelet power when compared with YA. The frequency main effect was significant (0-0.1 Hz: 9.91 $\pm$ 17.12 cm^2, 0.1-0.5 Hz: 10.11 $\pm$ 15.77 cm^2, 0.5-1 Hz: 5.69 $\pm$ 13.06 cm^2; $F_{2,200}$ = 11.648, P <0.001, η_p^2 = 0.104), indicating greater ML wavelet power in the 0-0.1 and 0.1-0.5 Hz bands when compared with the 0.5-1 Hz band. The task x frequency interaction was significant ($F_{6,600}$ = 5.325, P <0.001, η_p^2 = 0.051), indicating that the pattern of ML wavelet power across frequency bands differed depending on task condition. During proprioceptive DT and multitask, ML wavelet power was significantly greater at the 0-0.1 and 0.1-0.5 Hz bands when compared with the 0.5-1 Hz band. During the cognitive DT, ML wavelet power was significantly greater at the 0.1-0.5 Hz bands when compared with the 0-0.1 Hz bands. Finally, the task x frequency x group interaction was significant ($F_{6,600}$ = 3.511, P = 0.002, η_p^2 = 0.034), indicating that group differences in AP wavelet power across frequency bands were dependent on task condition. During balance ST, OA demonstrated significantly greater ML wavelet power when compared with YA at the 0.1-0.5 and 0.5-1 Hz bands. During proprioceptive DT, cognitive DT, and multitask, OA exhibited significantly greater ML wavelet power across all frequency bands when compared with YA. All other main effects and interactions were not significant.

INSERT FIGURE 22

Total COP 0-1 Hz wavelet power

The group main effect was significant (OA: 0.4 $\pm$ 0.067 cm^2, YA: 0.14 $\pm$ 0.02 cm^2; $F_{1,100}$ = 20.627, P <0.001, η_p^2 = 0.171; Fig. 23), indicating that the OA group exhibited significantly greater total COP wavelet power when compared with YA. The frequency main effect was significant (0-0.1 Hz: 0.014 $\pm$ 0.03 cm^2, 0.1-0.5 Hz: 0.038 $\pm$ 0.06 cm^2, 0.5-1 Hz: 0.029 $\pm$ 0.056 cm^2; $F_{2,200}$ = 49.318, P <0.001, η_p^2 = 0.330), indicating greater ML wavelet power in the 0.1-0.5 Hz band when compared with the 0-0.1 and 0.5-1 Hz bands. Additionally, wavelet power in the 0.5-1 Hz band was significantly greater when compared with the 0-0.1 Hz band. The frequency x group interaction was significant ($F_{2,200}$ = 10.686, P <0.001, η_p^2 = 0.097), indicating that OA demonstrated greater total COP wavelet power across all frequency bands when compared with YA, with the largest group difference observed at the 0.1-0.5 Hz band. All other main effects and interactions were not significant.

INSERT FIGURE 23

Age-associated differences in dual-task cognitive accuracy

The group main effect was significant (OA: 4.44 $\pm$ 0.77 cm^2, YA: 4.72 $\pm$ 0.54 cm^2; $F_{1,100}$ = 8.820, P = 0.004, η_p^2 = 0.081; Fig. 24), indicating that YA demonstrated significantly greater cognitive task accuracy when compared with OA. All other main effects and interactions were not significant.

INSERT FIGURE 24

4. Discussion

The purpose of this study was to characterize age-associated changes in sensory reweighting during dual-task conditions on an unstable surface. The novelty of our findings is that age-associated differences in sensory reweighting under unstable surface are task-, direction-, and frequency-specific. Specifically, we found that: A) OA exhibited greater postural sway when compared with YA across all directions; B) dual-task conditions decreased postural sway when compared with the Balance ST; and C) Proprioceptive DT and multitask conditions drove the most pronounced age-associated changes in low-frequency oscillations, with OA showing greater reliance on visual and vestibular inputs when proprioceptive input was disrupted from multiple sources simultaneously.

Age-associated and task-dependent changes in postural sway

Older adults exhibited greater postural sway when compared with YA across all directions (AP, ML, and Total COP). This is consistent with age-associated declines in sensory integration, neuromuscular function, and motor response speed that contribute to reduced postural stability (Rizzato A, 2026), and these deficits were expected to be more pronounced on an unstable surface, where proprioceptive reliability is further reduced (Patel M, 2011).

Contrary to our hypothesis, dual-task conditions did not increase postural sway when compared with the balance ST (Fig 17). In fact, ML sway was significantly greater during Balance ST when compared with proprioceptive DT and multitask conditions (Fig 17B). These findings extend prior work suggesting that directing conscious attention toward a highly automated behavior interferes with the automatic processes that normally regulate it, whereas externally directing attention toward a suprapostural task allowed postural control to operate more automatically, resulting in reduced sway (Wulf G, 2001). This was observed across both groups and surface conditions (see Chapter 2), suggesting that attentional focus mechanisms operate regardless of age and surface stability.

Age-associated differences in dual-task cognitive accuracy

Older adults demonstrated significantly lower cognitive task accuracy when compared with YA (Fig. 24). However, accuracy did not differ across dual-task conditions in either group, suggesting that the nature of the concurrent postural demand did not influence cognitive performance. This pattern reflects a general dual-task deficit in older adults rather than a selective prioritization strategy. Older adults exhibited reduced cognitive accuracy and greater postural sway displacement when compared with younger adults, suggesting that their limited attentional resources were not able to support both tasks simultaneously (Doumas M, 2009).

Age-associated increases in low-frequency oscillations

Despite the absence of dual-task effects on postural sway at the behavioral level, low-frequency oscillations revealed age-associated differences in the underlying multisensory interaction mechanisms of postural control. OA demonstrated greater wavelet power when compared with YA across the 0-1, 1-2, and 2-4 Hz bands, irrespective of task condition (Fig. 18-20). These findings are consistent with previous work from our laboratory demonstrating that low-frequency oscillations are sensitive to age-, task-, and disease-associated postural control deficits that global postural sway outcomes fail to capture (Meyer Vega M, 2026; Meyer-Vega et al., 2025).

Specifically, within the 0-1 Hz range, the pattern of age-associated differences was task- and direction-specific. In the AP direction, both the proprioceptive DT and multitask conditions showed the most pronounced age-associated differences, with OA exhibiting greater wavelet power in the 0-0.1 and 0.1-0.5 Hz bands (Fig. 21F-H), reflecting greater visual and vestibular contributions to postural control (Jafari H, 2023; Redfern MS, 2001). On a foam surface, ankle proprioception is already compromised, and the simultaneous addition of a cervical joint-position task further disrupts neck proprioception (Alkhamis, 2025). When both proprioceptive sources are compromised simultaneously, this appears to drive a compensatory increase in visual and vestibular reliance, which is disproportionately greater in older adults. This supports our hypothesis that an unstable surface during quiet-standing would increase visual and vestibular reliance but suggests that this response is age-dependent and most pronounced when proprioceptive input is disrupted from multiple sources simultaneously. In contrast, during cognitive DT, age-associated differences emerged only at the 0.5-1 Hz band (Fig. 21G). When proprioceptive input is partially reduced by the foam surface but not further disrupted by a concurrent motor task, OA appear to increase reliance on the remaining proprioceptive input to maintain postural control (Jafari H, 2023; Redfern MS, 2001).

The ML direction showed a broader pattern of age-associated differences, with OA exhibiting greater ML wavelet power across all frequency bands in all dual-task conditions, not just the proprioceptive DT (Fig. 22). The total COP 0-1 Hz analysis revealed a distinct pattern where wavelet power was greater only at the 0.1-0.5 Hz band, irrespective of task condition (Fig. 23). This vestibular-dominant pattern in total COP is consistent with the expected sensory reweighting response to an unstable surface in quiet-standing, where reduced plantar mechanoreceptor reliability shifts towards a greater vestibular reliance (Horak, 2006; Jafari H, 2023; Patel M, 2011). That OA demonstrated greater wavelet power across all bands in this analysis further suggests that this reweighting response is amplified with age, requiring greater oscillatory activity to achieve the same postural outcome. Together, these findings suggest that aging reduces the ability to adapt sensory contributions to meet the demands of an unstable surface, and that this limitation is further compromised when proprioceptive input is disrupted from multiple sources at the same time.

Several limitations should be acknowledged. This study employed a cross-sectional design, which precluded causal inferences about age-associated changes in sensory reweighting. Participants were community-dwelling older adults without neurological disorders, limiting the generalizability to clinical populations with greater sensory deficits. Future studies should examine sensory reweighting during dual-task conditions on an unstable surface in populations at a greater elevated fall risk, such as individuals with peripheral neuropathy, stroke, and vestibular dysfunction.

In conclusion, age-associated differences in multisensory interaction during dual-task conditions on an unstable surface are task-, direction-, and frequency-specific, a pattern that global sway measures alone cannot detect. Older adults demonstrate greater reliance on visual and vestibular inputs during proprioceptive DT when proprioceptive input was simultaneously compromised by the foam surface and the cervical motor task. These findings should not be interpreted as a reason to avoid dual-task conditions in older adults; rather, they highlight the potential of dual-task training on unstable surfaces as a targeted rehabilitation strategy to improve sensory reweighting mechanisms and reduce fall risk.

Chapter 4: Adiposity Predicts Postural Sway in Older but Not Younger Adults: A Novel Age-Dependent Relationship

Abstract

Background: Aging is associated with increases in fat mass (FM) and decreases in fat-free mass (FFM), yet it remains unknown whether these indices independently predict force plate-derived postural sway and low-frequency postural oscillations. **Methods:** Eighty-seven participants: 44 younger adults (YA; 26 ± 5 years old) and 43 older adults (OA; 69 ± 6 years old), completed body composition assessment using bioimpedance spectroscopy and postural sway assessment using a force plate. Fat mass index (FMI), fat-free mass index (FFMI), and FM/FFM ratio were derived from FM and FFM. Wavelet analysis extracted low-frequency oscillations (0-1 Hz) from the COP signal. Multiple linear regressions were used to analyze body composition indices as predictors of COP sway displacement and 0-1 Hz power, separately for YA and OA. **Results:** OA exhibited significantly greater COP sway displacement and 0-1 Hz power when compared to YA, despite no significant group differences in body composition indices. FM/FFM ratio and FMI significantly predicted COP sway displacement (R^2 = 0.195, p = 0.016; R^2 = 0.218, p = 0.009) and low-frequency oscillations (R^2 = 0.235, p = 0.006; R^2 = 0.236, p = 0.006) in OA but not YA. FFMI did not significantly predict postural sway in either group. **Conclusion:** FMI, but not FFMI, predicts postural sway and low-frequency postural oscillations specifically in OA, despite comparable body composition profiles between groups. This age-dependent relationship suggests that increases in YA FM does not meaningfully affect balance but does create

postural instability in OA. These findings highlight the importance of body composition assessment when evaluating fall risk in OA and suggest that interventions targeting FM reduction may be more effective than lean mass preservation alone for improving postural stability in aging populations.

1. Introduction

Falls represent one of the leading causes of fatal and non-fatal injuries in older adults, with approximately one-third of individuals aged 65 and older experiencing at least one fall every year (Burns et al., 2016; Vaishya & Vaish, 2020). The consequences of falls extend beyond physical injury, including reduced mobility, fear of falling, and loss of independence (Adam et al., 2024; Florence et al., 2018). Impaired postural control is a primary contributor to fall risk in this population (Fletcher & Strzalkowski, 2026). Therefore, identifying factors associated with postural control decline in older adults is essential for developing effective fall-prevention strategies.

Aging is accompanied by significant changes in body composition, including increases in fat mass (FM) and decreases in fat-free mass (FFM) and skeletal muscle mass, even when body weight and physical activity remain stable (Bouchard et al., 2007; Merchant et al., 2021; St-Onge & Gallagher, 2010). Most studies examining the relation between body composition and postural control have relied on BMI as a proxy for total body fat percentage (Almurdi, 2024; Cho et al., 2017; Hita-Contreras et al., 2013). However, BMI is considered an inadequate marker of body composition because it cannot distinguish between FM and FFM. BMI also fails to capture the differential contributions of fat and fat-free mass compartments to postural control (Mainenti et al., 2011; Merchant et al., 2021; St-Onge & Gallagher, 2010). Indeed, fat mass index (FMI) and fat-free mass index (FFMI), derived by normalizing FM and FFM to height square, respectively, along with the FM/FFM ratio, have been recommended as better measures of functional outcomes in older adults (Brech et al., 2021; Merchant et al., 2021). The FM/FFM ratio further captures the relative balance between fat and fat-free mass as a single composite measure of body composition (Rugila et al., 2022; Xiao et al., 2018). A higher FM/FFM ratio – indicating a greater proportion of FM relative to lean mass is associated with poor health outcomes, even among individuals with normal BMI (AlMasud et al., 2025). Taken together, these indices offer a more comprehensive assessment of body composition, capturing subtle differences that may influence physical function and postural control in older adults (AlMasud et al., 2025).

An increase in FM and a decline in skeletal muscle mass in older adults have been associated with impaired postural control and increased fall risk (Neri et al., 2021; Shinonaga et al., 2005). Individuals with high FM spend less time within the limits of stability, suggesting difficulties in controlling balance even in the absence of multisensory interaction deficits (Delfa-de la Morena et al., 2021; Dutil et al., 2013). Furthermore, when overweight and obese individuals lost weight, their center of pressure (COP) sway displacement improved, and a strong relation was observed between the amount of weight lost and the improvement in postural control (Teasdale et al., 2007). However, no studies to date have examined whether FMI, FFMI, and FM/FFM ratio independently predict force plate-derived postural sway in community-dwelling adults, nor whether this relation differs between younger and older adults.

COP sway displacement is a proxy for postural sway magnitude and a biomarker of fall risk in older adults (Goble & Baweja, 2018a, 2018b). Wavelet analysis of the COP signal further decomposes postural sway into frequency-specific components, transforming postural sway from a global outcome measure into a mechanistic framework for examining the dynamics of postural sway. Previous work from our group demonstrated that most of the wavelet power of the COP signal is concentrated below 1 Hz, and that low-frequency oscillations in this band are associated with increased COP sway displacement and provide valuable insights into age- and task-associated postural control deficits (Meyer-Vega et al., 2025). This makes low-frequency oscillations below 1 Hz a theoretically meaningful target for examining the relation between body composition and postural control in older adults.

The purpose of this study is to examine whether FMI, FFMI, and FM/FFM ratio predict COP sway and low-frequency oscillations in community-dwelling older adults. Understanding which body composition components drive postural control impairment in older adults has direct implications for targeted fall prevention interventions. Specifically, investigations can potentially help prioritize reducing FM, preserving muscle mass, or both, and provide a simple, clinically accessible marker for fall-risk screening in community-dwelling populations. Based on prior evidence linking excess adiposity to impaired postural control in older adults (Mainenti et al., 2011; Meng & Gorniak, 2020), we hypothesized that higher fat mass indices would be associated with greater COP sway displacement.

2. Methods

Participants

Eighty-seven participants, including 44 younger adults (YA; 26 ± 5 years old) and 43 older adults (OA; 69 ± 6 years old) were enrolled in this cross-sectional study (see Table 5). Inclusion criteria were as follows: 1) young adults aged 18-35 or older adults aged 60 years and older; 2) no diagnosed history of neurological or musculoskeletal conditions; 3) no acute injuries affecting their ability to stand within the last six months prior to testing. Participants were excluded if they reported any medical conditions that could compromise safety during balance testing, difficulty understanding and following simple verbal instructions, current pregnancy, a cardiac pacemaker, or metal implants and/or prosthetic devices that could interfere with bioimpedance spectroscopy (BIS) measurements.

This study was approved by the Auburn University Institutional Review Board (Protocol #STUDY00000880) and followed the latest revisions of the Declaration of Helsinki, except for being pre-registered as a clinical trial, given that this was a cross-sectional (not interventional) investigation. All participants provided written informed consent before participating in the study.

Equipment

Body composition was assessed using a bioimpedance spectroscopy device (SFB7; ImpediMed, Brisbane, Australia). This device measures impedance across a frequency range of 3 to 1000 kHz, generating 256 measurements per assessment, from which FFM and FM are estimated (ImpediMed, 2026). The device we utilize has been shown to be a valid and reliable tool for estimating total body water, from which FFM and FM are derived

(Moon et al., 2008). Device calibration was verified daily prior to testing using the manufacturer's standard calibration protocol.

Postural sway was assessed using the BTrackS Balance Tracking System (Balance Tracking Systems, San Diego, CA, USA), which includes a force plate (BTrackS Balance Plate) and accompanying software for COP data acquisition. The BTrackS has been validated as a reliable tool for acquiring COP data related to postural sway (Goble et al., 2019; O'Connor et al., 2016; Richmond et al., 2018). COP data were sampled at 25 Hz as determined by the manufacturer and stored it on a local PC for offline analysis.

Experimental Protocol

Body composition. Upon arrival at the laboratory, participants were asked to remove all jewelry, shoes, and socks. Participants were weighed, and height was assessed using a standard laboratory scale. Participants were then asked to rest supine on a padded examination table for 10 minutes, with legs uncrossed and arms relaxed at their sides. Prior to BIS, each participant's height, weight, age, and sex were entered. Following the rest period, single-tab gel electrodes were placed at four sites, including two on the dorsal surface of the right hand, positioned between the metacarpophalangeal joints and the ulnar styloid process, and two on the dorsal surface of the right foot, positioned between the metatarsophalangeal joints and at the level of the medial and lateral malleoli, with a minimum separation of 5 cm between electrodes (Fig. 25A). Three BIS measurements were obtained at 10-second intervals using the BIS device, and the values were averaged for analysis.

Postural sway. The Better Balance test (BBT) quantifies postural sway through COP displacement during quiet standing (Goble & Baweja, 2018a). Participants stood on the balance plate with their hands on their hips, feet shoulder-width apart, and eyes closed for four 20-second trials (Fig. 25B). The first trial served as a familiarization; COP data from the remaining 3 trials were averaged to calculate postural sway (cm). Participants were instructed to stand as still as possible and to avoid talking during each trial (Goble & Baweja, 2018a, 2018b; Goble et al., 2019).

INSERT FIGURE 25

Data analysis

Quantification of postural sway. COP sway displacement is a proxy for postural sway magnitude and, thus, larger BBT values are indicative of greater postural sway (Goble & Baweja, 2018a; Goble et al., 2019). COP sway displacement was determined by the distance between successive registered COP locations according to the following formula (Goble & Baweja, 2018a):

$$\text{COP sway displacement} = [(COP_{x^2} - COP_{x^1})^2 + (COP_{y^2} - COP_{y^1})^2]^{0.5} \qquad \text{Equation 1}$$

Where COP_{x2} and COP_{x1} are adjacent time points in the COP_x (mediolateral) timeseries, and COP_{y2} and COP_{y1} are adjacent time points in the COP_y (anteroposterior) timeseries. The total COP sway displacement is then obtained by summing these individual distances over the entire time series.

In addition, continuous wavelet transform analysis was performed on the COP signal using a base MATLAB function developed by Torrence and Compo (available at: http://paos.colorado.edu/research/wavelets) (Torrence & Compo, 1998). The absolute wavelet power within the 0-1 Hz frequency band was extracted from the COP signal and used as an index of low-frequency oscillations in postural sway. For more details about the continuous wavelet transform analysis, refer to Baweja et al. (2011) and Meyer Vega et al. (2026)(Baweja et al., 2011; Meyer-Vega et al., 2025).

Quantification of FMI and FFMI. FFMI and FMI were calculated as follows (Messner et al., 2024; VanItallie et al., 1990):

$$\text{FFMI} = \text{FFM (kg)} / \text{height squared } (\text{m}^2) \qquad \text{Equation 2}$$

$$\text{FMI} = \text{FM (kg)} / \text{height squared } (\text{m}^2) \qquad \text{Equation 3}$$

Statistical Analysis

Any participant who exhibited values outside ±3 SD were excluded as an outlier. Four participants were excluded based on this criterion, resulting in a final sample of 83 participants (42 YA; 41 OA). Shapiro-Wilk testing was used to assess normality, and, when the normality assumption was violated for all variables, nonparametric tests were employed. Mann-Whitney U tests were then used to examine sex differences (male vs female) and group differences (younger adults vs older adults) in body composition indices (FMI, FFMI, FM/FFM ratio) and postural sway outcomes (postural sway and 0-1 Hz frequency band). Spearman rank-order correlations were further utilized to examine associations between body composition indices and postural sway outcomes.

Moreover, we performed multiple linear regression using the forced-entry method to examine the relationship between body composition indices and postural sway outcomes for YA and OA, with sex included as a covariate. The relative importance of the predictor was estimated using the partial correlation (part r). In a secondary analysis, older adults were classified into low fall-risk (postural sway ≤31 cm, n = 31) and high fall-risk (postural sway >31 cm, n = 12) subgroups based on established normative cutoff criteria to examine whether the regression findings were driven by a specific fall-risk group (Goble & Baweja, 2018a).

All analyses were performed using IBM SPSS Statistics (IBM SPSS version 29; SPSS Inc., Chicago, IL, USA), and graphs were created using SigmaPlot® (Inpixon Inc., version 15 for Windows) and JMP® (SAS Institute Inc.). The alpha level for all statistical tests was set at $p < 0.05$. Data are reported as mean ± SD in the text.

3. Results

Body composition

No significant age group differences existed for FFMI (YA: 18.93 ± 3.02 kg/m^2, OA: 17.88 ± 3.19 kg/m^2; U = 661.00, $p = 0.069$), FMI (YA: 6.52 ± 2.55 kg/m^2, OA: 7.42 ± 2.85 kg/m^2; U = 699.00, $p = 0.140$). or the FM/FFM ratio (YA: 0.36 ± 0.15 kg/m^2, OA: 0.42 ± 0.15 kg/m^2; U = 677.00, $p = 0.094$; see Table 5). Moreover, females demonstrated a higher FM/FFM ratio (Females: 0.46 ± 0.13 kg/m^2, Males: 0.26 ± 0.97 kg/m^2; U = 206.00, $p < 0.001$) and FMI (Females: 7.69 ± 2.66 kg/m^2, Males: 5.65 ± 2.32 kg/m^2; U = 434.00, $p < 0.001$) when compared with males, while males exhibited greater FFMI when compared with females (Females: 16.80 ± 2.33 kg/m^2, Males: 21.25 ± 2.21 kg/m^2; U = 128.00, $p < 0.001$, see Table 6).

INSERT TABLE 5

Postural sway

OA demonstrated significantly greater COP sway displacement (YA: 17.08 $\pm$ 5.19 cm, OA: 24.14 $\pm$ 7.82 cm; U = 376.00, $p < 0.001$) and greater total COP wavelet power in the 0-1 Hz band (YA: 0.009 $\pm$ 0.006 cm^2, OA: 0.02 $\pm$ 0.01 cm^2; U = 476.00, $p < 0.001$, see Table 5) when compared with YA. Moreover, no significant sex differences were found in COP sway displacement (Females: 21.24 $\pm$ 8.03 cm, Males: 20.71 $\pm$ 7.33 cm; U = 773.00, $p = 0.835$) and total COP wavelet power in the 0-1 Hz band (Females: 0.015 $\pm$ 0.013 cm^2, Males: 0.012 $\pm$ 0.007 cm^2; U = 760.00, $p = 0.740$, see Table 6).

INSERT TABLE 6

Correlations between body composition indices and postural sway

The FM/FMM ratio was significantly associated with total COP wavelet power in the 0-1 Hz band (r = 0.242, $p = 0.028$). Similarly, FMI was significantly associated with total COP wavelet power in the 0-1 Hz band (r = 0.238, $p = 0.030$). FFMI was not significantly correlated with any postural sway outcome (all $p > 0.05$). Additionally, FM/FFM ratio and FMI were highly intercorrelated (r = 0.917, $p < 0.001$).

Association between body composition indices and COP sway displacement

OA exhibited significantly greater COP sway displacement when compared with YA. Furthermore, body composition indices did not differ significantly between groups, yet the FM/FFM ratio and FMI were significantly correlated with postural sway outcomes. To test whether body composition indices predicted postural sway differently in younger and older adults, we performed multiple linear regression analyses to determine the association between body composition indices and COP sway displacement, with sex included as a covariate.

Across OA, the FM/FFM ratio was significantly associated with greater COP sway displacement ($R^2 = 0.195$, $p = 0.016$; Fig. 26A), indicating that a higher fat-to-muscle ratio accounts for ~20% of the increase in variance in postural sway. FMI showed a comparable relation ($R^2 = 0.218$, $p = 0.009$; Fig. 26B), accounting for ~22% of the variance. Neither association was observed in YA (FM/FFM: $p = 0.747$; FMI: $p = 0.556$). FFMI was not significantly associated with COP sway displacement in either group (OA: $p = 0.177$, YA: $p = 0.155$). To formally test whether these associations differed by age group, Age x Body Composition interactions were included in regression models using the full sample. The Age x FM/FFM ratio interaction ($R^2 = 0.331$, $p = 0.009$) and the Age x FMI interaction ($R^2 = 0.343$, $p = 0.004$) terms were significant, confirming that fat mass indices are significantly stronger predictors of COP sway displacement in OA when compared with YA. Thus, although both groups showed no significant differences in body composition profiles, fat mass indices, but not fat-free mass index, predicted postural sway specifically in OA, suggesting an age-associated relation between increased fat mass and decreased postural control.

INSERT FIGURE 26

Association between body composition indices and total COP wavelet power from 0-1 Hz

OA exhibited significantly greater total COP wavelet power in the 0-1 Hz band when compared with YA. Additionally, the FM/FFM ratio and FMI were significantly correlated with low-frequency oscillations in this band. To test whether body composition indices predicted low-frequency oscillations differently in younger and older adults, we performed multiple linear regression analyses to determine the association between body composition indices and total COP wavelet power in the 0-1 Hz band, with sex included as a covariate.

Across OA, the FM/FFM ratio was associated with greater total COP wavelet power in OA in the 0-1 Hz band (R^2 = 0.235, *p* = 0.006; Fig. 27A), indicating that a higher fat-to-muscle ratio accounts for approximately ~24% of the variance in low-frequency oscillations. FMI showed a comparable relation (R^2 = 0.236, *p* = 0.006; Fig. 27B), accounting for ~24% of the variance. Neither association was observed in YA (FM/FFM: *p* = 0.346; FMI: *p* = 0.350). FFMI was not significantly associated with total low-frequency oscillations in either group (OA: *p* = 0.246, YA: *p* = 0.141). To formally test whether these associations differed by age group, Age x Body Composition interactions were included in regression models using the full sample. The Age x FM/FFM ratio interaction (R^2 = 0.217, *p* = 0.014) and the Age x FMI interaction (R^2 = 0.178, *p* = 0.044) terms models were significant, confirming that fat mass indices are significantly stronger predictors of low-frequency oscillations in OA when compared with YA. Thus, fat mass indices but not fat-free mass index predicted low-frequency postural oscillation specifically in older adults, extending the COP sway finding into the frequency domain and further supporting an age-dependent relation between fat mass and postural control.

INSERT FIGURE 27

Fall Risk Subgroup Analysis

Within the low fall-risk group, FFMI was significantly correlated with COP sway displacement (r = 0.443, *p* = 0.013), and FMI was significantly correlated with total COP wavelet power from the 0-1 Hz band (r = 0.359, p = 0.047). No significant correlation was observed in the high fall-risk group.

Regression analyses revealed no significant models in either fall-risk group for COP sway displacement (low fall-risk: p = 0.296; high fall-risk: p =0 .657) or total COP wavelet power from 0-1 Hz band (low fall-risk: p = 0.144; high fall-risk: p = 0.173). Thus, the body composition-postural sway relation observed across the full older adult sample was not attributable to a specific fall risk subgroup.

4. Discussion

This study builds on prior evidence examining factors that affect postural sway and fall risk in older adults. Our primary findings were that fat mass indices (i.e., FM/FFM and FMI) were significantly associated with COP sway displacement and low-frequency postural oscillations exclusively in older adults, whereas no such relationships were observed in younger adults. This was despite no significant differences in adiposity profiles between groups, suggesting that the relation between fat mass and postural control is age-dependent rather than driven by differences in adiposity per se. Moreover, FFMI was not significantly associated with postural sway in either age group, indicating that the quantity of muscle mass does not predict postural control. These findings extend prior work suggesting that specific adiposity measures, rather than body mass or BMI, are critical for understanding postural dysfunction in aging (Meng & Gorniak, 2020), and an in-depth discussion of our findings is provided in the following paragraphs.

A reasonable explanation for the age-dependent fat mass-postural sway relationship may involve altered biomechanics and COP displacement. In general, overweight and obese individuals possess an anteriorly displaced COP that elicits greater trunk extension while standing in a manner to counteract the excessive weight. In support of this hypothesis, Frames et al. reported that higher BMI was associated with greater fall risk and increased postural sway, and these authors speculated that postural sway could be an adaptive strategy in obese individuals to provide additional stability under conditions of altered COP and muscle weakness (Frames et al., 2018). Both obesity and aging independently promote chronic low-grade systemic inflammation, which has been shown to impair neuromuscular activation and reduce muscle strength in older adults (Liang & Zhang, 2026), potentially explaining why fat mass becomes a meaningful predictor of postural instability specifically in this population.

The finding that FM/FFM and FMI predicted low-frequency COP oscillations (0-1 Hz band) in older adults provides additional insights. The 0-1 Hz frequency band was specifically targeted based on previous work from our laboratory demonstrating that most of the COP signal's wavelet power is concentrated below 1 Hz and that low-frequency oscillations in this band are associated with increased COP displacement, providing valuable insights into age-associated postural control deficits (Meyer-Vega et al., 2025). Low-frequency postural sway is believed to reflect balance adjustment and feedback-driven postural corrections (Zatsiorsky & Duarte, 2000). Moreover, the aforementioned study by Frames and colleagues indicates that obese fallers possess a lower complexity of anterior-posterior COP time series (Frames et al., 2018), suggesting that excess body mass constrains the dynamic range and adaptive capacity of the postural control system.

In contrast, while lean mass provides stabilizing musculature, the absence of an FFMI relationship with postural sway outcomes is informative and warrants brief discussion. This finding suggests that preserved muscle mass during aging does not substantially mitigate postural dysfunction. Rather, the deleterious effects of excess fat mass appear to override the protective influence of maintained lean tissue, particularly in the context of age-associated sensory and neuromuscular decline. Critically, while our data are preliminary, as discussed in more detail below, one interpretation of our findings is that interventions targeting fat mass reduction and lean mass preservation during aging, rather than lean mass preservation alone, may be more effective for restoring postural stability in older adults. Indeed, this hypothesis is supported by a report from Teasdale and colleagues who demonstrated that substantial weight loss over a 12-month period improves postural control outcomes in a smaller cohort of middle-aged men (Teasdale et al., 2007).

Experimental Considerations

Though we view our findings as a novel contribution towards better understanding factors that influence postural control during aging, some certain limitations should be acknowledged. First, although BIS is a valid measure of body composition, the device does not provide compartmental lean and adiposity data, such as other devices (e.g., dual-energy x-ray absorptiometry – DXA, or MRI). Given this limitation, future research using these techniques is needed to determine whether visceral adiposity is a strong predictor of increased postural sway.

A second limitation is that participants were not instructed to fast for a standardized period prior to visiting the laboratory, which could have confounded BIS measurements, as reported in the literature (Androutsos et al., 2015; Forejt et al., 2023). However, unrestricted food and liquid intake prior to testing has been shown not to cause clinically meaningful changes in body fat percentage as estimated by BIS, suggesting that this limitation is likely to have minimal impact on the validity of our body composition estimates (Mundstock et al., 2021). Third, though FFMI showed poor associations with outcomes, we posit that more sophisticated measures are needed to further explore this relationship. For instance, upper- and lower-leg muscle quality assessments using MRI, combined with functional outcomes (e.g., isokinetic dynamometry), would be informative as potential predictors. Finally, the cross-sectional design employed in this study prevents causal inference, and findings are limited to healthy, community-dwelling older adults assessed during quiet standing. Thus, longitudinal studies with larger, more diverse samples and dynamic balance assessments are needed to confirm that alterations in fat mass significantly influence postural control.

Conclusion

In conclusion, this study demonstrates that indices of fat mass, rather than fat-free mass, are significantly associated with postural sway, specifically in older adults, whereas no such associations were observed in younger adults despite comparable body composition profiles. FFMI did not predict postural sway in either group, suggesting that whole-body fat-free mass index does not capture the muscle-specific contributions to postural control. These findings highlight the importance of considering body composition assessments when assessing fall risk and carry implications for designing interventions to improve postural control in aging populations.

Chapter 5: Integrated Discussion

Postural control is not a simple motor behavior; it requires the dynamic interaction of visual, vestibular, and proprioceptive inputs, the allocation of attentional resources, and the coordination of neuromuscular responses that continuously adapt to task and environmental demands (Chen J, 2023; Huxhold O, 2006; Redfern MS, 2001). Despite its complexity, postural control has traditionally been assessed using subjective and performance-based clinical tools that measure only its behavioral outcome: how fast someone walks, how long they balance, or how quickly they stand from a chair (Meyer-Vega M, 2025). However, these tools have consistently demonstrated insufficient sensitivity to capture the complexity of fall risk and balance in aging and neurological populations (Meyer-Vega M, 2025; Rose DJ, 2006).

To develop a more comprehensive understanding of the underlying mechanisms of postural control, the four studies comprising this dissertation examine balance from multiple perspectives. Chapter 1 establishes the clinical problem: current fall risk assessments demonstrate inconsistent discriminative accuracy. Chapters 2 and 3, which are supported by two manuscripts currently under review, establish the methodological foundation of this work. These studies show that low-frequency oscillations may provide a more objective biomarker of fall risk. They also demonstrate how sensory reweighting mechanisms of postural control adapt to different tasks and surface demands in healthy young and older adults. Chapter 4 approaches postural control from a different angle by demonstrating that fat mass predicts postural instability in older adults and that adiposity independently contributes to age-associated changes in postural control. Taken together, these studies suggest that understanding behavioral outcomes alone does not fully explain fall risk. Understanding why individuals fall requires a closer examination of the mechanisms underlying postural control.

The clinical problem: Current fall risk assessments

Fall risk assessments in stroke survivors currently lack standardization across both research and clinical practice (Meyer-Vega M, 2025). Across the included studies in the systematic review, over 27 assessment tools were identified, with inconsistent definitions of fall, varying cut-off values, and no consensus on which tool to use. Despite this variability, the Better Balance Scale (BBS) and the Timed Up and Go (TUG) remain the most commonly used tools in clinical settings (Dos Santos RB, 2023). We found that both assessments were able to distinguish fallers from non-fallers among stroke survivors. However, statistical significance alone does not establish clinical sufficiency. The moderate heterogeneity observed across the included studies, combined with the limitations of these tools in fully capturing the complexity of balance impairments, suggests that neither test should be used as a standalone fall risk screening tool.

The BBS and TUG were not specifically developed for stroke survivors. They were originally designed for older adults, and even in this population, their standalone diagnostic accuracy remains limited (Barry E, 2014; Lima CA, 2018). Moreover, these tests were not designed as fall-risk assessment tools; they were developed as measures of functional balance and mobility (Berg KO, 1992; Blum L, 2008). For these reasons, these assessments may be more appropriately used as part of a broader, multifactorial fall-risk model that considers the complex neuromuscular and postural control impairments present in this population. As a result, clinicians are often forced to make rehabilitation decisions using tools that identify fall risk without adequately capturing the underlying mechanisms contributing to postural instability. Importantly, this limitation is not unique to the stroke population. Similar issues exist across aging and other neurological conditions, where current fall risk assessments can identify who is at risk of falling but provide limited insight into the underlying mechanisms driving that risk (Rajagopalan R, 2017).

Low-frequency oscillations as a biomarker of fall risk

Postural control is defined by the relationship between an individual's center of pressure (COP) and their base of support (Pineda RC, 2020). The COP signal captured during quiet standing is a rich physiological signal whose oscillatory structure provides information about how the nervous system actively regulates balance across multiple timescales simultaneously (Jafari H, 2023; Redfern MS, 2001). However, traditional linear measures reduce this signal to a single total displacement metric (cm), quantifying how much the body moves but ignoring the time-frequency structure that provides critical information about how the system achieves this regulation (Chagdes JR, 2009).

The oscillatory content of the COP signal is not uniformly distributed across frequencies. Most of the COP signal power is concentrated between 0 and 4 Hz, and within this range, the 0-1 Hz band carries the most important clinical diagnostic information (Meyer Vega M, 2026; Meyer-Vega et al., 2025). Distinct sub-bands within this range have been associated with specific sensory contributions to postural control: visual (0-0.1 Hz), vestibular (0.1-0.5 Hz), and proprioceptive (0.5-1 Hz) inputs (Chagdes JR, 2009;

Oppenheim U, 1999). Modulation of power across these frequency bands reflects shifts in sensory reweighting, specifically which inputs the nervous system is primarily relying on, and how these contributions reorganize in response to external demands (Chagdes JR, 2009; Jafari H, 2023).

Across the aging population, we have previously found that ~86% of the power in the COP signal is concentrated below 1 Hz, and that older adults at high fall risk exhibit significantly greater wavelet power across all frequency bands when compared with their low fall-risk peers (Meyer-Vega et al., 2025). Importantly, the change in 0-1 Hz wavelet power from single to dual-task accounted for approximately 57% of the increase in postural sway displacement, a relation observed only in the high fall-risk group but absent in the low fall-risk group. Moreover, total sway displacement did not differ significantly between single and dual-task conditions. This was only evident when we analyzed the oscillatory structure of the COP signal in which task-associated differences emerged, with wavelet power in the 0-1 Hz band significantly reduced during dual-task when compared with the single-task condition. These findings suggest that relying on sway displacement alone is insufficient to fully capture the underlying strategies of postural control, as two individuals can produce comparable sway displacement even when their oscillations are completely distinct.

This distinction between quantity and quality becomes even more critical when a neurological condition disrupts postural control. In Huntington's disease (HD), we examined whether objective biomarkers of postural sway can track disease severity and reflect changes in sensory regulation across the HD spectrum. We found that progressive weakening of oscillatory-sway coupling distinguishes manifest HD from premanifest stages. Premanifest HD individuals demonstrate early sensory reweighting deficits only when vision is removed, while manifest HD individuals show decoupled oscillatory activity that fails to support stable postural control regulation (Meyer Vega M, 2026). This progressive decoupling may serve as a biomarker of disease conversion prior to the onset of motor symptoms.

These previous findings raised the question of how sensory reweighting specifically reorganizes under different task and surface demands in healthy older adults. Understanding what the intact postural control system does under these conditions is a necessary first step because neurologic conditions such as HD and stroke are not merely clinical problems; they also serve as models that provide valuable insights into what happens when specific components of that system are disrupted. Moreover, Chapters 2 and 3 were designed to establish the foundation in healthy aging, so that in future studies, the disruptions observed in neurological disorders can be interpreted against a reference point. On a stable surface (Chapter 2), both older and younger adults exhibited reduced postural sway under dual-task conditions when compared with the balance single-task, suggesting that directing conscious attention toward a highly automated behavior (e.g., postural control) interferes with the automatic processes that normally regulate it, and that shifting attention toward an external task allows those processes to operate more efficiently. However, older adults exhibited the same postural sway when compared with younger adults, but at the expense of cognitive task accuracy, indicating a reallocation of attentional resources toward postural control (Brown LA, 2002; Yu SH, 2017). Yet this postural strategy relies on cognitive resources that may not be available when balance is unexpectedly challenged, precisely in the conditions in which most real-world falls occur (Brown LA, 2002; Schaefer, 2014).

While total sway displacement captured the behavioral outcome of these task differences, the time-frequency analysis revealed the internal processes underlying them, demonstrating that sensory reweighting was task- and direction-specific. Proprioceptive (motor) dual-task consistently produced greater AP wavelet power in both groups, suggesting that when the same sensory input is required for postural input and motor output, the conflict within that system imposes a greater reorganization demand (Weeks DL, 2003). In contrast, the cognitive dual-task produced the lowest AP wavelet power, supporting the idea that external attention redirection reduces demands on postural control (Polskaia N, 2015; Rafiee Manesh V, 2024).

On an unstable surface (Chapter 3), the same postural sway reduction pattern was observed, but the age-associated sensory reweighting differences became more evident. Age-associated differences in low-frequency oscillations were no longer only visible to a single direction or task but emerged across all COP directions (AP, ML, and total COP), with older adults exhibiting greater reliance on visual and vestibular inputs (0-0.1 and 0.1-0.5 Hz bands) when proprioceptive input reliability was simultaneously challenged by the foam surface and the nature of the proprioceptive dual-task, leaving older adults with reduced access to the sensory inputs they most rely upon (Liu Z, 2023). During the multitasking condition, age-associated differences become evident in the 0.1-0.5 Hz band (vestibular input), suggesting that older adults rely more on vestibular input to compensate for proprioceptive demands that exceed their system's capacity, a pattern not observed in younger adults and likely reflecting an age-associated degradation in sensory reweighing capacity (Osoba MY, 2019). These findings suggest that the effects of sensory reweighing under increasing task and surface demands are disproportionately greater in older adults, and that these costs become more evident when the same sensory input is challenged simultaneously. However, sensory reweighing and attentional mechanisms are not the only contributors to postural instability in aging. Chapter 4 introduces an independent pathway.

Body Composition as an Independent Contributor to Postural Instability in Older Adults

While Chapters 2 and 3 examined the sensory reweighting and attentional mechanisms of postural control, Chapter 4 examined whether fat mass index (FMI), fat-free mass index (FFMI), and the FM/FFM ratio predict COP sway displacement and low-frequency oscillations in the 0-1 Hz band in community-dwelling older adults. Body composition is an important factor in maintaining balance, yet it is generally overlooked in fall risk assessments (Howcroft, 2013). Identifying which body composition components drive postural instability has direct implications for fall prevention, as it can help determine whether intervention should prioritize reducing fat mass, preserving muscle mass, or both.

We found that fat mass indices, specifically FMI and the FM/FFM ratio, were significantly associated with COP sway displacement and low-frequency oscillations in the 0-1 Hz band exclusively in older adults, despite body composition profiles not differing significantly between older and younger adults. The absence of a significant association between FFMI and postural sway in either group indicates that it is not the loss of lean tissue per se, but the accumulation of fat mass relative to lean mass, that destabilizes postural control in older adults. Excess fat mass anteriorly displaces the COP, requiring greater compensatory effort to counteract the added weight (Frames et al., 2018). Moreover, obesity and aging independently promote chronic low-grade inflammation that impairs neuromuscular activation and reduces muscle strength (Liang & Zhang, 2026). This likely explains why fat mass becomes a meaningful predictor of postural instability, specifically in older adults. Notably, FMI was also associated with greater low-frequency oscillations in the 0-1 Hz band, the band that was most sensitive to age- and task-associated differences in Chapters 2 and 3, further reinforcing the importance of considering the COP signal when assessing postural control. This finding reframes body composition not only as a metabolic or cardiovascular health factor but also as a direct and overlooked contributor to fall risk in older adults.

Clinical Implications

The findings of this dissertation suggest that postural control should play a more critical role in the management of neurological disorders and aging, as well as in the design of fall-prevention programs. Despite falls being a leading cause of injury-related death and disability, postural control remains an overlooked rehabilitation target, often addressed secondarily after motor and cognitive deficits (Ockerman J, 2021). Postural instability in neurological disorders is not a simple consequence of motor dysfunction, it also reflects the disruption of a complex sensory integration system that is already affected in healthy older adults (Horak, 2006; Palakurthi B, 2019). Recognizing the importance of postural control as a primary rehabilitation target is a necessary shift to improve fall-prevention outcomes and quality of life in these populations. These findings also have direct implications for clinical practice guidelines (CPGs). CPGs should move toward recommending standardized, objective, instrumented assessment tools that capture postural control dynamics, such as force plates and wearable inertial sensors (Dos Santos RB, 2023). By analyzing their low-frequency oscillations rather than relying solely on behavioral outcomes, clinicians and researchers can identify the sensory and neuromuscular mechanisms that drive postural instability before they become evident as functional deficits, thereby shifting fall risk assessments from detection to prevention.

Strengths and Limitations

This dissertation has several strengths. By combining a systematic review and meta-analysis with experimental studies in healthy young and older adults, as well as neurological populations, this work examined postural control across the full spectrum, from intact systems to their disruption in disease. In Chapters 2 and 3, the same participants (over 100 individuals) were tested on stable and unstable surfaces using the same equipment, which isolated the effects of surface instability from differences between samples. This sample size is notably larger for dual-task postural control research, where studies are often limited by smaller sample sizes.

Several limitations should be acknowledged. The cross-sectional design across Chapters 2-4 precludes causal inference; longitudinal studies are needed to address whether the observed age-associated differences reflect true trajectories. All balance testing was conducted in controlled laboratory settings, which do not fully capture the unpredictable attentional demands in real-world environments where most falls occur. Moreover, body composition in Chapter 4 was assessed using bioimpedance spectroscopy, which does not provide data on compartmental adiposity. Future studies using DXA or MRI would allow for a more precise examination of whether visceral adiposity drives the observed relationships. Finally, and importantly, across all four studies, participants were predominantly recruited from a single geographic region and were predominantly Caucasian, limiting the generalizability of the findings to more diverse populations.

Future directions

Longitudinal designs are needed to establish whether the age-associated sensory reweighting deficits and the fat mass-postural sway relationship represent true aging trajectories. Having characterized how sensory reweighting mechanisms operate in healthy aging, the dual-task design developed in Chapters 2 and 3 can now be extended to neurological populations, where it may reveal how specific disease processes disrupt postural control. Finally, the most important direction is translating time-frequency analysis from controlled laboratory settings into clinical practice. These methods currently require offline signal processing and specialized software, limiting their accessibility. The development of validated, clinically objective tools capable of real-time low-frequency oscillatory analysis would make these measurements accessible to clinicians for fall-risk assessment in practice.

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Appendices

Appendix A: Chapter 1 - Are We Falling Short? Evaluating the Accuracy of Common Clinical Fall Risk Assessments in Stroke Survivors: A Systematic Review and Meta-Analysis

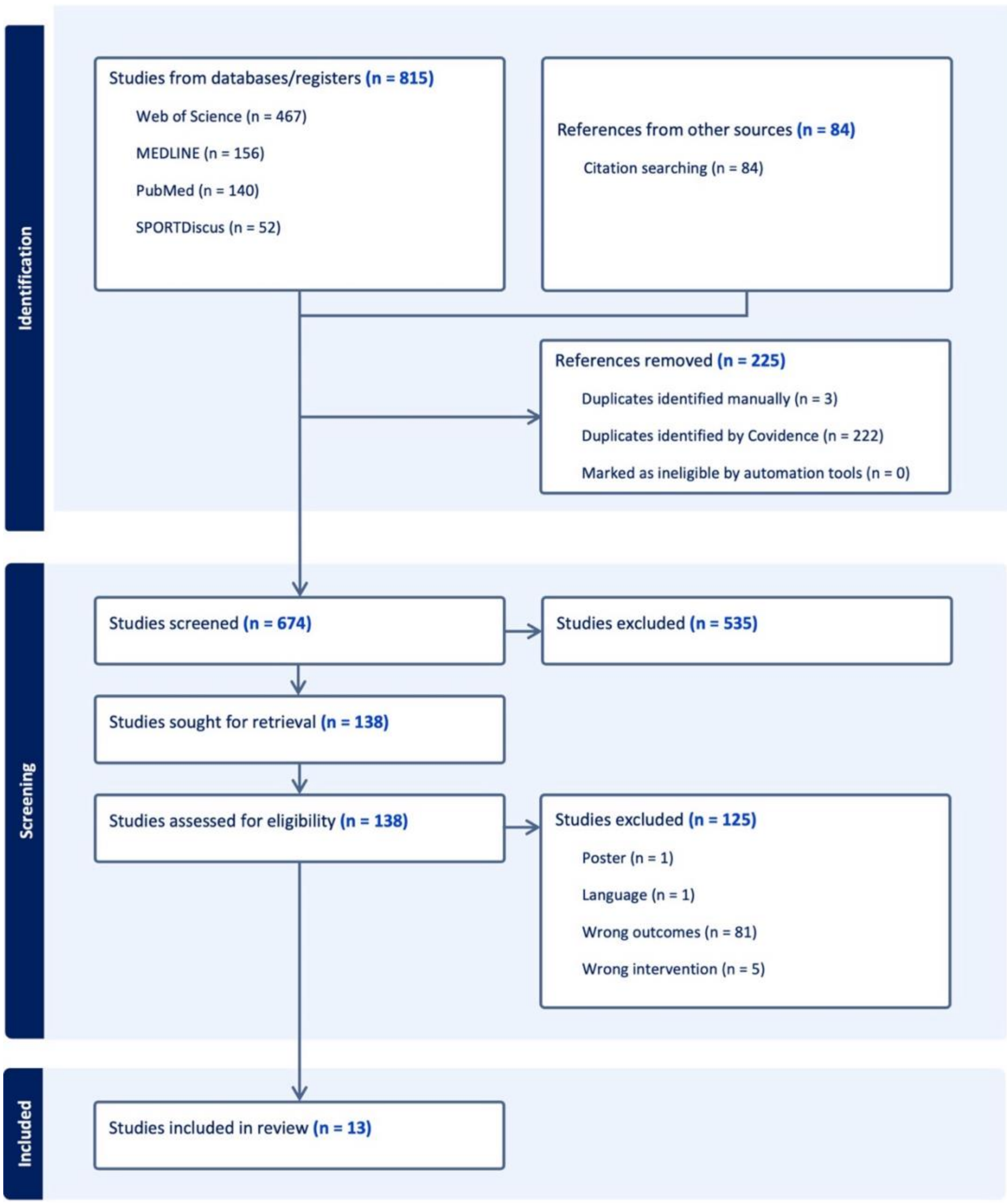

Figure 1. PRISMA 2020 flowchart of study selection.

Table 1. Characteristics of the Berg Balance Scale (BBS) and the Timed Up and Go (TUG) test from the 13 included studies.

Study	Test	Cut-off	Sensitivity (%)	Specificity (%)
Andersson et al., 2006	BBS	< 45 p	63	65
	TUG	> 14 s.	50	78
Ashburn et al., 2008	BBS	≤ 48.5 p	85	49
Beninato et al., 2009	BBS	49 p	78	72
Fiedorová et al., 2022	BBS	≤ 42 p	56.3	67.3
Jalayondeja et al., 2014	BBS	≤ 42 p	64	51
	TUG	≥14 s.	84	21
Liu & Ng, 2019	BBS	47.5 p	68	86
	TUG	14.21 s.	41	95
Maeda et al., 2009	BBS	29 p	80	78
Persson et al., 2011	BBS	≤ 42 p	69	65
	TUG	≥15 s.	63	58
Sahin et al., 2019	BBS	46.5 p	75	76.9
Tsang et al., 2013	BBS	50.5 p	52	80.2
	TUG	19 s.	60.9	60.9
Lee et al., 2021	TUG	18.58 s.	77.8	54.8
Pinto et al., 2014	TUG	25 s.	36	90
Yang et al., 2016	TUG	14.8 s.	55	55.9

S = seconds; p = points

Table 2. Demographic and clinical characteristics of stroke survivors from the 13 included studies.

Study	Total	Fallers	Non-fallers	Age (year)	Time post-stroke	Male	Female	Right stroke	Left stroke	Unknown/ Bilateral
Andersson et al., 2006	159	68	91	73	Acute	NR	NR	70	85	4
Ashburn et al., 2008	115	48	67	70	Subacute	77	38	57	57	1
Beninato et al., 2009	27	9	18	57	Chronic	15	12	13	14	0
Fiedorová et al., 2022	84	32	52	68	Acute	42	42	NR	NR	NR
Jalayondeja et al., 2014	97	25	72	62	Acute	59	38	NR	NR	NR
Liu & Ng, 2019	137	41	96	61	Chronic	69	68	83	54	0
Maeda et al., 2009	72	27	45	68	Subacute-chronic	42	30	34	35	3
Persson et al., 2011	96	46	50	73	Acute	56	40	45	51	0
Sahin et al., 2019	50	26	24	59	Chronic	30	20	32	18	0
Tsang et al., 2013	106	25	81	57	Chronic	73	33	46	60	0
Lee et al., 2021	166	34	132	NR	Mixed	114	52	NR	NR	NR
Pinto et al., 2014	150	56	94	56	Subacute to chronic	73	77	74	76	0
Yang et al., 2016	88	20	68	63	Chronic	64	24	NR	NR	NR
Total n (%)	**1,347**	**457 (33.9)**	**890 (66.1)**	**64 ± 6**		**714 (60.1)**	**474 (39.9)**	**454 (49.8)**	**450 (49.3)**	**8 (0.9)**

Values represent the number of participants, otherwise noted; NR = Not reported.

Table 3. Study characteristics of the included studies examining fall risk in stroke survivors (N = 13).

Study	**Study design**	**Setting**	**Follow up duration**	**Fall definition**	**Fall ascertainment**
Andersson et al., 2006	Prospective cohort	Inpatient	6 or 12 months	*"A fall was defined as an event in which the patient unintentionally came to rest on the ground or floor, regardless of whether or not an injury was sustained"*	Staff observation during hospital stay; self-reported interview
Ashburn et al., 2008	Prospective cohort	Community	12 months	*"A person coming to rest unintentionally on the ground or other lower level, not as a result of a major intrinsic event or overwhelming hazard"*	Falls diary and telephone calls
Beninato et al., 2009	Retrospective cross-sectional	Community	6 months	*"A person coming to rest on the ground or other lower-level unintentionally, which is not as a result of a major intrinsic event or overwhelming hazard"*	Retrospective self-reported questionnaire
Fiedorová et al., 2022	Prospective cross-sectional	Inpatient	6 months	*"Unexpected and unplanned event in which a person is found on the floor or another horizontal surface, with or without injury"*	Falls diary and telephone calls

Jalayondeja et al., 2014	Prospective cross-sectional	Community	6 months	*"Unintentional event resulting in coming to rest on the ground or floor, that was not the result of dizziness, fainting, sustaining a violent blow, loss of consciousness, or other overwhelming external factor"*	Falls diary and telephone calls
Liu & Ng, 2019	Retrospective cross-sectional	Community	None	Not explicitly defined	Self-reported falls
Maeda et al., 2009	Prospective cohort	Inpatient	Duration of hospitalization (~83 days)	*"An incident in which the subject unintentionally came to rest or move on a level below knee height"*	Staff-reported falls
Persson et al., 2011	Prospective cohort	Inpatient	12 months	*"An event in which the person unintentionally found himself or herself below sitting-level or on the ground"*	Self-reported falls
Sahin et al., 2019	Retrospective cross-sectional	Outpatient/clinical	None	Not explicitly defined	Self-reported falls
Tsang et al., 2013	Retrospective cross-sectional	Community	None	Not explicitly defined	Self-reported falls

Lee et al., 2021	Retrospective cohort	Inpatient	Duration of hospitalization (~12-week)	*"Unintentionally coming to rest on the ground, floor, or lower level that is not the result of a seizure, stroke/myocardial infarction, or major displacing force"*	Staff-reported falls
Pinto et al., 2014	Retrospective cross-sectional	Community	None	*"Inadvertently coming to rest on the ground, floor, or other lower level, excluding intentional change in position to rest in furniture, wall, or other objects"*	Staff-reported falls
Yang et al., 2016	Retrospective cross-sectional	Community	None	Not explicitly defined	Staff-reported falls

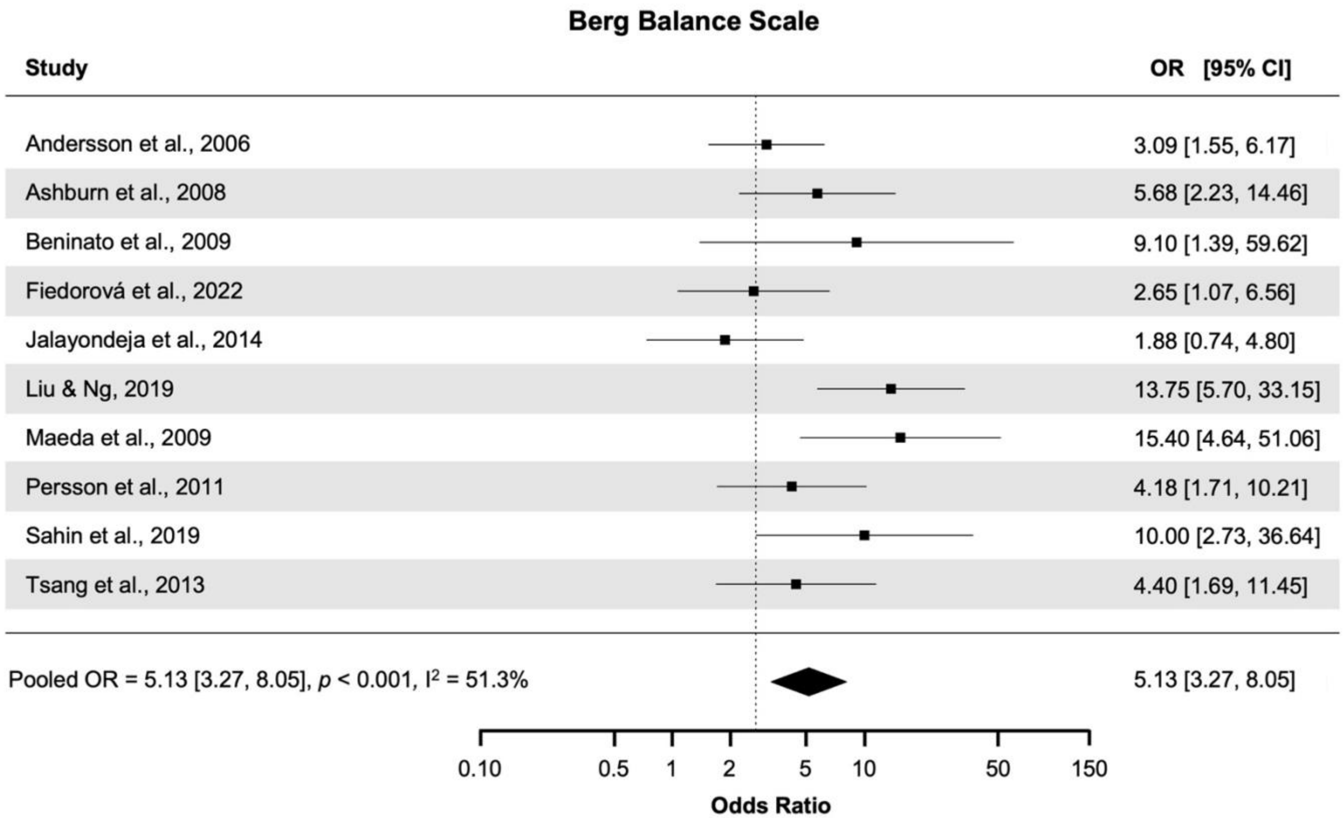

Figure 2. Forest plot of studies included in the meta-analysis examining the overall pooled diagnostic accuracy of the Berg Balance Scale for identifying fall risk in stroke survivors.

Legend: The forest plot displays each study's effect size (odds ratio) along with its 95% confidence interval (CI). The diamond at the bottom represents the pooled effect size association (OR = 5.13, 95% CI [3.27, 8.05], $p < 0.001$), indicating that stroke survivors classified as high fall risk by the BBS had a higher odds of being true fallers when compared to those classified as low fall risk. Moderate heterogeneity was observed across studies ($I^2 = 51.34\%$).

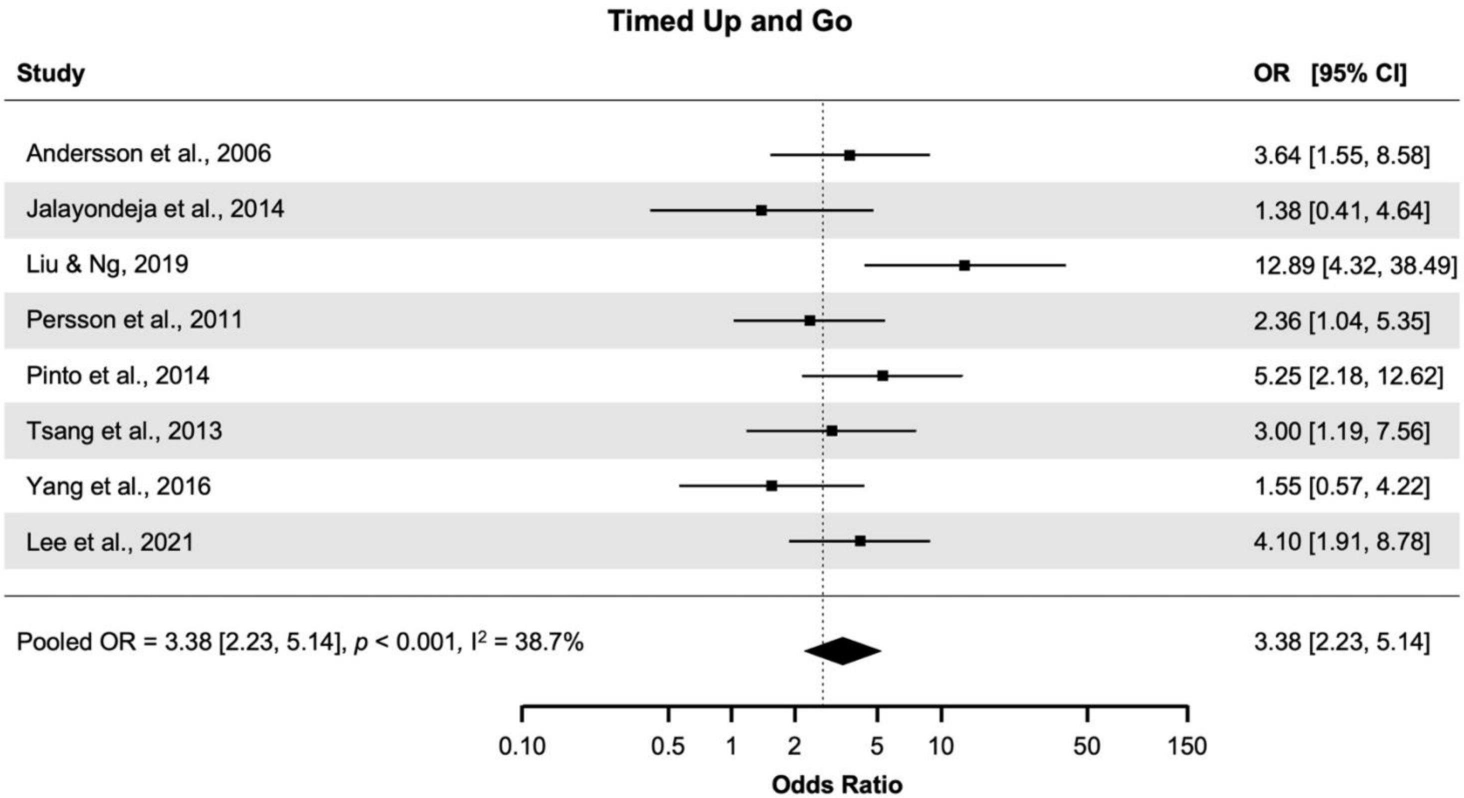

Figure 3. Forest plot of studies included in the meta-analysis examining the overall pooled diagnostic accuracy of the Timed Up and Go for identifying fall risk in stroke survivors.

Legend: The forest plot displays each study's effect size (odds ratio) along with its 95% confidence interval (CI). The diamond at the bottom represents the pooled effect size association (OR = 3.38, 95% CI [2.23, 5.14], $p < 0.001$), indicating that stroke survivors classified as high fall risk by the TUG had a higher odds of being true fallers when compared to those classified as low fall risk. Moderate heterogeneity was observed across studies (I^2 = 38.69%).

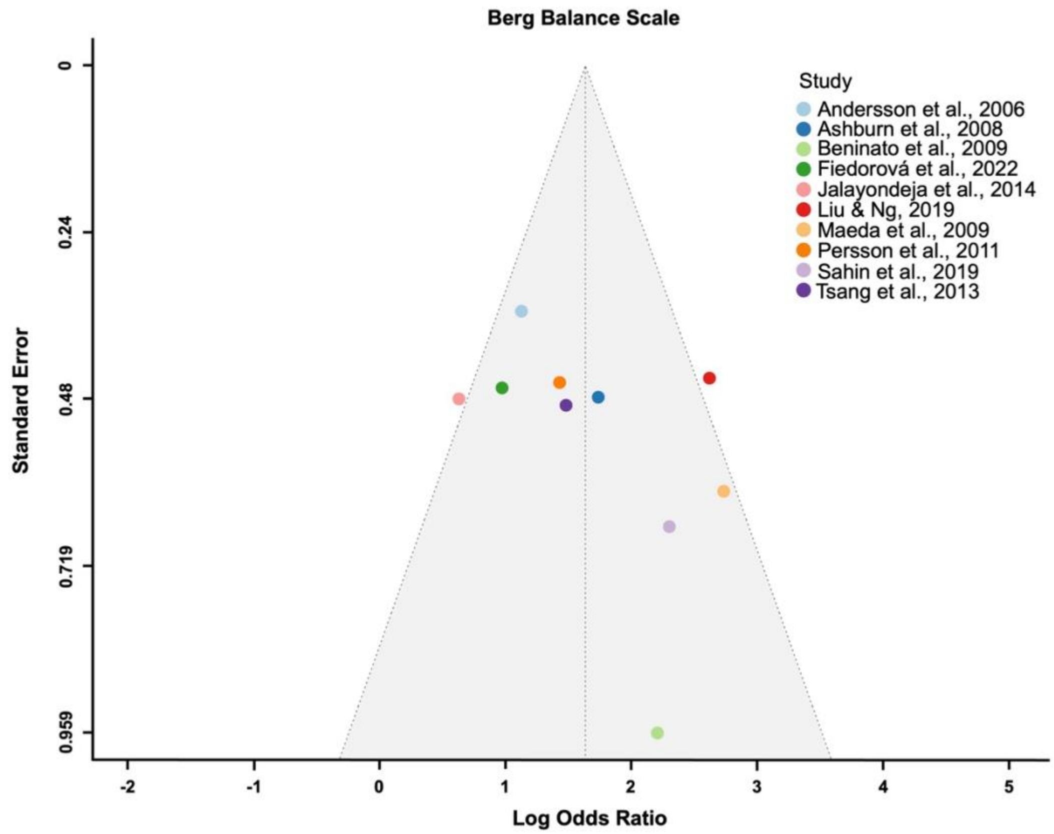

Figure 4. Funnel plot of the 10 studies included in the meta-analysis of the Berg Balance Scale.

Legend: Each colored point represents an individual study. The x-axis represents the log odds ratio, and the y-axis represents the standard error of each study's effect size. The symmetrical distribution of studies suggests an absence of publication bias, confirmed by the Egger's weighted regression test ($t(8) = 1.467$, $p = 0.181$) and the rank correlation test ($\tau = 0.244$, $p = 0.381$).

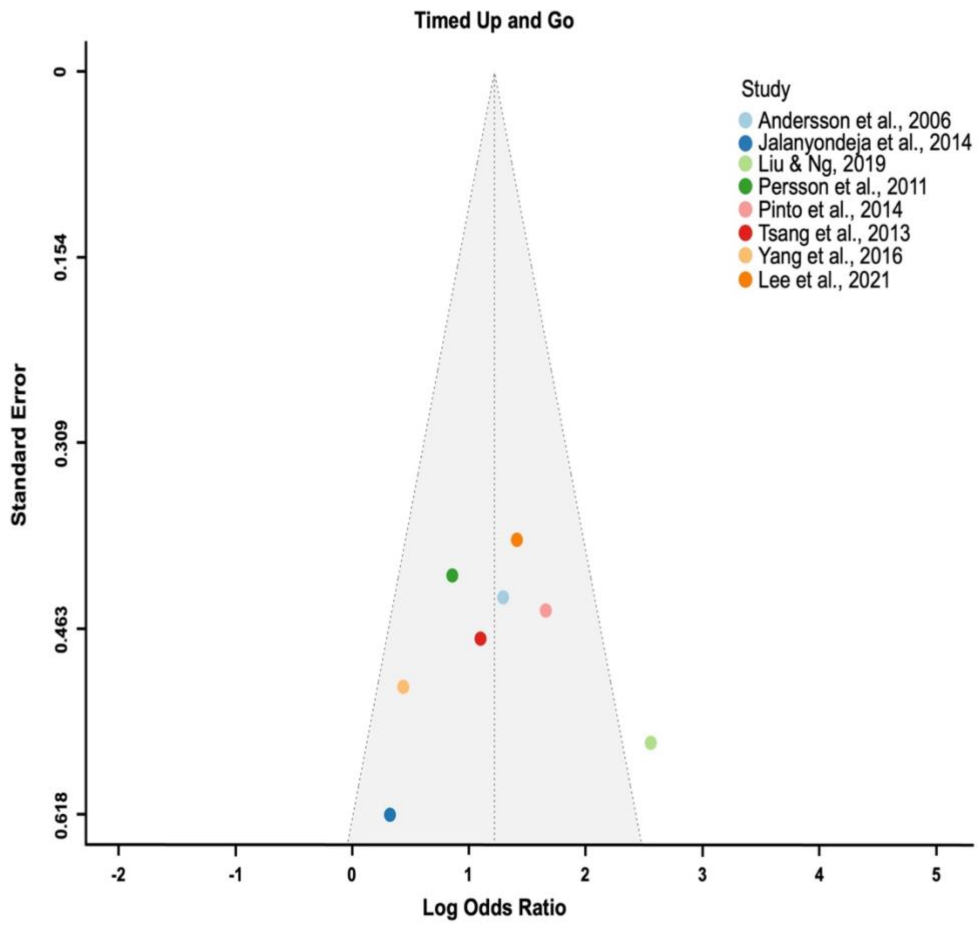

Figure 5. Funnel plot of the 8 studies included in the meta-analysis of the Timed Up and Go.

Legend: Each colored point represents an individual study. The x-axis represents the log odds ratio, and the y-axis represents the standard error of each study's effect size. The symmetrical distribution of studies suggests an absence of publication bias, confirmed by Egger's weighted regression test ($t(6) = -0.269$, $p = 0.797$) and the rank correlation test ($\tau = -0.143$, $p = 0.720$).

Study	Risk of bias				Applicability concerns		
	Patient Selection	Index Test	Reference Standard	Flow & Timing	Patient Selection	Index Test	Reference Standard
Andersson et al. 2006	L	U	U	U	L	L	L
Ashburn et al. 2008	L	U	L	L	L	L	L
Beninato et al. 2009	H	H	H	U	L	L	U
Fiedorová et al. 2022	L	H	U	L	L	L	L
Jalayondeja et al. 2014	L	H	L	L	L	L	L
Lee et al. 2021	L	H	U	L	L	L	L
Liu & Ng 2019	H	H	H	U	L	L	L
Maeda et al. 2009	L	H	L	L	L	L	L
Persson et al. 2011	L	H	L	L	L	L	L
Pinto et al. 2014	H	H	H	U	L	L	L
Sahin et al. 2019	H	H	H	U	L	L	L
Tsang et al. 2013	H	H	H	U	L	L	L
Yang et al. 2016	H	H	H	U	L	L	L
L = Low; H = High; U = Unclear							

Figure 6. Quality assessment of individual studies using the QUADAS-2 tool.

Appendix B: Chapter 2 – Mechanisms of Multisensory Interaction During Dual-Task Postural Control in Aging: I. Stable Surface

Table 4. Participants' demographics, Mean (standard deviation).

	Younger adults	**Older adults**
N	51	51
Age (years)	25 (4)	70 (7)
Sex (F/M)	30/21	35/16
Weight (kg)	78.63 (25.15)	75.33 (19.48)
Height (cm)	166.22 (28.64)	170.33 (11.55)
BMI (kg/m^2)	25.94 (6.48)	25.68 (6.6)
Ethnicity		
White	27	49
Black/African American	4	1
Hispanic/Latino	14	1
Asian	2	0
Middle Eastern	4	0

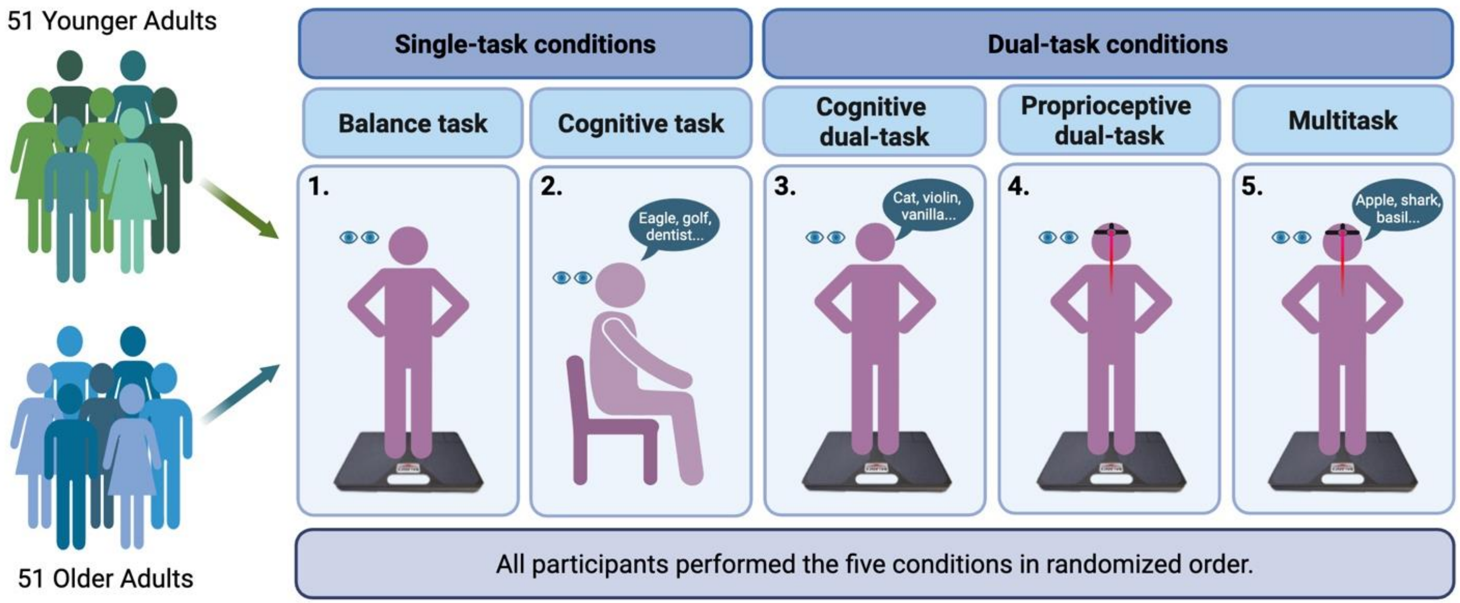

Figure 7. Study design.

Legend: Fifty-one younger adults and 51 older adults completed five randomized tasks on a firm surface with their eyes open

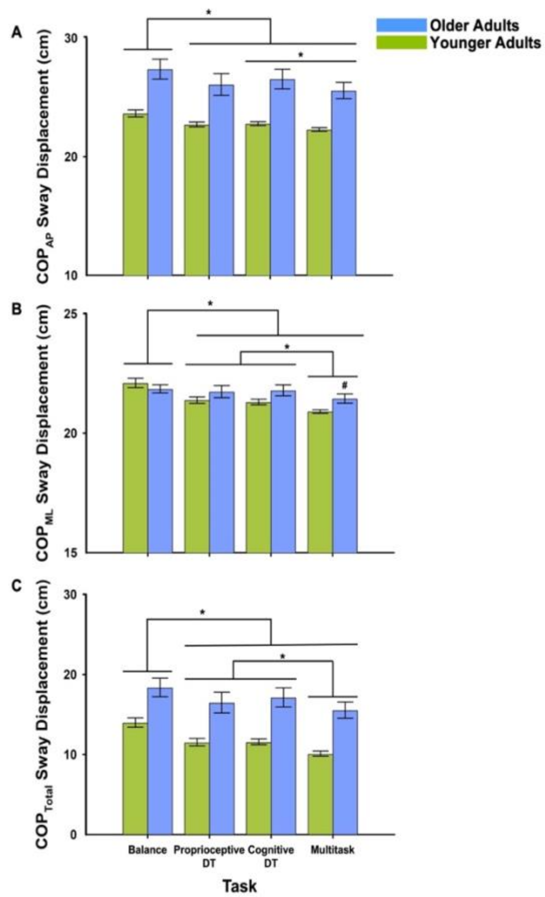

Figure 8. Average postural sway metrics during balance and dual-task conditions on a stable surface.

Legend: **(A)** OA exhibited significantly greater AP sway displacement when compared with YA. AP sway displacement was greater during Balance ST when compared with all other tasks, while cognitive DT demonstrated greater AP sway displacement when compared with the multitask. **(B)** ML sway displacement was greater during the Balance ST when compared with all other tasks, while proprioceptive DT and cognitive DT demonstrated greater ML sway displacement when compared with multitask. OA demonstrated significantly greater ML sway displacement when compared with YA during the multitask condition. **(C)** OA exhibited significantly greater total COP sway displacement when compared with YA. Balance ST demonstrated greater sway displacement when compared with all other tasks, while proprioceptive DT and cognitive DT demonstrated greater total COP sway displacement when compared with the multitask. # Indicates a significant group difference. * Indicates a significant task difference.

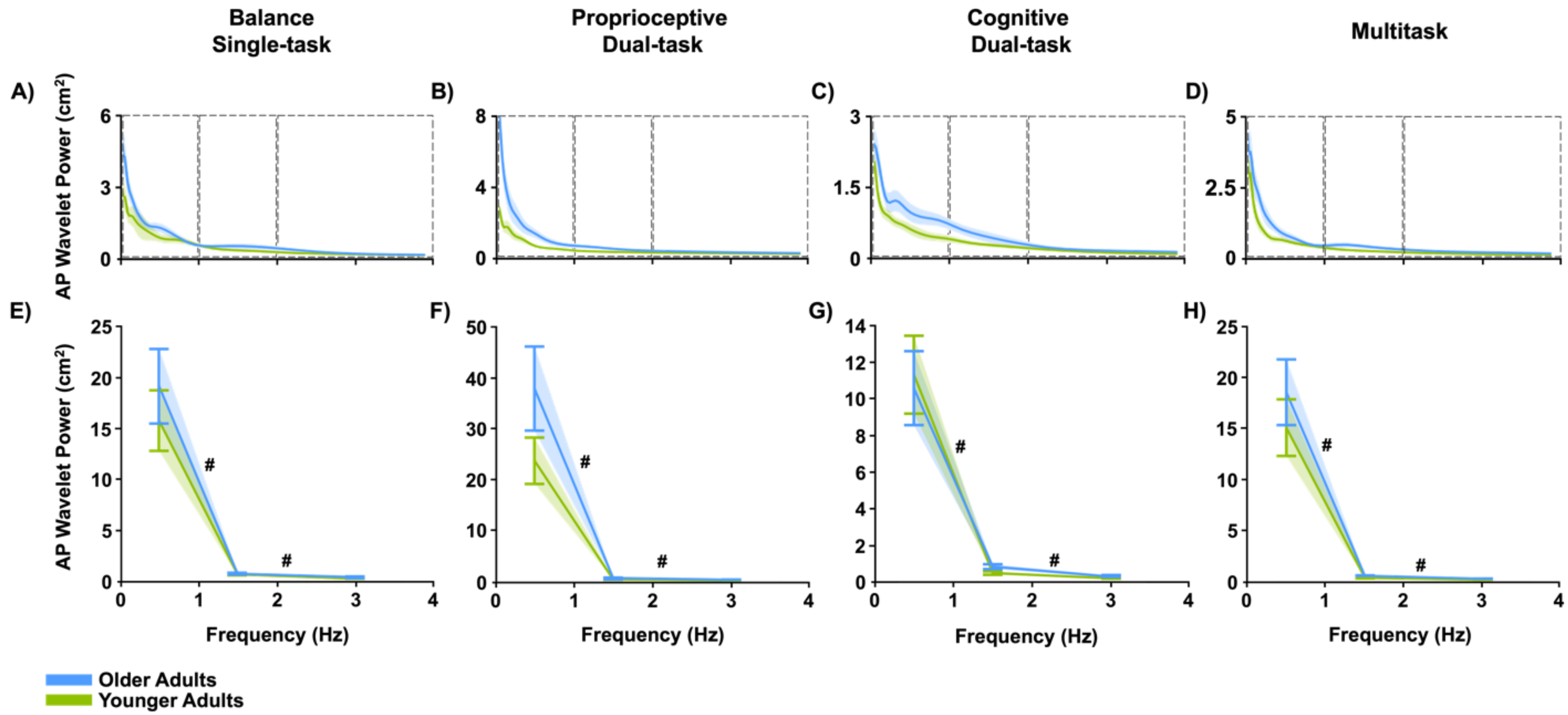

Figure 9. Wavelet power spectrum of AP 0-4 Hz signal.

Legend: **(A-D)** AP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** AP wavelet power was significantly greater in the 0-1 Hz bands when compared with the 1-2 and 2-4 Hz bands across all tasks, with the 1-2 Hz band demonstrating greater power when compared with the 2-4 Hz band. Proprioceptive DT demonstrated greater AP wavelet power when compared with all other tasks. #Indicates a significant difference between frequency bands.

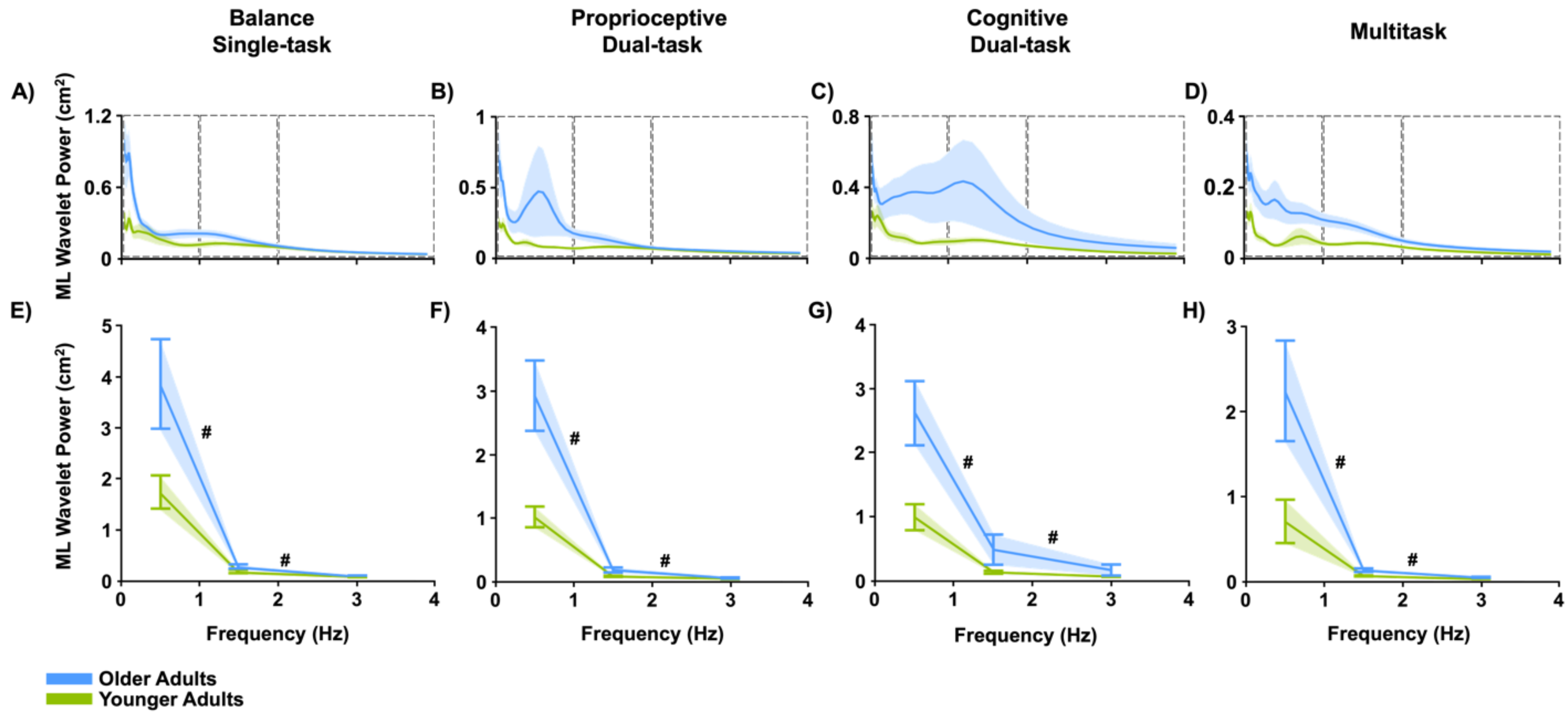

Figure 10. Wavelet power spectrum of ML 0-4 Hz signal.

Legend: **(A-D)** ML wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** ML wavelet power was significantly greater in the 0-1 Hz band when compared with the 1-2 and 2-4 Hz bands across all tasks, with the 1-2 Hz band demonstrating greater power when compared with the 2-4 Hz band. OA demonstrated significantly greater ML wavelet power when compared with YA in the 0-1 and 1-2 Hz bands. # Indicates a significant difference between frequency bands.

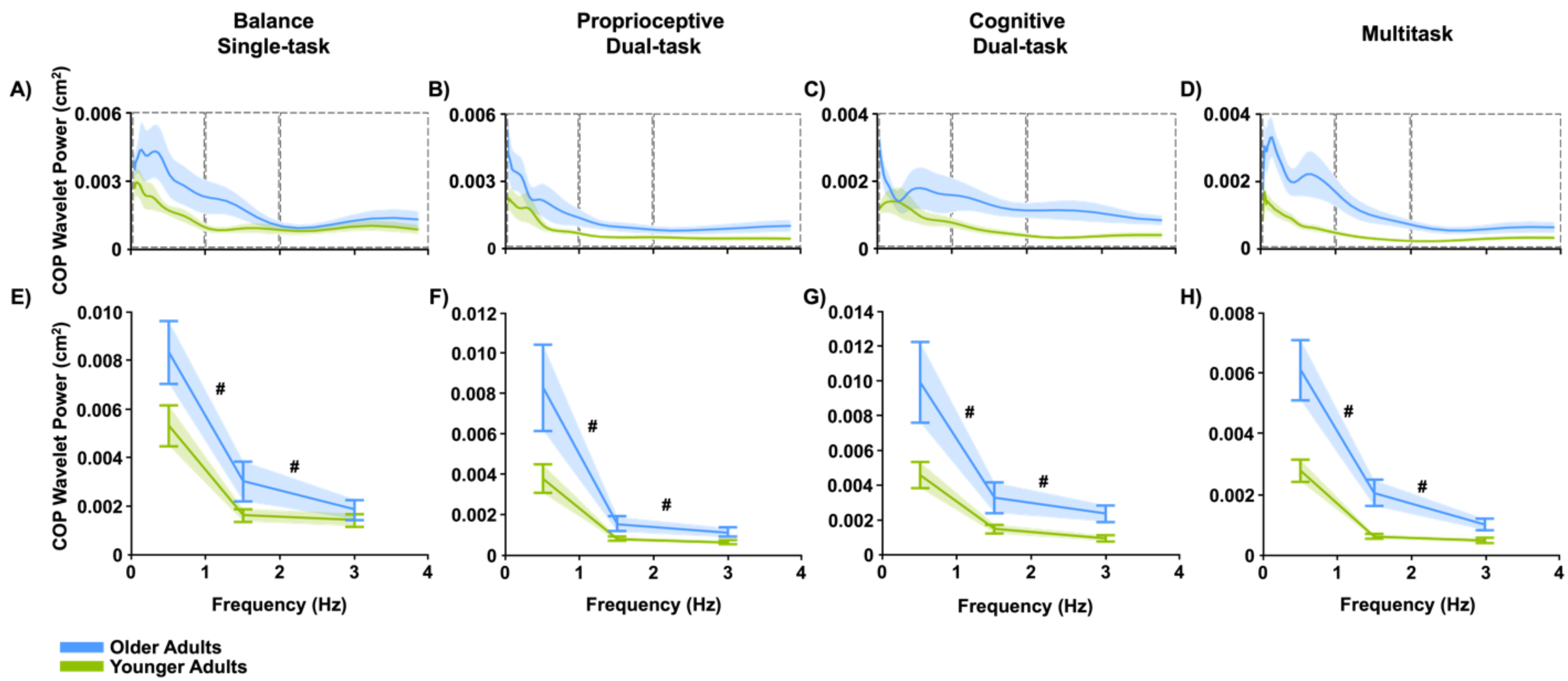

Figure 11. Wavelet power spectrum of the COP 0-4 Hz signal.

Legend: **(A-D)** COP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** Total COP wavelet power was significantly greater in the 0-1 Hz band when compared with the 1-2 and 2-4 Hz bands across all tasks, with the 1-2 Hz band demonstrating greater power when compared with the 2-4 Hz band. OA demonstrated significantly greater total COP wavelet power when compared with YA across all frequency bands. Multitask demonstrated lower total COP wavelet power when compared with all other tasks. # Indicates a significant difference between frequency bands.

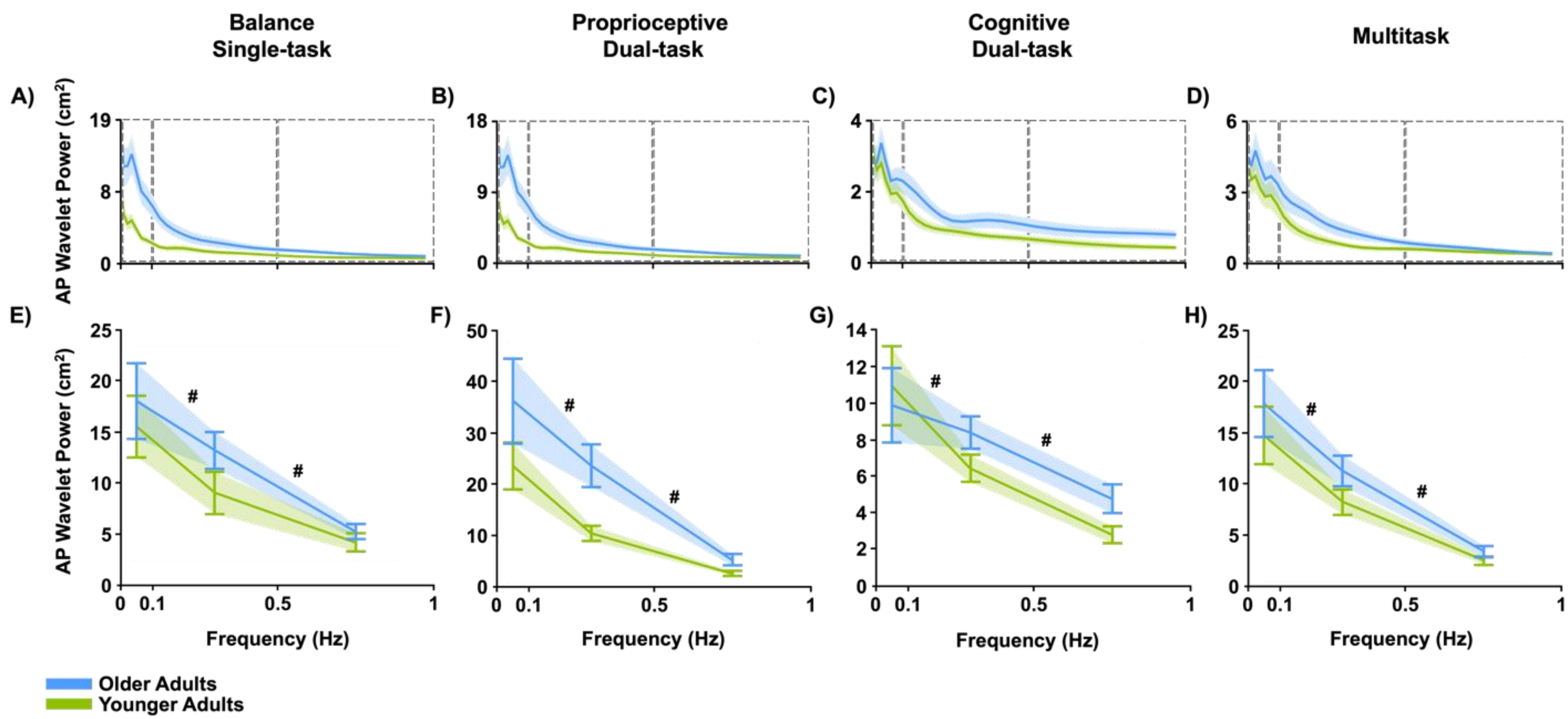

Figure 12. Wavelet power spectrum of AP 0-1 Hz signal.

Legend: **(A-D)** AP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** OA demonstrated significantly greater AP wavelet power when compared with YA. AP wavelet power was significantly greater in the 0-0.1 Hz band when compared with the 0.1-0.5 and 0.5-1 Hz bands across all tasks, with the 0.1-0.5 Hz band demonstrating greater power when compared with the 0.5-1 Hz band. Proprioceptive DT demonstrated greater AP wavelet power at the 0-0.1 Hz band when compared with all other tasks, while Cognitive DT demonstrated significantly lower AP wavelet power at the 0-0.1 Hz band when compared with Balance ST and multitask. # Indicates a significant difference between frequency bands.

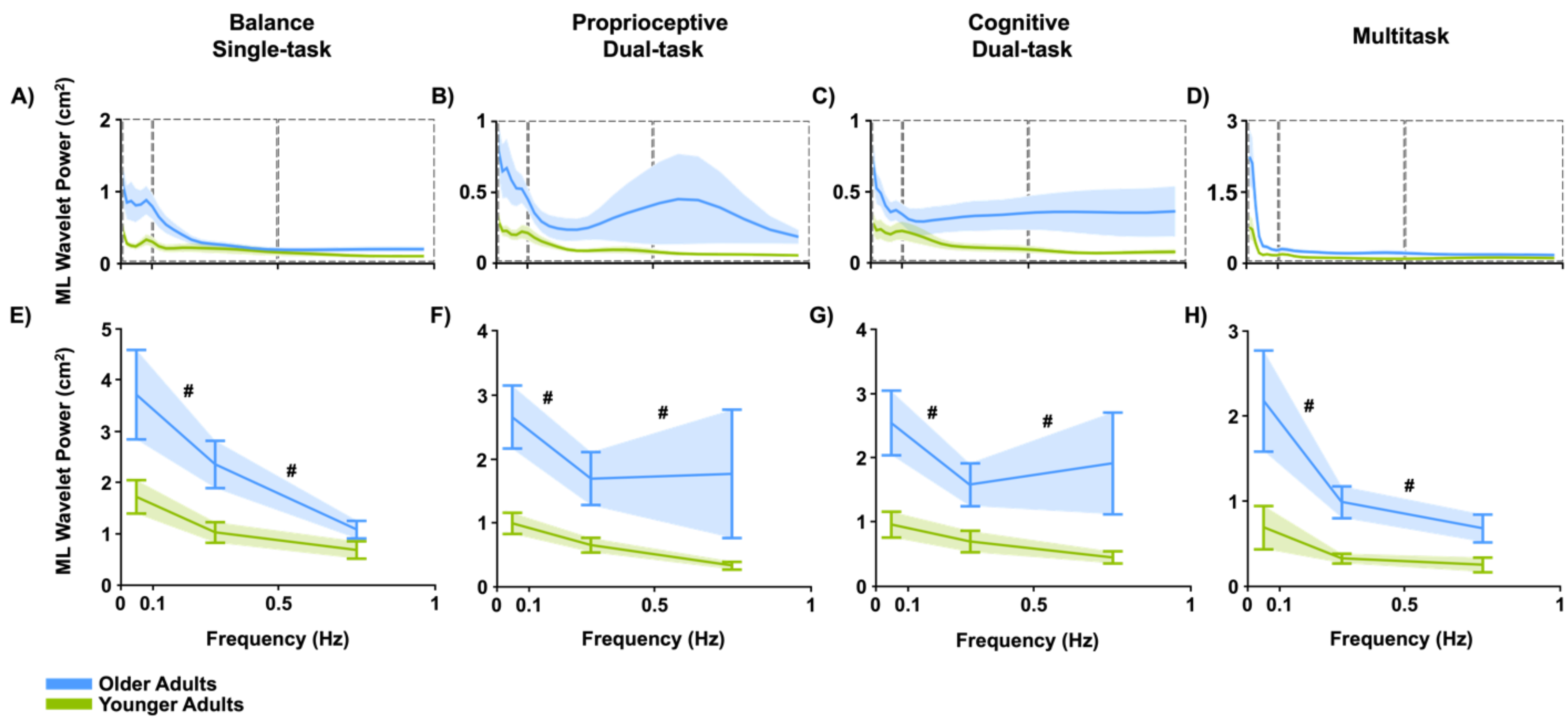

Figure 13. Wavelet power spectrum of ML 0-1 Hz signal.

Legend: **(A-D)** ML wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** OA demonstrated significantly greater ML wavelet power when compared with YA across all frequency bands. ML wavelet power was significantly greater in the 0-0.1 Hz band when compared with the 0.1-0.5 and 0.5-1 Hz bands across all tasks. Balance ST demonstrated greater ML wavelet power when compared with multitask. # Indicates a significant difference between frequency bands.

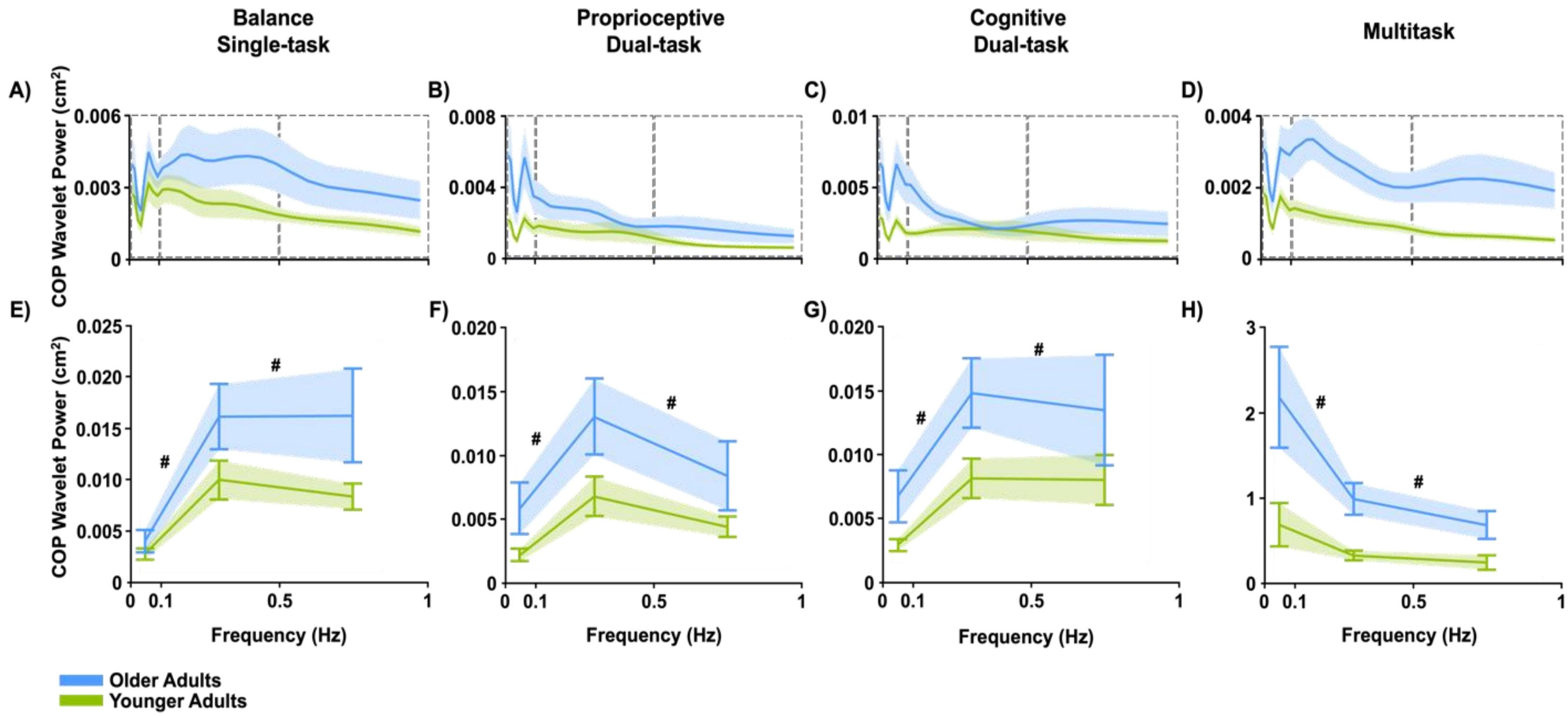

Figure 14. Wavelet power spectrum of the COP 0-1 Hz signal.

Legend: **(A-D)** COP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** OA demonstrated significantly greater total COP wavelet power than YA across all frequency bands. Total COP wavelet power was significantly greater in the 0.1-0.5 and 0.5-1 Hz bands when compared with the 0-0.1 Hz band across all tasks. Proprioceptive DT demonstrated a distinct pattern, with the greatest wavelet power in the 0.1-0.5 Hz band when compared with the 0-0.1 and 0.5-1 Hz bands. Balance ST demonstrated greater total COP wavelet power when compared with multitask. # Indicates a significant difference between frequency bands.

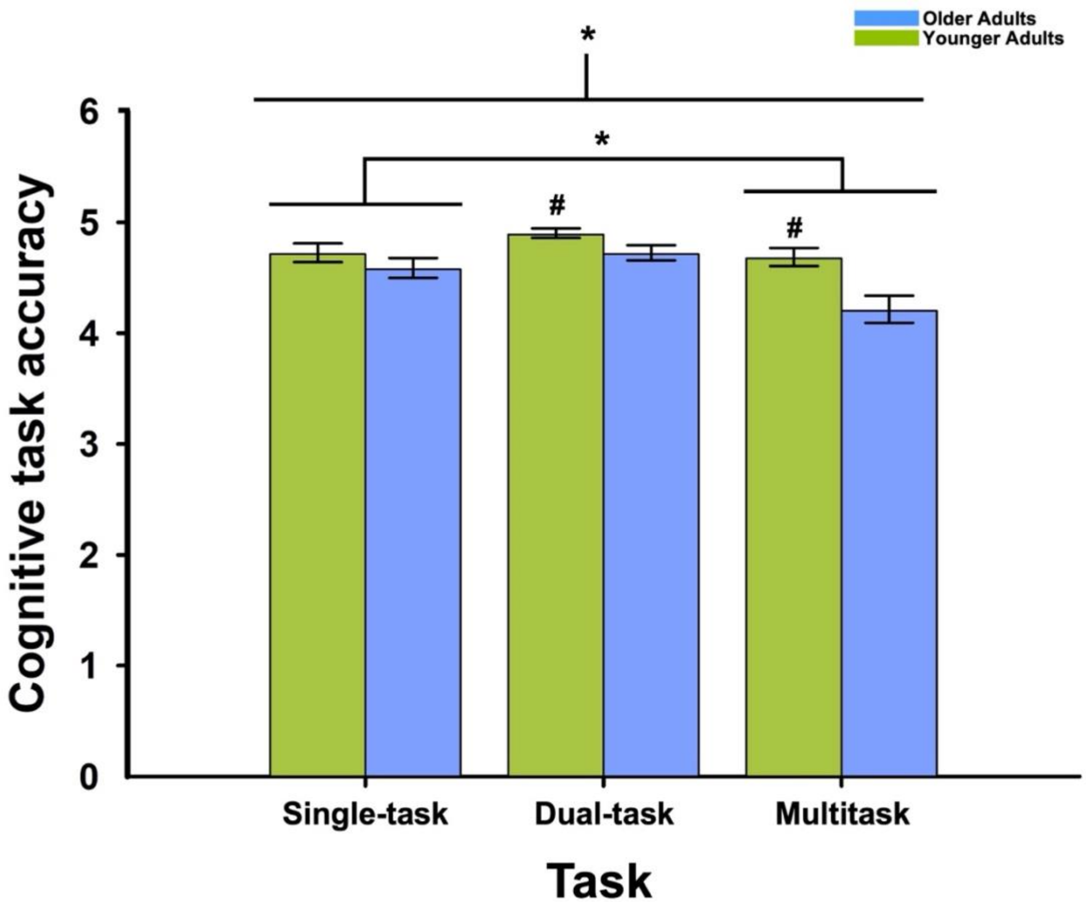

Figure 15. Cognitive task accuracy across task conditions for older (blue) and younger (green) adults.

Legend: YA demonstrated significantly greater cognitive task accuracy during cognitive DT and multitask conditions when compared with OA. * Indicates a significant difference between groups. # indicates a significant difference between task conditions.

Appendix C: Chapter 3 – Mechanisms of Multisensory Interaction During Dual-Task Postural Control in Aging: II. Unstable Surface

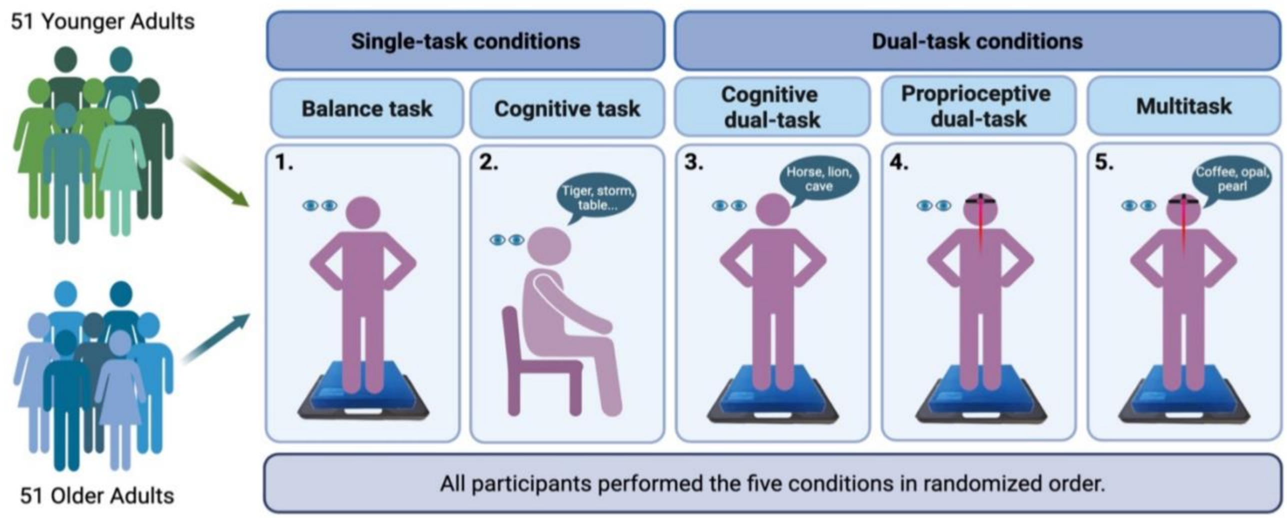

Figure 16. Study design.

Legend: Fifty-one younger adults and 51 older adults completed five randomized tasks on an unstable surface with eyes open.

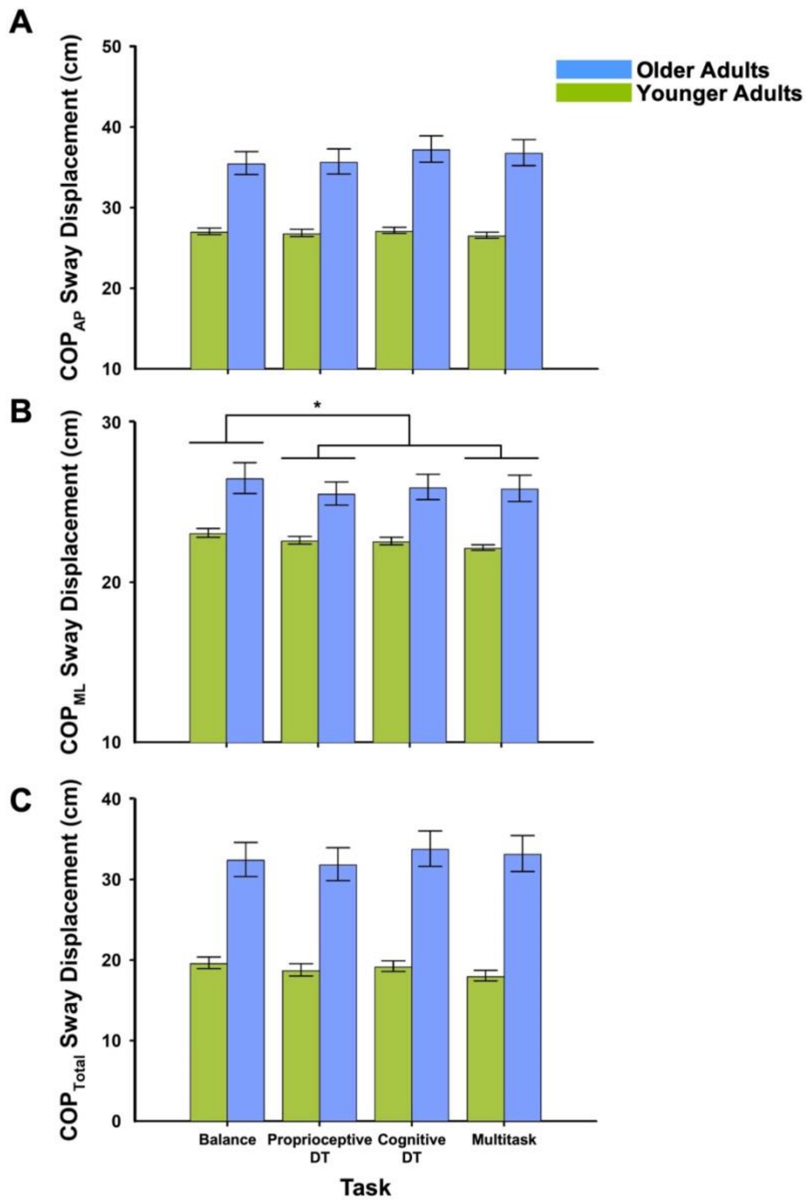

Figure 17. Average postural sway metrics during balance and dual-task conditions on a stable surface.

Legend: **(A)** OA exhibited significantly greater AP sway displacement when compared with YA across all task conditions. **(B)** OA exhibited significantly greater ML sway displacement when compared with YA across all task conditions. ML sway displacement was greater during Balance ST when compared with the proprioceptive DT and multitask conditions. **(C)** OA exhibited greater COP sway displacement when compared with YA across all task conditions. * Indicates a significant task difference.

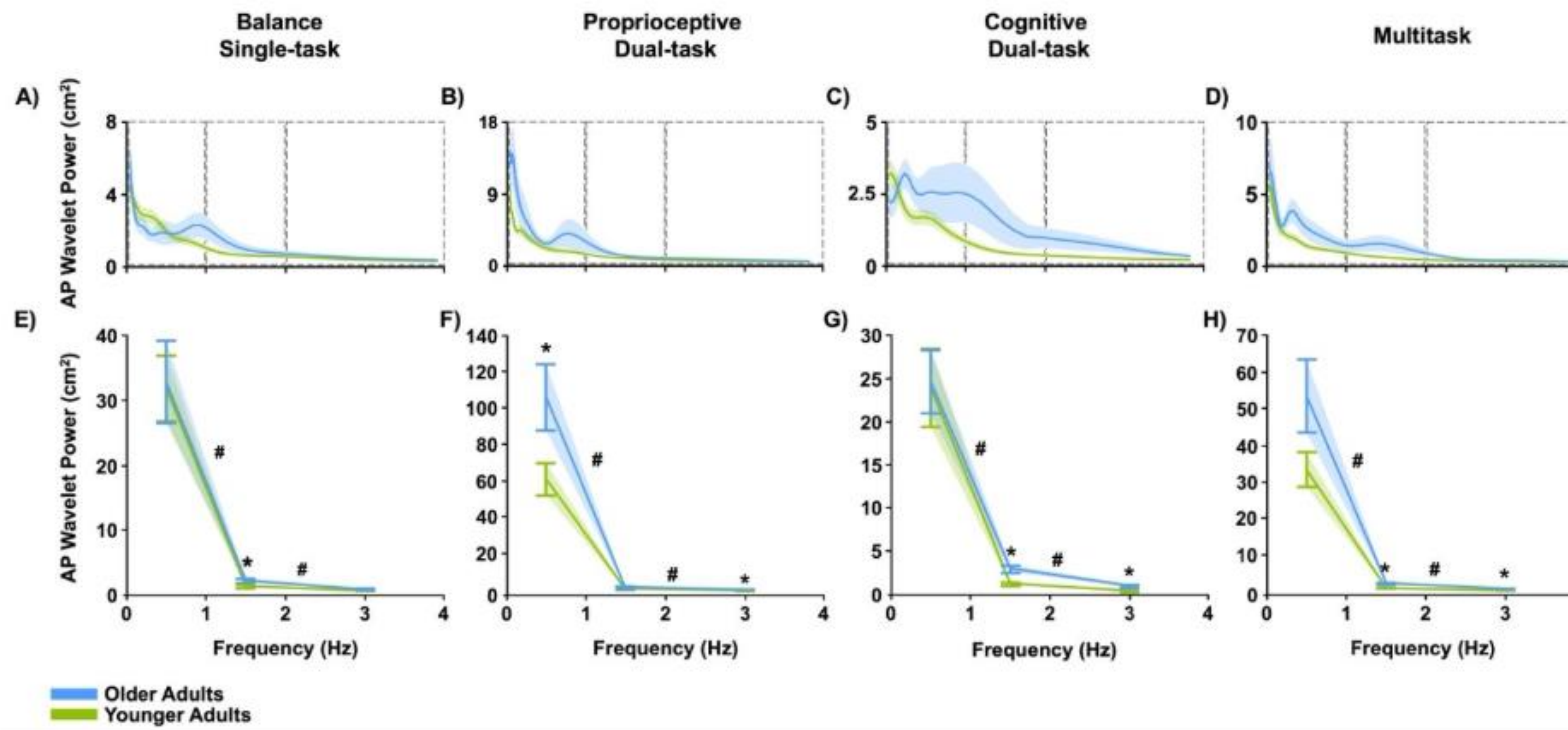

Figure 18. Wavelet power spectrum of AP 0-4 Hz signal.

Legend: **(A-D)** AP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** AP wavelet power was significantly greater in the 0-1 Hz band when compared with the 1-2 and 2-4 Hz bands. OA exhibited significantly greater AP wavelet power in the proprioceptive DT when compared with YA at 0-1 and 2-4 Hz bands. * Indicates a significant group difference; # indicates a significant difference between frequency bands.

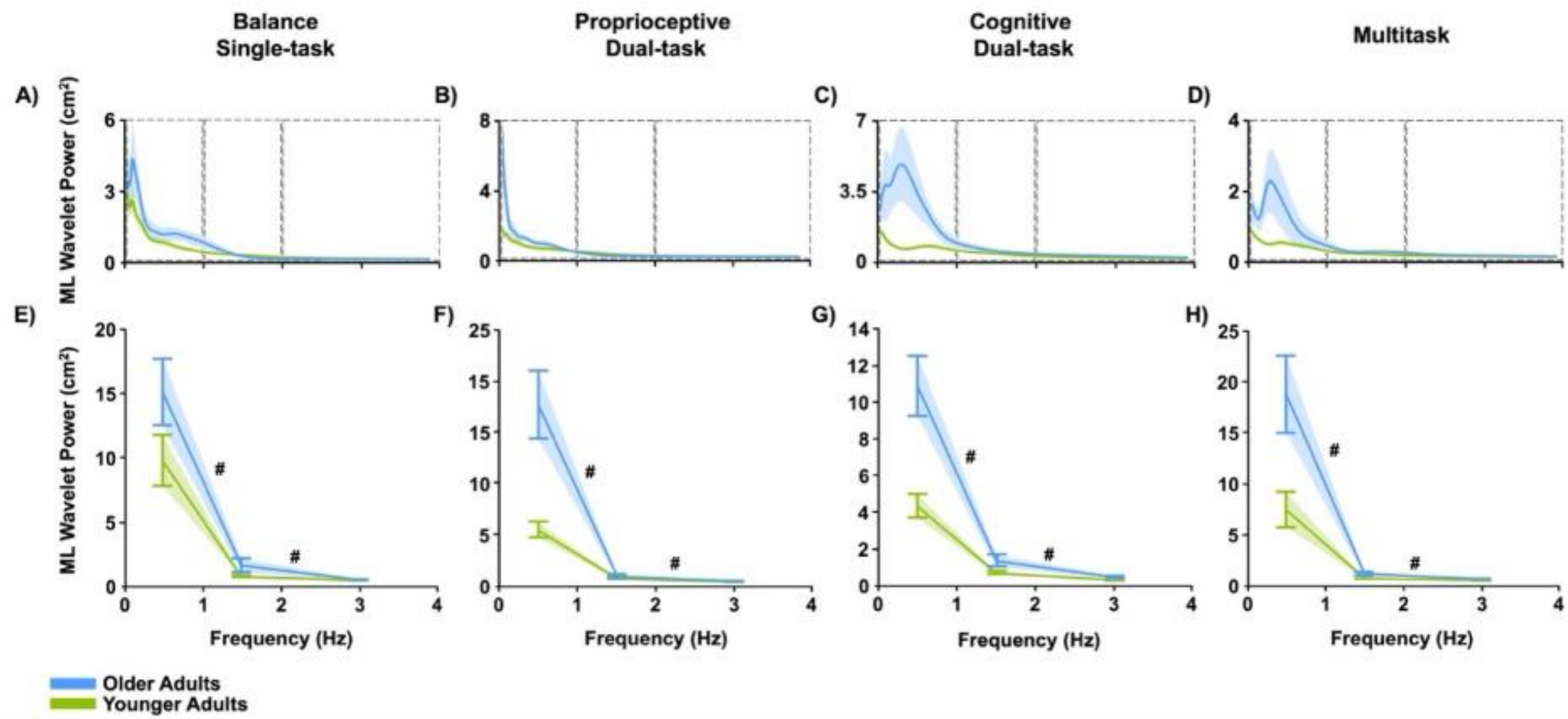

Figure 19. Wavelet power spectrum of ML 0-4 Hz signal.

Legend: (**A-D)** ML wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** ML wavelet power was significantly greater in the 0-1 Hz when compared with the 1-2 and 2-4 Hz bands. OA exhibited significantly greater ML wavelet power across all frequency bands when compared with YA. # Indicates a significant difference between frequency bands.

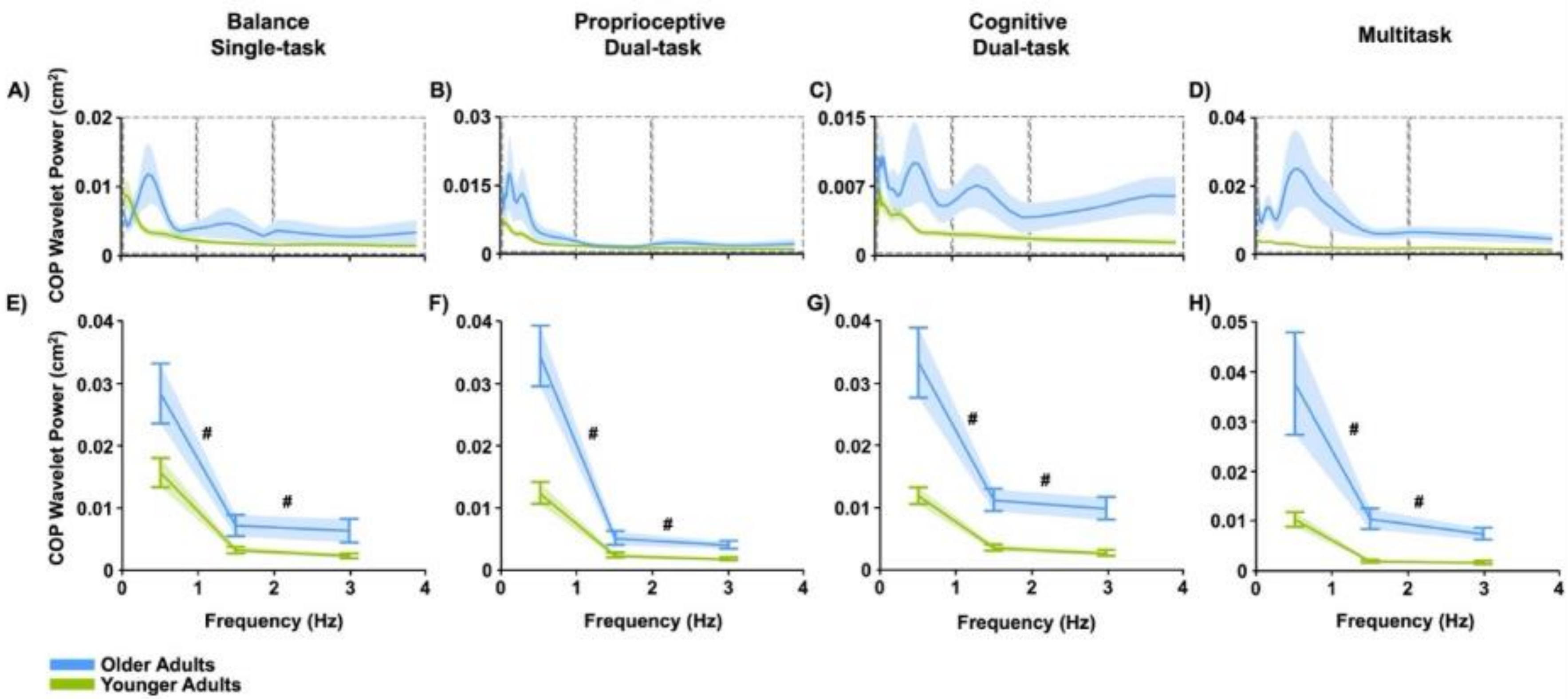

Figure 20. Wavelet power spectrum of the COP 0-4 Hz signal.

Legend: **(A-D)** Total COP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** Total COP wavelet power was significantly greater in the 0-1 Hz when compared with the 1-2 and 2-4 Hz bands. OA exhibited significantly greater total COP wavelet power across all frequency bands when compared with YA. # Indicates a significant difference between frequency bands.

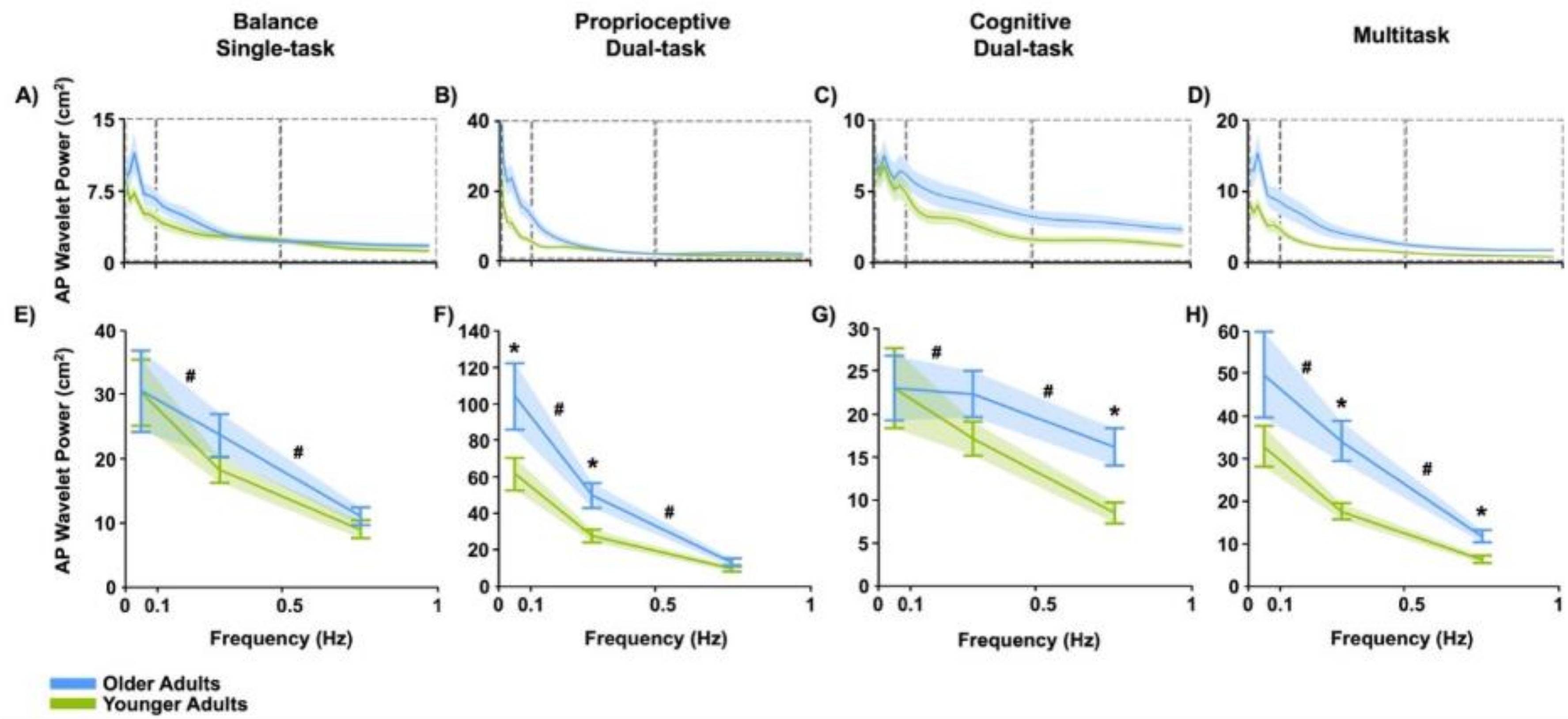

Figure 21. Wavelet power spectrum of AP 0-1 Hz signal.

Legend: **(A-D)** AP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** AP wavelet power was significantly greater from 0-0.1 Hz when compared with all other bands, and greater in the 0.1-0.5 Hz when compared with the 0.5-1 Hz band. Proprioceptive DT exhibited greater AP wavelet power when compared with all other tasks. During proprioceptive DT, OA exhibited significantly greater AP wavelet power when compared with YA in the 0-0.1 and 0.1-0.5 Hz bands. During cognitive DT, age-associated differences emerg*ed* at the 0.5-1 Hz bands. During multitask, OA exhibited significantly greater AP wavelet power when compared with YA at the 0.1-0.5 and 0.5-1 Hz bands. * Indicates a significant group difference; # indicates a significant difference between frequency bands

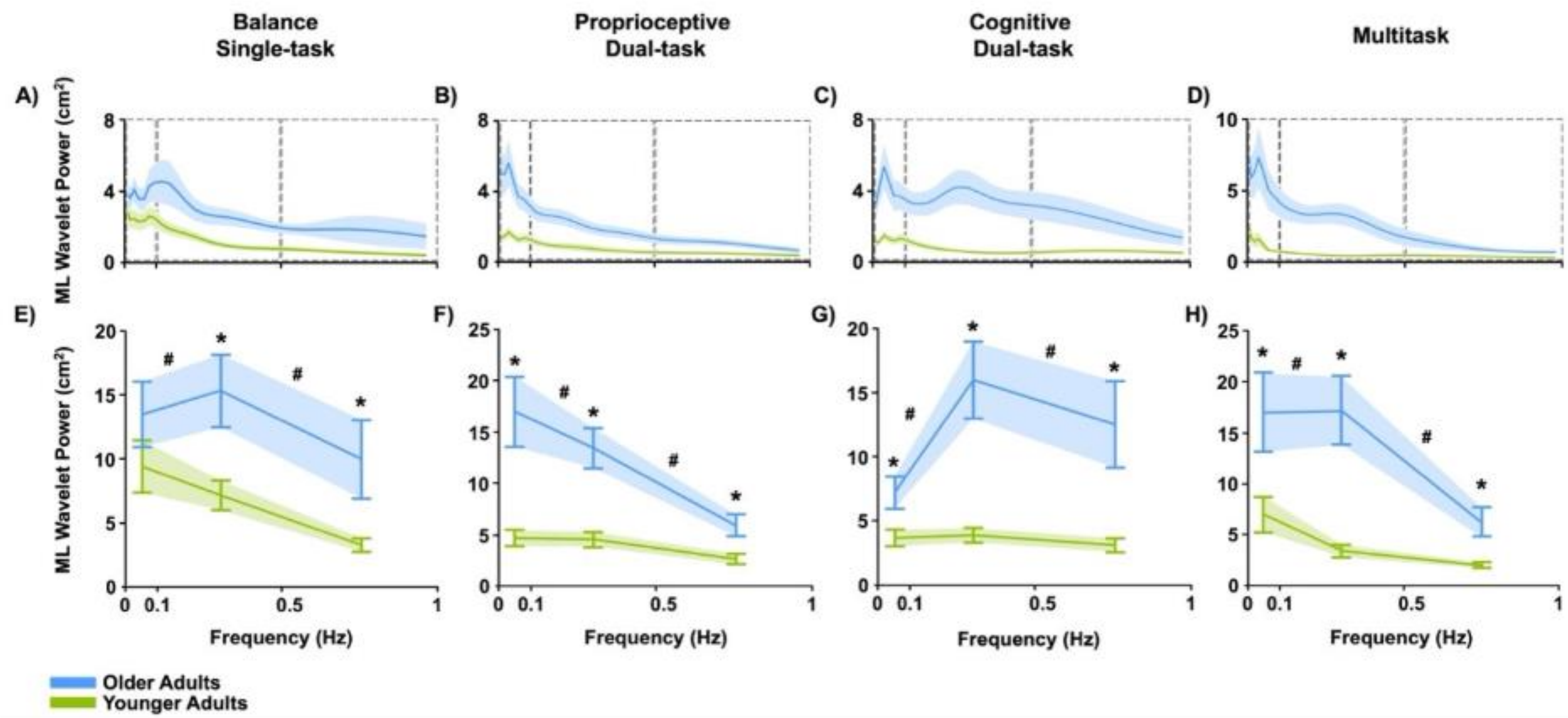

Figure 22. Wavelet power spectrum of ML 0-1 Hz signal

Legend: **(A-D)** ML wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). **(E-H)** ML wavelet power was significantly greater in the 0-0.1 and 0.1-0.5 Hz bands when compared with the 0.5-1 Hz band across all task conditions. During Balance ST, OA exhibited significantly greater ML wavelet power when compared with YA at the 0.1-0.5 and 0.5-1 Hz bands. During all other tasks, OA exhibited significantly greater ML wavelet power across all frequency bands when compared with YA. * Indicates a significant group difference; # indicates a significant difference between frequency bands.

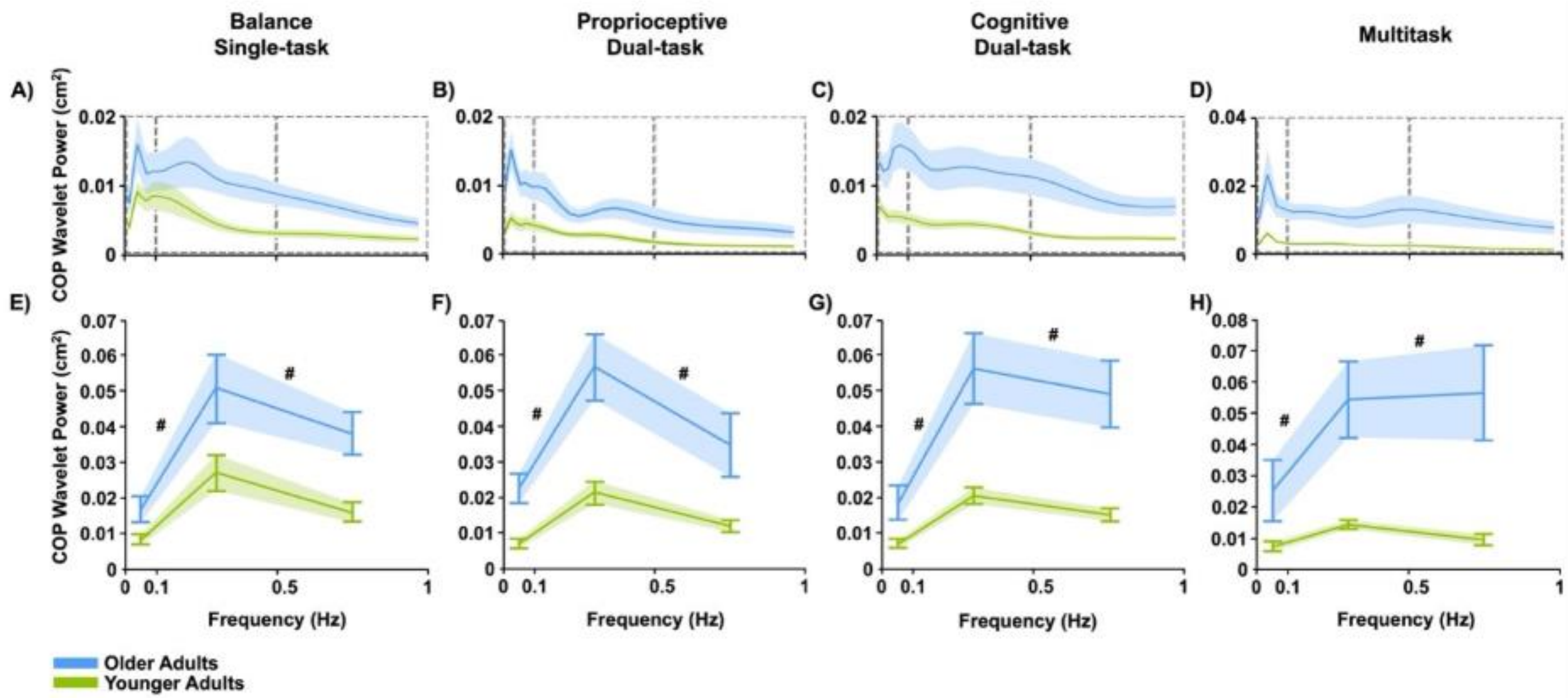

Figure 23. Wavelet power spectrum of the COP 0-1 Hz signal.

Legend: **(A-D)** Total COP wavelet power spectrum during Balance ST, Proprioceptive DT, cognitive DT, and multitask conditions for OA (blue) and YA (green). Total COP wavelet power was significantly greater in the 0.1-0.5 Hz band when compared with the 0-0.1 and 0.5-1 Hz bands, and greater in the 0.5-1 Hz band when compared with the 0-0.1 Hz band, across all task conditions. OA exhibited significantly greater total COP wavelet power across all frequency bands when compared with YA. # Indicates a significant difference between frequency bands.

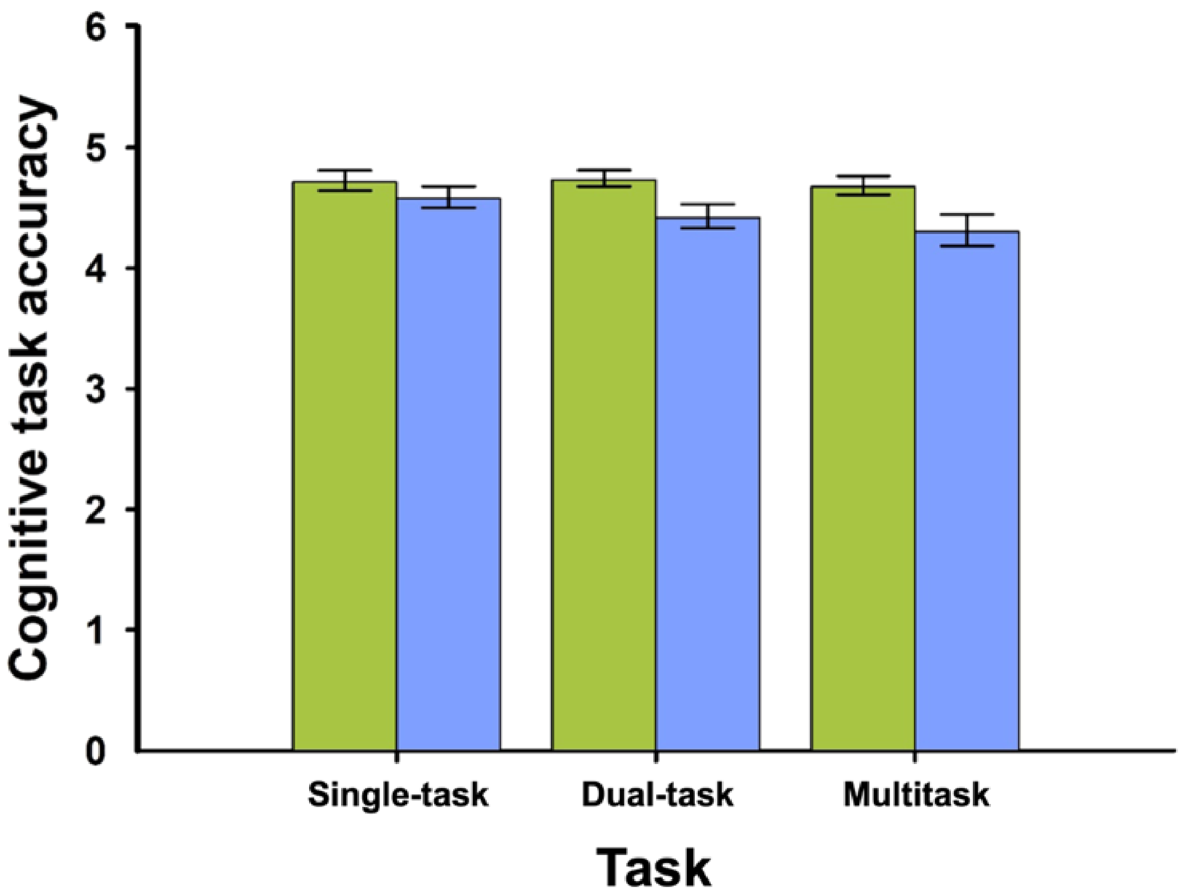

Figure 24. Cognitive task accuracy across task conditions for older (blue) and younger (green) adults.

Legend: YA demonstrated significantly greater cognitive task accuracy when compared with OA, irrespective of task.

Appendix D: Chapter 4: Adiposity Predicts Postural Sway in Older but Not Younger Adults: A Novel Age-Dependent Relationship.

Table 5. Participants' characteristics and age-associated differences in body composition and postural sway outcomes (n=83).

	Younger adults	Older adults	U	*P* value
N	42	41	-	-
Age (years)	26 ± 5	69 ± 6	0.00	< 0.001*
Height (m)	1.72 ± 0.09	1.69 ± 0.11	721.00	0.202
Weight (kg)	75.38 ± 14	73.19 ± 19	752.50	0.323
FM/FMM ratio	0.36 ± 0.15	0.42 ± 0.15	677.00	0.094
FFMI (kg/m^2)	18.93 ± 3.02	17.88 ± 3.19	661.00	0.069
FMI (kg/m^2)	6.52 ± 2.55	7.42 ± 2.85	699.00	0.140
COP sway displacement (cm)	17.08 ± 5.19 cm	24.14 ± 7.82	376.00	< 0.001*
Total COP wavelet power in the 0-1 Hz (cm^2)	0.009 ± 0.006	0.02 ± 0.01 cm^2	476.00	< 0.001*

Values are expressed as mean ± SD. * Significant at $p < 0.05$. Abbreviations: FM/FMM = fat mass to fat free mass ratio; FFMI = fat-free mass index; FMI = fat-mass index; COP = center of pressure.

Table 6. Sex differences in body composition and postural sway outcomes (n=83).

	Males	**Females**	**U**	***P* value**
N	30	53	-	-
FM/FMM ratio	0.26 ± 0.97	0.46 ± 0.13	206.00	< 0.001*
FFMI (kg/m^2)	21.25 ± 2.21	16.80 ± 2.33	128.00	< 0.001*
FMI (kg/m^2)	5.65 ± 2.32	7.69 ± 2.66	434.00	< 0.001*
COP sway displacement (cm)	20.71 ± 7.33	21.24 ± 8.03	773.00	0.835
Total COP wavelet power in the 0-1 Hz (cm^2)	0.012 ± 0.007	0.015 ± 0.013	760.00	0.740

Values are expressed as mean ± SD. * Significant at $p < 0.05$. Abbreviations: FM/FMM = fat mass to fat free mass ratio; FFMI = fat-free mass index; FMI = fat-mass index; COP = center of pressure.

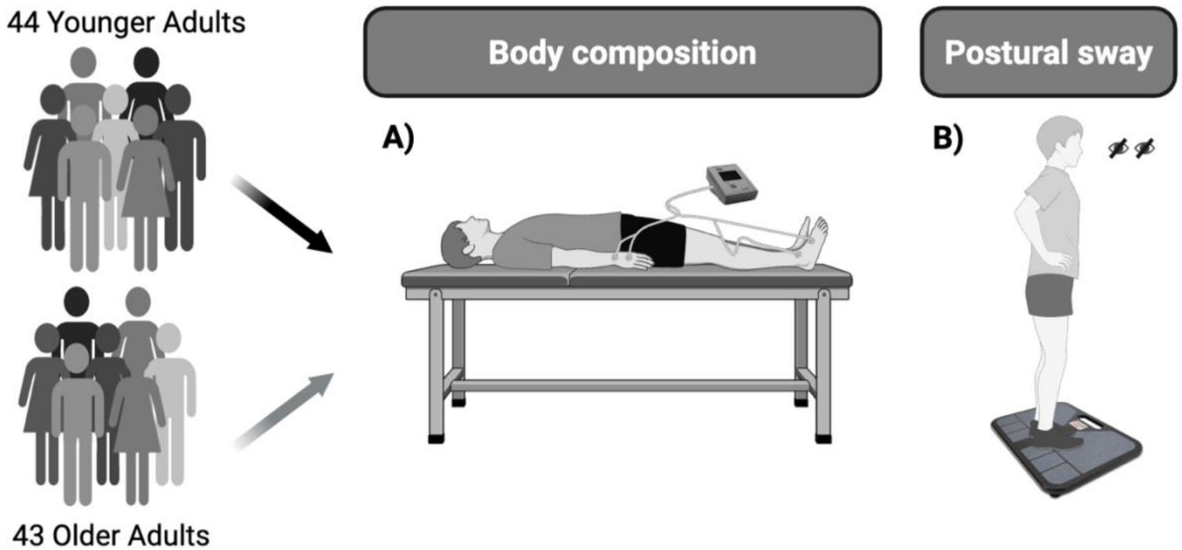

Figure 25. Study design.

Legend: Eighty-seven community-dwelling participants (YA: 44; OA: 43) completed two assessments in a single experimental session. **(A)** Body composition was assessed using bioimpedance spectroscopy in a supine position, from which fat mass index, fat-free mass index, and FM/FFM ratio were derived. **(B)** Postural sway was assessed using the Better Balance Test, during which participants stood on the force plate with hands on their hips, feet shoulder-width apart, and eyes closed.

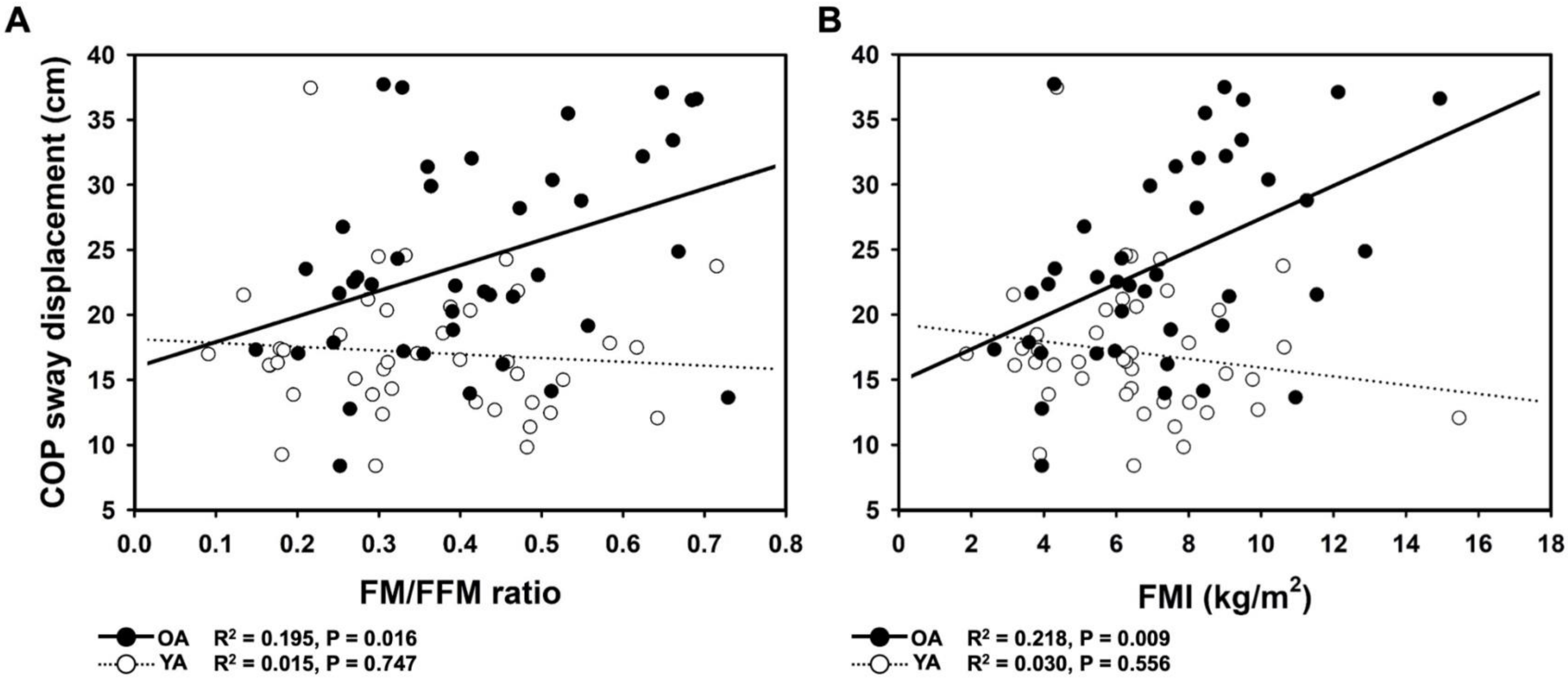

Figure 26. Age-dependent association between fat mass indices and COP sway displacement in older adults.

Legend: **(A)** FM/FFM ratio is associated with greater COP sway displacement in older adults ($R^2 = 0.195$, $p = 0.016$), accounting for ~20% of the variance in postural sway, but not in younger adults ($R^2 = 0.015$, $p = 0.747$). **(B)** Fat mass index (FMI) is associated with greater COP sway displacement in older adults ($R^2 = 0.218$, $p = 0.009$), accounting for ~22% of the variance in postural sway, but not in younger adults ($R^2 = 0.030$, $p = 0.556$).

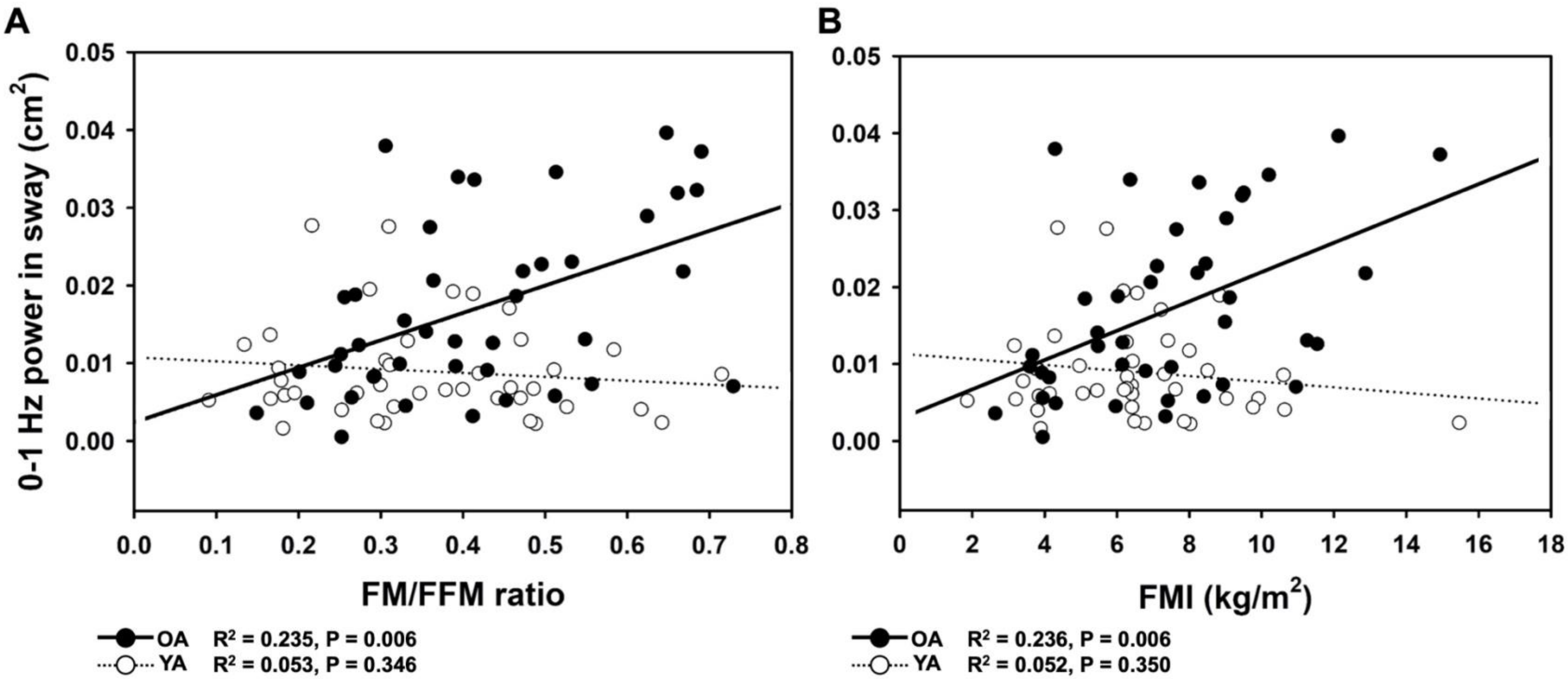

Figure 27. Age-dependent association between fat mass indices and low-frequency oscillations (0-1 Hz) in older adults.

Legend: **(A)** FM/FFM ratio is associated with greater COP wavelet power in the 0-1 Hz band in older adults (R^2 = 0.235, p = 0.006), accounting for ~23% of the variance in low-frequency postural oscillations, but not in younger adults (R^2 = 0.053, p = 0.346). **(B)** Fat mass index (FMI) is associated with greater COP wavelet power in the 0-1 Hz band in older adults (R^2 = 0.236, p = 0.006), accounting for ~24% of the variance in low-frequency postural oscillations, but not in younger adults (R^2 = 0.052, p = 0.350).

Appendix E: Proposal "Multisensory Interaction Mechanisms of Postural Control: A Dual-Task Approach to Understanding Age-Associated Fall Risk."

SPECIFIC AIMS

Effective postural control requires the dynamic interaction of visual, vestibular, and proprioceptive inputs, which are influenced by environmental and task demands (Huxhold O, 2006; Oliveira et al., 2011). Among these environmental factors, surface stability has a significant impact on postural control (Promsri A, 2024). Stable surfaces provide consistent sensory feedback and require minimal neuromuscular effort, allowing postural control to be maintained through efficient stability mechanisms (Horak FB, 1986). In contrast, unstable surfaces require greater sensory interaction and neuromuscular coordination, primarily challenging proprioceptive and vestibular inputs, resulting in an increased reliance on visual information (Horak FB, 1986; Promsri A, 2020; Promsri A, 2024). This creates a natural framework to test how different sensory systems are reweighted to maintain balance. However, current fall risk assessments primarily evaluate overall postural sway without identifying how individual sensory systems contribute to postural control (Horak FB, 2009).

This limitation is particularly exacerbated in everyday activities that involve dual tasking, where competing attentional demands challenge the brain's ability to integrate multisensory information, increasing the risk of falls (Huxhold O, 2006; Woollacott M, 2002). While multisensory interaction during dual tasking is an automatic process in healthy younger adults, older individuals must consciously allocate limited cognitive resources to maintain balance (Wang J, 2024). Hence, the dual-task paradigm has been investigated as a potential biomarker of fall risk (Bayot M, 2020). However, despite its clinical relevance, findings have been inconsistent, mainly due to the limitations of traditional postural control assessments that fail to isolate the contributions of specific sensory systems (Baltich J, 2014; Chagdes JR, 2009). Aging involves a gradual decline in sensory processing; yet, the mechanisms by which these changes disrupt sensory reweighting during dual-task conditions remain poorly understood (Eikema DJ, 2012; Zhang S, 2020).

To **address this gap**, this proposal will study the relative contributions of visual, vestibular, and proprioceptive systems using time-frequency domain analysis to examine the low-frequency oscillations of the center of pressure (COP) signals during dual-task conditions. Specific frequency bands have been suggested to correspond to distinct sensory inputs: (0-0.1 Hz, 0.1-0.5 Hz, and 0.5-1 Hz, respectively), enabling real-time capture of sensory interaction changes while systematically manipulating sensory inputs (Chagdes JR, 2009; Jafari H, 2023; Redfern MS, 2001): standing on a firm surface **(Aim 1)** versus an unstable surface **(Aim 2)** (Goble et al., 2020). The **central objective** is to use *aging as a model of progressive sensory system decline to advance our understanding of the neural* *mechanisms underlying multisensory interaction* under dual-task demands that reflect real-world challenges.

Specific aim 1 will investigate age-associated changes in multisensory interaction during stable dual-task conditions using time-frequency analysis. Hypothesis 1a: Older adults will demonstrate greater visual dependence when compared with younger adults, evidenced by increased contributions to the visual frequency band. **1b:** The multitask condition will produce greater COP sway displacement and low-frequency oscillations when compared with the cognitive and motor dual-task conditions.

Specific aim 2 will characterize age-associated changes in multisensory interaction during unstable dual-task conditions using time-frequency analysis. Hypothesis 2a: Older adults will demonstrate impaired sensory reweighting ability, as evidenced by an increased reliance on visual cues when compared with younger adults. **2b:** Dual-task interference will be significantly greater in older adults when compared with younger adults, and it will increase COP sway displacement and low-frequency oscillations as the task becomes more challenging.

Previous aging studies have examined the effects of dual tasks on overall postural sway. However, no studies have used time-frequency domain analysis to identify which specific sensory systems are disrupted during dual-task conditions. Therefore, achieving these aims as an exploratory framework will enhance our understanding of multisensory interaction mechanisms that contribute to age-associated fall risk during dual-task conditions.

A. BACKGROUND AND SIGNIFICANCE

Falls affect 36 million older adults each year in the United States, representing the leading cause of injury-related death and a significant predictor of disability (Giovannini S, 2022; Shankar KN, 2023). These events generate costs exceeding $50 billion annually (Florence et al., 2018), creating a substantial financial burden for both healthcare systems and individuals. These numbers reflect more than statistics; they represent millions of individuals who are losing independence and experiencing reduced quality of life. Despite this enormous burden, current clinical assessments often evaluate global mobility as a proxy for fall risk, rather than identifying the specific underlying mechanisms required to maintain postural control (Mancini M, 2010). Falls also constitute the largest category of preventable adverse events (Dykes PC, 2023), **underscoring a critical gap between what is needed and what is currently implemented in clinical practice**.

Aging involves progressive declines in strength, flexibility, mobility, and multisensory interaction efficiency, all of which contribute to impaired balance (Brech GC, 2022; de Barros GM, 2021; Mahoney JR, 2019). Effective postural control depends on the continuous interaction among visual, vestibular, and proprioceptive inputs (Huxhold O, 2006; Redfern MS, 2001).This process of sensory reweighting allows the nervous system to dynamically adapt to task demands and environmental constraints (Awosika OO, 2023;

Yelnik A, 2008). However, the specific sensory interaction patterns that enable older adults to adapt or fail to adapt during dual-task conditions remain poorly characterized. Comparing younger and older adults enables us to <u>examine age-associated changes in multisensory interaction during dual-task conditions, thereby contributing to our understanding of how these processes change with age</u>. In younger adults, multisensory interaction during dual tasks is essentially an automatic process, allowing balance to be preserved with minimal conscious effort (de Barros GM, 2021; Wang J, 2024). In contrast, older adults experience greater costs when postural control must compete with cognitive or motor demands (Wang J, 2024). However, research examining the effects of dual tasking on postural control has yielded conflicting findings. Some groups have reported decreased postural control under dual-task conditions (Motealleh A, 2021; Shim S, 2012). While others have found that postural control either increases or remains unperturbed (Ghai S, 2017; Salihu AT, 2022).

These inconsistencies highlight a fundamental limitation of traditional clinical assessments, which often quantify how fast someone completes a task or rely on subjective performance scoring (Barry E, 2014; Bogle Thorbahn LD, 1996). Additionally, linear COP measurements provide valuable information for objectively quantifying the magnitude of postural sway (Hadamus A, 2022). However, traditional analyses use these signals to calculate total COP sway displacement (cm), instead of analyzing the underlying COP signal across multiple time scales (Chagdes JR, 2009). This limits their ability to determine which sensory systems are disrupted or how their contributions shift under specific task demands (Baltich J, 2014; Chagdes JR, 2009). **Therefore, this exploratory study will use time-frequency domain analysis to investigate multisensory interaction patterns during dual-task conditions**. By examining COP signal dynamics over time, rather than the overall sway displacement as the final outcome, this approach may identify how individual sensory systems contribute to postural control and how these processes change in response to aging and dual-task conditions (Baltich J, 2014; Cavanaugh JT, 2007; Chagdes JR, 2009). In aging populations, where sensory inputs progressively decline, this method may help identify potential compensatory strategies and altered sensory reweighting under cognitive and motor demands (Wagner AR, 2012; Wang J, 2024).

The **significance of this proposal** lies in its potential to advance our understanding of multisensory interaction processes that maintain postural control during everyday tasks and contribute to fall risk. By using *aging as a model for sensory decline,* we can establish an explanatory framework for patterns of multisensory interaction. This may facilitate the interpretation of pathological conditions in future studies, informing the development of personalized rehabilitation strategies and clinical diagnostic innovations. Ultimately, it can <u>*bridge the gap between research and clinical application*</u>, advancing mechanistically driven interventions to reduce fall risk and maintain independence and quality of life in vulnerable populations.

B. INNOVATION

B.1. Clinical innovation – Mechanism-driven fall risk assessments. Despite widespread recognition that current fall risk assessments lack objectivity and diagnostic accuracy, they remain the standard clinical practice (Harris JE, 2005; Meyer-Vega et al., 2025). These assessments often misclassify individuals, either by overestimating fall risk – restricting independence, increasing fear of falling, and leading to unnecessary additional interventions – or underestimating fall risk, which limits access to rehabilitation interventions (Barry E, 2014; Lafontant K, 2024; Pimenta C, 2022). This limitation underscores the need for methodological approaches that can serve as <u>*objective biomarkers of fall risk*</u>. The clinical innovation of this proposal shifts the focus from the conventional question of "*Are they at fall risk*?" to the more informative question "*What are the factors that drive their fall risk?"*. By identifying whether postural instability results from visual, vestibular, or proprioceptive deficits, this approach enables clinicians to prescribe targeted, mechanistic interventions tailored to the individual's specific sensory deficit profile, rather than relying on nonspecific balance training.

B.2. Conceptual innovation – Dual-task comparative approach. Most aging studies examine dual-task effects in isolation, limiting our understanding of how different task demands affect postural control. This proposal is conceptually innovative because it compares cognitive versus motor dual-task paradigms within the same individuals across progressively challenging conditions. Cognitive dual tasks primarily challenge attention and executive function (Woollacott M, 2002). In contrast, motor dual tasks impose competing motor demands (Saraiva M, 2023), allowing us to determine which type of dual-task produces greater age-associated deficits in multisensory interaction. By examining these dual tasks conditions under stable **(Aim 1)** and unstable surfaces **(Aim 2)**, we can determine whether older adults employ different compensatory strategies and identify which sensory inputs are not being appropriately reweighted. Therefore, this exploratory framework will investigate how the aging nervous system dynamically reallocates sensory and cognitive resources across different dual-task conditions.

B.3. Technical innovation – Advanced signal analysis of postural control. Postural control is defined by the relationship between an individual's COP and their base of support (Terry K, 2011). This is objectively quantified using a force plate or wearable sensors to measure the COP sway displacement (O'Connor et al., 2016; Quijoux F, 2021). Traditional fall risk assessments derived from these measures provide a summary of overall sway; while valuable, the decomposition of the COP signals to reveal which sensory systems are actively contributing to postural control remains poorly understood or studied (Chagdes JR, 2009). Therefore, they have not yet been applied to examine multisensory reweighting under dual-task conditions. Importantly, there is evidence to suggest that distinct frequency bands in the COP signal reflect contributions from specific sensory inputs: visual (0-0.1 Hz), vestibular (0.1-0.5 Hz), and proprioception (0.5-1 Hz) (Kirchner M, 2012; Redfern MS, 2001). By identifying these frequency signatures in COP low-frequency oscillations, this approach transforms postural sway from a global outcome measure into a mechanistic framework for observing dynamic sensory reweighting processes.

C. PRELIMINARY DATA

C.1. <u>Standardization of balance and fall risk quantification:</u> The Better Balance Test (BBT) measures the average total COP sway displacement as a proxy for postural sway magnitude (Goble & Baweja, 2018a; Goble et al., 2019). The test involves three 20-second trials of eyes-closed quiet standing, where larger BBT values indicate greater postural sway and higher fall risk. The BBT is based on the world's largest normative dataset on postural sway across the lifespan, published by Dr. Baweja, in 2018 (Goble & Baweja, 2018a). This dataset comprises more than 16,356 community-dwelling individuals and provides age and sex percentiles, along with a validated fall risk classification: <30 cm indicates low fall risk, 31-39 cm moderate fall risk, and ≥40 cm high fall risk (Goble & Baweja, 2018a; Goble et al., 2019). These classifications enable standardized interpretation of fall risk across different age groups, sex, and multiple pathological conditions. We are currently expanding this data set from 5 to 100 years old in Southeast Alabama. With 603 participants collected at the SMaRT Lab so far, our preliminary findings, illustrated in **Figure 1**, demonstrate that postural sway develops from childhood through puberty, peaks in early adulthood, **begins to decline at 45 years of age, and continues throughout the rest of the lifespan**.

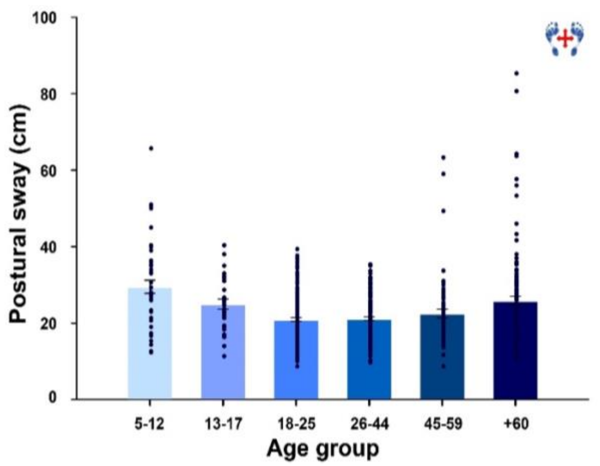

Figure 1. Postural sway across the lifespan. Postural sway develops from childhood through puberty and begins declining at 45 years of age, demonstrating progressive changes in postural control.

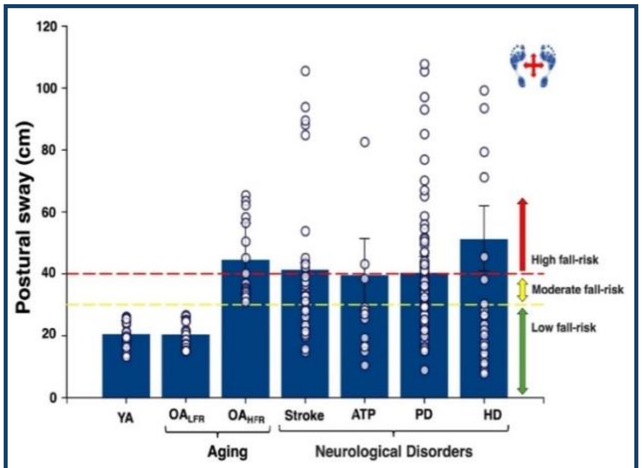

Figure 2. Better Balance Test stratifies fall risk across diverse populations. Progressive postural sway increases across young adults (YA), older adults at low (OA_{LFR}) and high fall risk (OA_{HFR}), and neurological disorders.

Building on this age-level differentiation, **Figure 3** demonstrates the BBT's ability to stratify fall risk across diverse populations, including young adults, OA_{LFR}, OA_{HFR}, and individuals with neurological disorders (acute stroke, Atypical Parkinson, Parkinson's Disease, and Huntington's disease). The x-axis represents postural sway as a function of each population group. Our preliminary findings show progressively greater postural sway from young adults to OA_{HFR} to neurological conditions, indicating higher fall risk. These preliminary findings suggest that the BBT has the potential to **differentiate low, moderate, and high fall risk categories and standardize fall risk assessment across aging and multiple neurological disorders.**

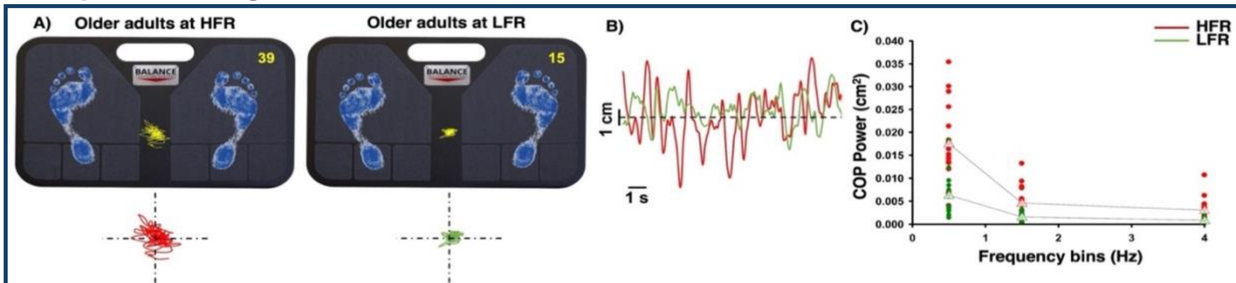

Figure 3. Representative Better Balance Test results of older adults at high fall risk (HFR) when compared with older adults at low fall risk (LFR). A) Total COP sway displacement during eyes-closed conditions, quiet standing; B) overlapping time series comparison of detrended sway signals; and C) time-frequency domain analysis showing differential power contributions across 0-4 Hz frequency bands.

To examine the underlying mechanisms that drive these fall risk differences, **Figure 3A** illustrates representative trials comparing one older adult at high fall risk (OA_{HFR}, 39 cm of sway) versus one at low fall risk (OA_{LFR}, 15 cm of sway) during eyes-closed standing on the force plate. **Figure 3B** shows the overlapping comparison of detrended sway signals between these two individuals over time. **Figure 3C** illustrates the time-frequency domain analysis of the COP signals, highlighting the differential power contributions across frequency bands from 0 to 4 Hz between OA_{HFR} and OA_{LFR}.

C.2. <u>Standardized quantification of multisensory interaction across the lifespan:</u> The modified Clinical Test of Sensory Interaction in Balance (mCTSIB) objectively evaluates the contribution of visual, proprioceptive, and vestibular inputs to balance by the total COP sway displacement (cm) across four different conditions on a force plate: 1) baseline condition (eyes open): all sensory inputs are available to maintain postural control; 2) proprioception condition (eyes closed): visual feedback is removed, increasing reliance on proprioceptive and vestibular systems (Goble et al., 2020). Since proprioception is more heavily utilized for postural control, this condition largely measures the contribution of proprioception to balance; 3) visual condition (eyes open with foam): visual and vestibular systems are available, but foam surface compromises proprioceptive input; and 4) vestibular condition (eyes closed with foam): visual and proprioceptive systems are compromised, shifting reliance primarily to the vestibular system. Dr. Baweja also published the world's largest mCTSIB normative dataset (1,276 participants, 20-59 years of age) (Goble & Baweja, 2018a; Goble et al., 2020). However, we are currently expanding this dataset to understand multisensory interaction across the lifespan from 5 to 100 years of age in Southeast Alabama. This normative dataset can enable the identification of sensory-specific postural control deficits in pathological conditions and tracking changes during rehabilitation interventions. With 539 participants collected at the SMaRT Lab so far, **Figure 4** illustrates that total COP sway displacement increased both across conditions (baseline < proprioception < visual < vestibular) and with advancing age groups. However, while we understand how multisensory interaction changes across the lifespan, **it remains unclear how different dual tasks affect sensory reweighting and further increase fall risk in aging populations** that already demonstrate high fall risk during single-task conditions.

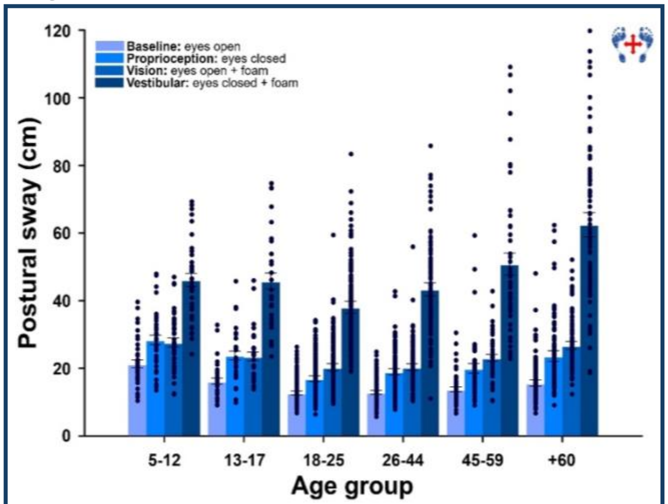

Figure 4. Multisensory interaction declines across the lifespan. Postural sway across age groups (5-12 to +60 years) under four mCTSIB conditions: baseline (eyes open), proprioception (eyes closed), vision (eyes open + foam), and vestibular (eyes closed + foam). Progressive increases in postural sway indicate an age-associated decline in multisensory interaction, which begins at approximately 45 years.

C.3. <u>Low-frequency oscillations reveal dual-task mechanisms invisible to traditional measures:</u> While objective postural sway measures provide valuable fall risk categorization, they fail to capture the dynamic sensory interaction processes underlying postural control during dual-task conditions. **Figure 5** illustrates this limitation by comparing OA_{HFR} and OA_{LFR} with eyes open, and quiet standing on the force plate under two conditions: single-task, and a cognitive dual-task condition using the Hopkins Verbal Learning Test (HVLT)—the same paradigm proposed in this study. **Figure 5A** shows that OA_{HFR} individuals demonstrated significantly greater postural sway when compared with OA_{LFR} using traditional COP sway displacement measures (cm). However, no significant differences were found between single and dual-task conditions. **Figure 5B** shows the underlying signatures of the COP signal, revealing the complex temporal dynamics that linear measures cannot detect. **Figures 5C and 5D** demonstrate that time-frequency analysis revealed hidden dual-task effects in the COP signal. **Figure 5C** demonstrates that most of the wavelet power is concentrated in the 0-1 Hz frequency range (~69% of total COP power), where multisensory interaction mechanisms are suggested to operate (Kirchner M, 2012; Redfern MS, 2001). **Figure 5D** shows that when the analysis was conducted on the 0-1 Hz frequency range, **significant differences between task conditions emerged that were completely invisible using traditional measures**. These findings, currently being finalized for publication submission, **validate our central hypothesis that multisensory interaction patterns during dual-task conditions operate in the time-frequency domain and require advanced signal processing techniques to detect**.

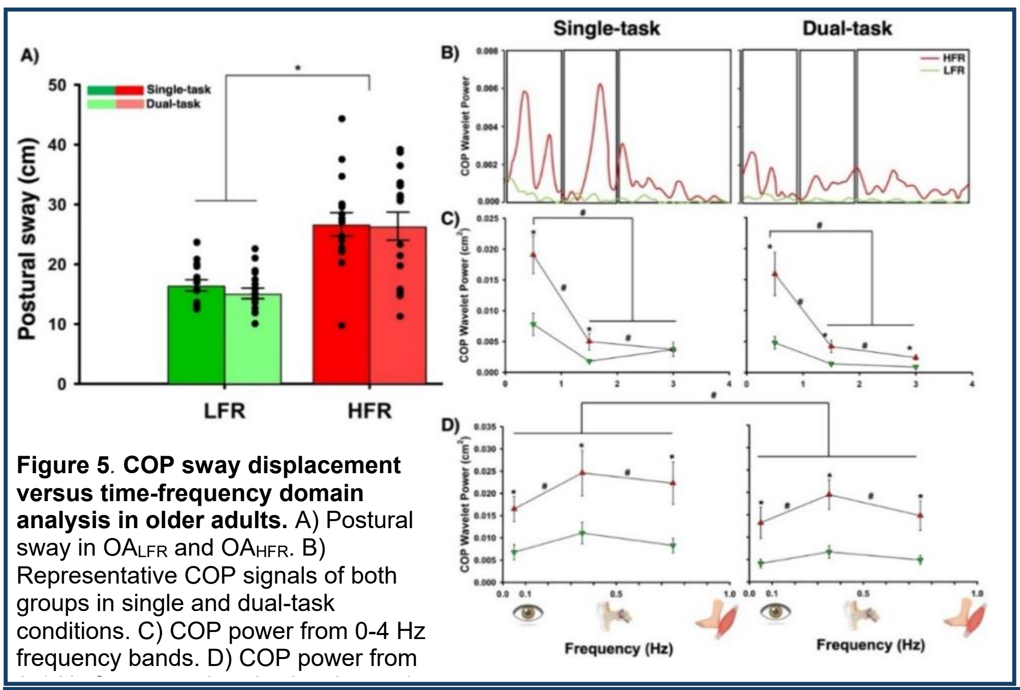

Figure 5. COP sway displacement versus time-frequency domain analysis in older adults. A) Postural sway in OA_{LFR} and OA_{HFR}. B) Representative COP signals of both groups in single and dual-task conditions. C) COP power from 0-4 Hz frequency bands. D) COP power from

D. APPROACH

D.1. PARTICIPANTS AND RECRUITMENT

We will recruit 25 younger adults (ages 18-35) and 25 healthy older adults (ages 60 and above) from the Auburn/Opelika community via flyers and social media posts to ensure a diverse cohort of potential participants.

Inclusion criteria: Healthy younger adults aged 18-35 or older adults aged 60 years and above, no history or diagnosis of neurological or musculoskeletal conditions, no acute injuries that could affect their ability to stand within the last six months, and the ability to perform simple motor and cognitive tasks.

Exclusion criteria: Difficulty understanding and/or following simple verbal instructions, inability to complete standing tasks safely, or any medical condition that could compromise safety during the balance testing.

D.2. GENERAL EXPERIMENTAL DESIGN

This study will employ an observational research design involving a single testing session. All participants will complete the same testing procedures, with conditions presented in randomized blocked order to minimize order effects. A three-minute rest period will be provided between each condition to reduce the effects of fatigue.

Better Balance Test (BBT): This test objectively evaluates static balance and fall risk (Goble & Baweja, 2018a). Postural sway will be quantified as the COP sway displacement (cm) during quiet standing on an FDA-approved portable force plate (BTrackS Balance Plate™). We will use this test to classify participants' fall risk before initiating the study protocol. Participants will be instructed to stand as still as possible on the force plate across three trials with their eyes closed, feet shoulder-width apart, and hands on their hips **(Figure 6)**. The three trials will be averaged to calculate the BBT criterion score.

Figure 6. The Better Balance Test

Aim 1: Investigate age-associated changes in multisensory interaction during stable dual-task conditions using time-frequency analysis.

Rationale: Firm surfaces provide the most controlled environment, where sensory inputs are not additionally challenged by surface instability. This allows for the establishment of baseline multisensory interaction patterns under dual-task conditions. Although aging involves progressive decline in visual, vestibular, and proprioceptive systems (Zhang S, 2020), a stable surface isolates these age-associated changes to be examined independently from the interaction with environmental perturbations.

Experimental design: Following the BBT classification of fall risk, all participants will perform the following tasks on a **firm/stable surface**. Each participant will complete three 20-second trials for each condition with eyes open.

Single-task conditions: These control conditions establish baseline performance for each component task. This ensures that the observed changes during dual-task standing reflect the interaction between postural control and secondary task demands, rather than limitations of the tasks themselves.

1. **Balance test:** Participants will stand as still as possible on the force plate with their hands on their hips, feet shoulder-width apart, and their eyes open, looking straight ahead **(Figure 7A).** This establishes a baseline postural control performance without additional cognitive or motor demands.
2. **Cognitive task:** Participants will perform the verbal memory encoding/recall task while seated using HVLT versions B, D, and F **(Figure 7B)**. This isolates cognitive performance independent of postural control demands.

Dual-task conditions: These conditions evaluate multisensory interaction in postural control by requiring participants to maintain balance while simultaneously performing a cognitive (verbal memory encoding) or motor (proprioceptive) dual-task.

1. **Cognitive dual-task:** Participants will stand as still as possible on the force plate while completing a verbal memory encoding/recall task **(Figure 7C)**, simulating daily activities that require cognitive processing during upright posture. For each trial, participants will hear the first five words from the Hopkins Verbal Learning Test (HVLT) versions A, C, and E (Brandt, 1991). The HVLT word list will be presented auditorily during the first 10 seconds, followed by 10 seconds of silence for encoding. Immediately after each trial, participants will be asked to recall the words in the order in which they were presented.
2. **Proprioceptive (motor) dual-task:** Participants will stand as still as possible on the force plate while performing the cervical joint position task (AlDahas A, 2024). A lightweight headband with an attached laser pointer will be placed on the participant's head (Bae S, 2023). Participants will be instructed to maintain the laser beam aligned with the center of the target “bullseye” **(Figure 7D)**. This task simulates real-world situations where postural control must be maintained while simultaneously coordinating precise proprioceptive control, creating direct competition for attentional resources (Saraiva M, 2023).
3. **Multitask:** Participants will stand as still as possible on the force plate while simultaneously performing both the verbal memory encoding and the cervical joint position tasks (**Figure 7E**). This condition presents the highest level of challenge by combining cognitive and motor demands with postural control. This places increased demands on proprioceptive resources as participants must manage competing cognitive attention and motor demands simultaneously. Motor task accuracy will be measured as binary target maintenance (1= on-target center, 0 = off-target center).

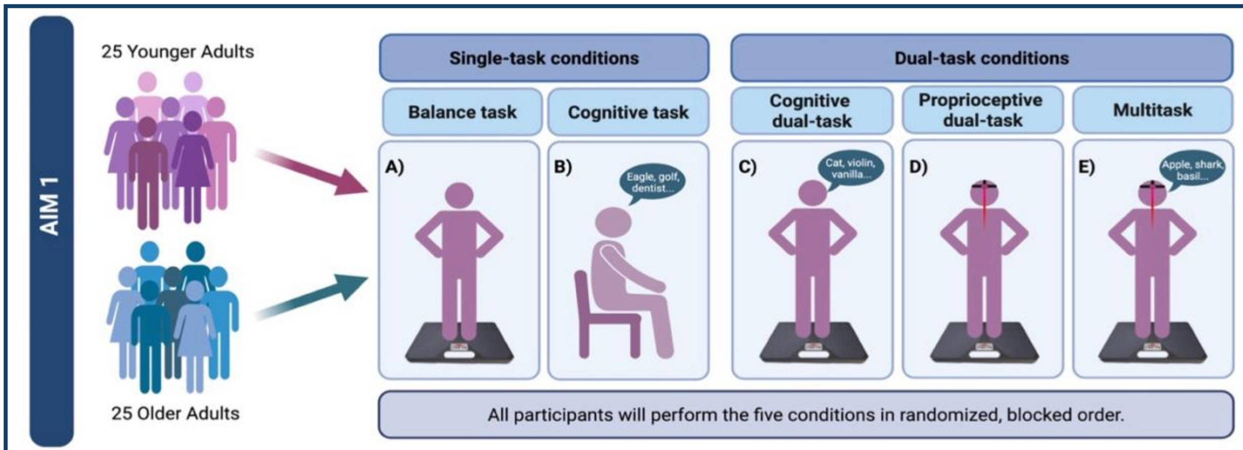

Figure 7. Experimental design for Aim 1. Twenty-five younger adults and 25 older adults will complete five randomized, blocked conditions on a stable surface with eyes open.

Aim 2: Characterize age-associated changes in multisensory interaction during unstable dual-task conditions using time-frequency analysis.

Rationale: An unstable surface places increased demands on proprioceptive and vestibular systems - sensory inputs that decline most with aging and are essential for adaptive postural control (Wagner AR, 2012; Wang J, 2024). Examining multisensory interaction during dual-task conditions on unstable surfaces will identify whether older adults exhibit disrupted sensory reweighting when these sensory inputs are challenged. This approach provides insight into the mechanisms by which postural control in unstable or unpredictable environments becomes particularly hazardous for older adults, advancing our understanding of how age-associated sensory decline contributes to fall risk.

Experimental design: Following the BBT classification, participants will perform the same single-task conditions **(Figures 8A-B)** as well as the cognitive dual-task **(Figure 8C)**, proprioceptive dual-task **(Figure 8D),** and the multitask condition **(Figure 8E)** as described in Aim 1. To achieve this Aim, all standing conditions will be completed on a **foam/unstable surface** placed on top of the force plate, with trial durations and randomization procedures identical to those described in Aim 1. The unstable surface increases demand on proprioceptive and vestibular systems, allowing the assessment of age-associated changes in sensory reweighting under environmental challenges.

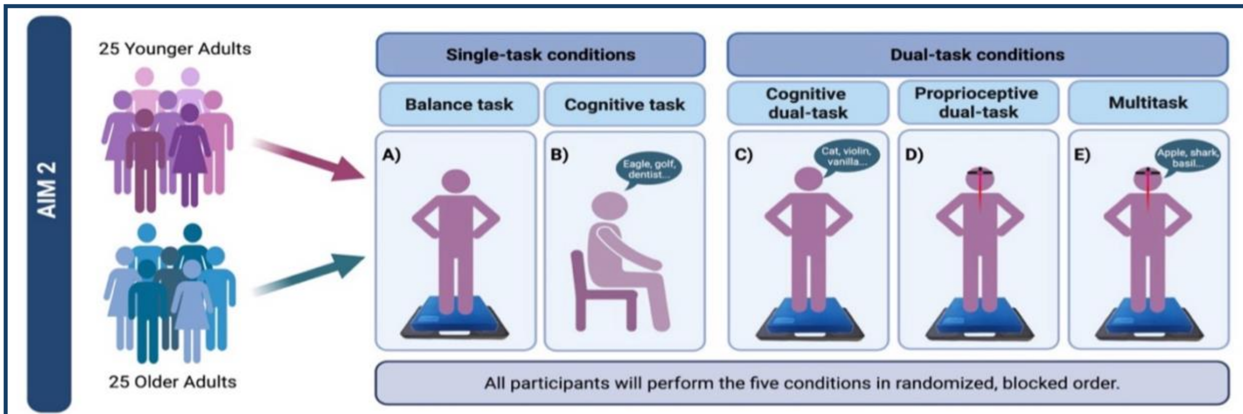

Figure 8. Experimental design for Aim 2. Twenty-five younger adults and 25 older adults will complete five randomized, blocked conditions on an unstable surface with eyes open.

Primary outcome measures for both aims*:* The COP sway displacement (cm) will be recorded by the force plate during all standing conditions, providing the primary data for time-frequency domain analysis.

Secondary outcomes: Cognitive task accuracy for the verbal memory task will be compared between standing (on-force plate) and sitting (off-force plate) conditions.

D.3. DATA ANALYSIS

Aims 1 and 2 require quantification of the time-frequency domain characteristics of postural sway. This will be achieved by applying the wavelet transform to the COP signal after it has been filtered. The spectral decomposition will enable the identification of the contributions of different sensory inputs within their respective frequency bands.

Quantification of Postural Sway

A custom-written program in MATLAB® will analyze the raw signals from the force plate to calculate all COP variables. The postural sway signal will be analyzed for the 20-second trial length, will be sampled at 25 Hz for 500 data points (Goble & Baweja, 2018a), and filtered using a 4th-order Butterworth filter with a low-pass cut-off of 4 Hz. Mediolateral (ML) and anteroposterior (AP) sway displacements will be determined using the following formulas (Goble & Baweja, 2018a):

$$ML = 24.25\ ((TR+BR) - (TL+BL)) / (TL+TR+BL+BR) \qquad \text{(Equation 1)}$$

$$AP = 15.50\ ((TL+TR) - (BL+BR)) / (TL+TR+BL+BR) \qquad \text{(Equation 2)}$$

Where TR, TL, BR, and BL are the sensor values from the top left, top right, bottom left, and bottom right corners of the force plate **(Figure 9).** The total COP sway displacement is determined by the distance between successive registered COP locations according to the following formula:

$$\text{Total COP sway displacement} = [(COP_{x^2} - COP_{x^1})^2 + (COP_{y^2} - COP_{y^1})^2]^{0.5} \qquad \text{(Equation 3)}$$

Where COP_{x2} and COP_{x1} are adjacent time-points in the mediolateral time series, and COP_{y2} and COP_{y1} are adjacent time-points in the anteroposterior time series. The total COP sway displacement is then obtained by summing all distances across the entire time series (Goble & Baweja, 2018a; Goble et al., 2020).

Figure 9. BTrackS Balance Plate™. The force plate contains four sensors positioned at the corners: TL (top left), TR (top right), BL (bottom left), and BR (bottom right). The yellow trace illustrates a representative COP sway displacement (17 cm) from a young adult during quiet standing. The COP is calculated using the four sensor values to determine mediolateral and anteroposterior

Wavelet transforms

Time-frequency analysis will be performed on the COP signals using continuous wavelet transform analysis (Torrence and Compo MATLAB function) (Torrence & Compo, 1998). The wavelet transform of the COP signal determines both the amplitude and the frequency of the signal, as well as how this amplitude varies with time. This is particularly well-suited for analyzing non-stationary signals such as postural control, because it can capture both low- and high-frequency components within specific time windows (Jafari H, 2023; Maatar D, 2011). Therefore, this approach can decompose the COP signal to examine how different frequency components change over time during dual-task conditions.

Signals will be detrended before analysis (MATLAB's detrend function). For this proposal, the COP signal will be divided into the following frequency bands, representing the different sensory contributions to postural control: <u>0-0.1 (visual input), 0.1-0.5 (vestibular input), and 0.5-1 Hz (proprioceptive input)</u> (Chagdes JR, 2009; Jafari H, 2023; Kirchner M, 2012). The **dependent variables** for the spectral analysis of the COP signal will be the normalized wavelet power within each frequency band, calculated as the absolute power in each band relative to the total signal power across the bandwidth.

D.4. STATISTICAL DATA ANALYSIS

Prior to data analysis, data will be screened for univariate and multivariate outliers using box plots and Mahalanobis distance. Normality will be assessed using the Shapiro-Wilk test and Q-Q plots. For repeated measures ANOVA, sphericity will be evaluated using Mauchly's test, with Greenhouse-Geisser or Huynh-Feldt corrections applied when violated. Homogeneity of variance will be assessed using Levene's test. Effect sizes (η^2) and p-values will be reported for all analyses.

AIM	Assessment	Dependent variable	Clinical measure	Statistical analysis
Baseline	Better Balance Test (BBT)	COP sway displacement (cm)	Balance and fall risk	One-way ANOVA model (2 groups x BBT scores).
1	Multisensory interaction on firm surface: linear measures	COP sway displacement (cm)	Multisensory interaction of postural control across different task conditions.	Two-way ANOVA model (2 groups x 4 tasks) with repeated measures on all factors to compare the differences in means from AP, ML, and total COP sway displacement.
	Multisensory interaction on firm surface: time-frequency domain analysis	Hertz (Hz)		Three-way ANOVA model (2 groups x 4 tasks x 3 frequency bands) with repeated measures on all factors to compare the normalized wavelet power from 0 to 1 Hz.
2	Multisensory interaction on unstable surface: linear measures	COP sway displacement (cm)	Multisensory interaction of postural control across different task conditions.	Two-way ANOVA model (2 groups x 4 tasks) with repeated measures on all factors to compare the differences in AP, ML, and total COP sway displacement.
	Multisensory interaction on unstable surface: time-frequency domain analysis	Hertz (Hz)		Three-way ANOVA model (2 groups x 4 tasks x 3 frequency bands) with repeated measures on all factors to compare the normalized wavelet power from 0 to 1 Hz.
Secondary analysis	Task accuracy during standing vs seated conditions	Cognitive task accuracy (% correct)	Task accuracy	Two-way ANOVA (2 groups x tasks: sitting versus standing conditions) with repeated measures on tasks to compare the difference in task accuracy.

For all statistical tests, α is set at <0.05, unless corrected for post-hoc analyses using the Bonferroni correction.

POTENTIAL DIFFICULTIES AND LIMITATIONS

1) **<u>Variability in testing duration:</u>** While we have allocated 45 minutes per session, some participants may require additional time to complete the tests. We will provide short

breaks between trials and rest periods as needed, ensuring participant comfort while maintaining data quality and protocol adherence.

2) **Accessibility:** Some interested participants may face difficulties traveling to our testing locations. Our equipment is designed for portability and accessibility, allowing for off-site testing at convenient locations. This approach promotes inclusivity by eliminating additional travel and reducing participation barriers.

ETHICAL ASPECTS OF THE PROPOSED RESEARCH

1) **Protection of Human Subjects:** All research protocols will comply with Auburn University's Institutional Review Board requirements. Participant confidentiality will be maintained through the use of unique subject IDs with no identifying information linked to data files. Data will be stored digitally on password-protected computers accessible only to study personnel. Physical copies will be kept in a secure, locked file cabinet with restricted access.
2) **Recruitment:** All participants will be recruited in accordance with the established inclusion and exclusion criteria, ensuring that only suitable individuals are selected. All participants will provide written informed consent after being informed of study procedures, risks, and potential benefits. Recruitment materials will be available in English and Spanish, with informational recruitment flyers displayed in multiple high-visibility locations providing study details, eligibility criteria, and contact information for those interested in participating.
3) **Potential risks*:*** The primary risk is ground-level falls during balance testing. Safety measures include: a) all participants will wear a gait belt, b) at least one trained staff member will stand next to the participant throughout testing, and c) testing will be immediately discontinued if a safety concern arises.

PROJECT TIMELINE

	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	July
Proposal											
IRB Approval											
Recruitment											
Data Collection		pilot									
Data Analysis											
Conferences			SFN			AHA					
Manuscript Writing											
Dissertation Defense											

Appendix F: Study Protocol – Institutional Review Board

AUBURN UNIVERSITY
Institutional Review Board

BASIC PROTOCOL INFORMATION:

Title: *Multisensory Interaction Mechanisms of Postural Control: A Dual-Task Approach to Understand Age-Associated Fall Risk*

Version: 1

Version Date: 9/24/2025

Other IRBs associated with this project: *24-758 EP 2405*

FUNDING INFORMATION:

Check all that apply.

☒ Not funded by any source.
☐ Internal funding. Provide the source/mechanism of internal support:
☐ U.S. Federal government funding (i.e., DoD, NIH, NSF, etc.) via one or more direct awards or a sub-award. Provide the source of federal support:
☐ Other sources of funding (please specify):

PRINCIPAL INVESTIGATOR:

Name: Harsimran S. Baweja
Department: Kinesiology
Telephone Number: (334) 844 1456
Email Address: hsb0025@auburn.edu
Department Head/Chair Name: Dr. Matthew Miller
☒ PI is not a student.
☒ I have read the PI eligibility statement and confirm that the above-named PI meets the criteria to be a PI on an IRB protocol at AU.

*****ALL KEY STUDY PERSONNEL MUST BE ADDED THROUGH 'LOCAL STUDY TEAM MEMBERS' IN ENDEAVOR. PLEASE ENSURE THAT ALL PERSONNEL HAVE COMPLETED THE NECESSARY MODULES TO CONDUCT RESEARCH AS SPECIFIED IN HRP-103 – INVESTIGATOR MANUAL. YOU CAN CHECK THE STATUS OF CITI TRAINING BY CLICKING ON THE 'TRAINING' TAB IN ENDEAVOR. TRAINING THAT OCCURS OUTSIDE OF CITI MUST BE UPLOADED UNDER THE 'LOCAL SITE DOCUMENTS' SECTION OF YOUR PROTOCOL. *****

1.0 Study Summary

This study examines age-associated changes in multisensory interaction during dual-task conditions that mimic everyday activities. Falls affect 36 million older adults annually in the United States, representing the leading cause of injury-related death.[1,2] Current fall risk assessments provide only overall balance scores without identifying which specific sensory systems contribute to fall risk (visual, vestibular, and proprioception), limiting the development of targeted rehab interventions.[3,4] This gap is particularly problematic during dual-task activities where competing attentional demands challenge the brain's ability to integrate multisensory information needed to maintain balance.[4,5] We are seeking to test our central objective of using aging as a model of progressive sensory system decline to advance our understanding of the neural mechanisms underlying multisensory interaction under dual-task demands that reflect real-world challenges. We will compare balance control mechanisms between younger adults (ages 18-35, n = 25) and older adults (ages 60+, n = 25) while they perform cognitive and motor dual tasks, while maintaining balance on both stable **(Aim 1)** and unstable surfaces **(Aim 2)**. Participants will stand on a computerized force plate while performing the dual tasks. The force plate will record their center of pressure (COP) displacement (proxy for fall risk)[6], and we will use advanced computer analysis called time-frequency analysis (wavelet transform) to break down these COP signals into specific frequencies that correspond to different sensory systems: visual (0-0.1 Hz), vestibular (0.1-0.5 Hz), and proprioception (0.5-1 Hz) contributions to balance.[7,8] These frequency patterns, particularly the low-frequency oscillations (0-1 Hz), reflect the dynamic processes of how the nervous system maintains balance.[9] All participants will complete a single testing session that lasts 45 minutes, during which different task conditions will be presented in a randomized order. We will assess COP displacement and time-frequency analysis to determine which sensory systems older adults rely on the most during different dual-task conditions and how this differs from younger adults. This study aims to advance our understanding of specific sensory system deficits that contribute to fall risk in aging populations and inform the development of targeted rehabilitation interventions.

2.0 Objectives

2.1 Describe the purpose, specific aims, and objectives.

The purpose of this study is to use aging as a model of progressive sensory system decline to advance our understanding of the neural mechanisms underlying multisensory interaction under dual-task demands that reflect real-world scenarios. We will utilize two complementary specific aims to address our hypotheses:

Aim 1: We will investigate age-associated changes in multisensory interaction during stable dual-task conditions using time-frequency analysis.

Aim 2: We will characterize age-associated changes in multisensory interaction during unstable dual-task conditions using time-frequency analysis.

2.2 State the hypotheses to be tested.

Hypothesis 1a: Older adults will demonstrate greater visual dependence when compared with younger adults, evidenced by increased contributions to the visual frequency band.

Hypothesis 1b: The multitask condition will produce greater COP sway displacement and low-frequency oscillations when compared with the cognitive and motor dual-task conditions.

Hypothesis 2a: Older adults will demonstrate impaired sensory reweighting ability, as evidenced by an increased reliance on visual cues when compared with younger adults.

Hypothesis 2b: Dual-task interference will be significantly greater in older adults when compared with younger adults, and it will increase COP sway displacement and low-frequency oscillations as the task becomes more challenging.

2.3 State the hypotheses to be tested.

Falls affect 36 million older adults each year in the United States and are the leading cause of injury-related death, generating over $50 billion in annual healthcare costs.[1,10] Despite this enormous burden, current fall risk assessments have significant limitations. More than 27 different tests are currently used in clinical settings, but they only provide overall balance scores that subjectively indicate whether someone might fall, without determining the underlying factors that contribute to their risk.[3,11] This **limitation** results in generic rehabilitation approaches where all individuals receive the same treatment, despite having different underlying causes for their fall risk. Therefore, these tests cannot objectively determine whether balance impairments stem from vision deficits, vestibular dysfunction of the inner ear, or proprioceptive deficits related to body position sensing.[9,12] These three sensory inputs are essential for maintaining efficient balance control.[5]

This limitation is particularly problematic during everyday activities that require performing two tasks simultaneously, such as walking while talking or carrying objects. Most falls occur during these dual-task situations. Therefore, the dual-task paradigm has been investigated as a potential biomarker of fall risk.[13] However, research on balance during dual-task conditions has produced conflicting findings. Some groups have reported decreased balance control under dual-task conditions,[14,15] while others have found that balance control either remains unchanged or increases.[16,17] These inconsistencies primarily result from traditional fall risk assessments that fail to isolate the contributions of the specific sensory systems (vision, proprioception, and vestibular).[9,12] Therefore, a **knowledge gap** remains regarding how age-associated mechanisms progressively disrupt multisensory interaction mechanisms during dual-task conditions.[18,19] This prevents clinicians and physical therapists from understanding the underlying mechanisms of fall risk, limiting their ability to develop targeted rehabilitation interventions based on individual sensory deficits rather than generic balance training approaches.

2.4 Describe any relevant preliminary data.

Our laboratory has published the world's largest normative database of fall risk from more than 16,000 individuals across the lifespan.[6,20] Moreover, we have used advanced signal processing analysis techniques (time-frequency analysis) that examine the different frequency patterns in the COP signal that correspond to specific sensory inputs (vision, vestibular, and proprioception). In preliminary studies at the SMaRT Lab, we have compared older adults at high versus low risk of falls. Time-frequency analysis revealed significant differences between single and dual-task conditions that were *completely invisible* with the current fall risk assessments. These findings demonstrate that <u>our approach can detect balance deficits that current fall risk assessments miss</u>, potentially improving fall risk identification and treatment outcomes.

2.5 Provide the scientific or scholarly background for, rationale for, and significance of the research based on the existing literature and how it will add to existing knowledge.

There is a critical need to develop standardized objective methods that can identify specific sensory system deficits underlying fall risk in aging populations. Current fall risk assessments fail to do this because they cannot determine whether balance deficits stem from visual decline, vestibular dysfunction, or impairment of body position sense. Our approach uses time-frequency analysis to identify the unique signatures of each balance system during dual-task conditions that mirror real-world scenarios. Therefore, the significance of this study lies in its potential to advance our understanding of multisensory interaction processes that help or fail to maintain balance during everyday tasks and contribute to fall risk in older adults. This study will facilitate the development of personalized rehabilitation strategies and innovative clinical diagnostics. Ultimately, it can *<u>bridge the gap between research and clinical application</u>*, advancing mechanistically driven interventions to reduce fall risk and preserve independence and quality of life in vulnerable populations.

3.0 Study Intervention/Investigational Agent: N/A

3.1 Description:

3.2 Drug/Device Handling:

3.3 If the drug is investigational (has an IND) or the device has an IDE or a claim of abbreviated IDE (non-significant risk device), include the following information:

- **Identify the holder of the IND/IDE/Abbreviated IDE.**
- **If your test article meets the criteria for a waiver of IND or IDE, please describe**
- **Explain procedures followed to comply with sponsor requirements for FDA-regulated research for the following:**

FDA Regulation	IND Studies	IDE studies	Abbreviated IDE studies
21 CFR 11	X	X	
21 CFR 54	X	X	
21 CFR 210	X		
21 CFR 211	X		
21 CFR 312	X		
21 CFR 812		X	X
21 CFR 820		X	

4.0 Procedures Involved*

4.1 Describe and explain the study design.

Step-by-step study design:
Participants will only need to attend one testing session. The session will last ~45 minutes, including all consent procedures and balance tests.
Step 1. Recruitment. Potential participants will be recruited through flyers and social media platforms (e.g., Facebook, Instagram), using language approved by the IRB. We will also contact participants who have previously participated in our lab studies and consented to being contacted for future studies via email or phone. Prior to the in-person consent and testing visit, a member of the research team will contact potential participants to verify their eligibility.
Step 2. Consent and fill out a demographic questionnaire. If the potential participant qualifies for the study (based on the inclusion/exclusion criteria). They will be invited to the Kinesiology Building, room 136, at the SMaRT Neuroscience Lab, to consent or decline participation. If they verbally consent, they will be asked to sign the informed consent form and complete a demographic questionnaire.
Step 3. Equipment explanation and familiarization. Participants will receive an explanation, demonstration, and familiarization with the testing equipment and protocols.
Testing will be done in a quiet and distraction-free setting. As a **safety precaution** throughout the testing session, there will always be at least one staff member standing next to the participant, and participants will always wear a safe gait belt.
Step 4. Perform the **Better Balance Test (BBT)** – Initial assessment
The Better Balance Test measures overall balance and postural sway.
The test consists of four 20-second trials with a minimal inter-trial interval of ~10 seconds or as long as needed by the participant. Each trial will begin and end with an auditory tone. Participants will be instructed to stand as still as possible on the force plate with their eyes closed, hand on their hips, and feet shoulder width apart **(Figure 1)**.

Just prior to testing, the tester will read the following instructions to participants via an onscreen dialog box:

> This test consists of four, 20 seconds trials. The first trial is a practice trial, and the following three trials are used to measure your balance. For each trial, you will stand as still as possible on the BTrackS Balance Force Plate with your hand on your hips, feet shoulder width apart, and eyes closed. You will hear one tone at the beginning of each trial and another tone when each trial is completed. Do you have any questions?

Figure 1. Representative figure of the test from the manufacturer's website with permission.

Step 5. Completion of initial assessment and preparation for the main study. After participants complete the BBT, we will calculate their balance score. This information will help us understand their baseline balance abilities.

Testing order and structure for main study: Each test will consist of 3 trials, each lasting 20 seconds, with a minimal inter-trial interval of ~10 seconds or as long as needed by the participant. Each trial will begin and end with an auditory tone.

The main study has two blocks:

- **Block 1:** All standing tasks on a stable force plate.
- **Block 2:** All standing tasks on an unstable foam surface placed on top of the force plate.
- The seated cognitive task will be randomized within the overall session.

The different tests between each block will be presented in a randomized order.

For all standing tests, participants will be asked to stand barefoot with their feet shoulder-width apart and centered on the force plate. This is defined as having the medial malleoli (inner ankle bones) of the left and right feet aligned along the horizontal gridline of the plate, with the feet at equal distances from the plate's midline **(Figure 2)**.

Figure 2. Representative figure of the test from the manufacturer's website with permission.

Figure 2. Representative figure of the test from the manufacturer's website with permission.

Step 6. Stable surface block (4 conditions in randomized order).
a) Cognitive dual task: Participants will be instructed to stand as still as possible on the force plate with their eyes open, hand on their hips, and feet shoulder-width apart while simultaneously listening and remembering 5 words **(Figure 3A)**.

The words will be presented during the first 10 seconds, followed by 10 seconds of silence while they continue maintaining balance. After each trial, they will be asked to recall the words in the order they were presented.

b) Proprioceptive (motor) dual-task: Participants will be instructed to stand as still as possible on the force plate with their eyes open, hand on their hips, and feet shoulder-width apart while wearing a lightweight headband with a small laser pointer attached **(Figure 3B)**. They will have to use small head movements to keep the laser dot centered on the target circle in front of them.

c) Multitask: Participants will be instructed to stand as still as possible on the force plate with their eyes open, hand on their hips, and feet shoulder-width apart while simultaneously doing both tasks – listening to and remembering 5 words while keeping the laser dot on the target using head movements **(Figure 3C)**. After the end of each trial, they will be asked to recall the words in the order they were presented.

d) Balance on a stable surface (single-task): Participants will be instructed to stand as still as possible on top of the force plate with their eyes open, hand on their hips, and feet shoulder-width apart **(Figure 3D)**.

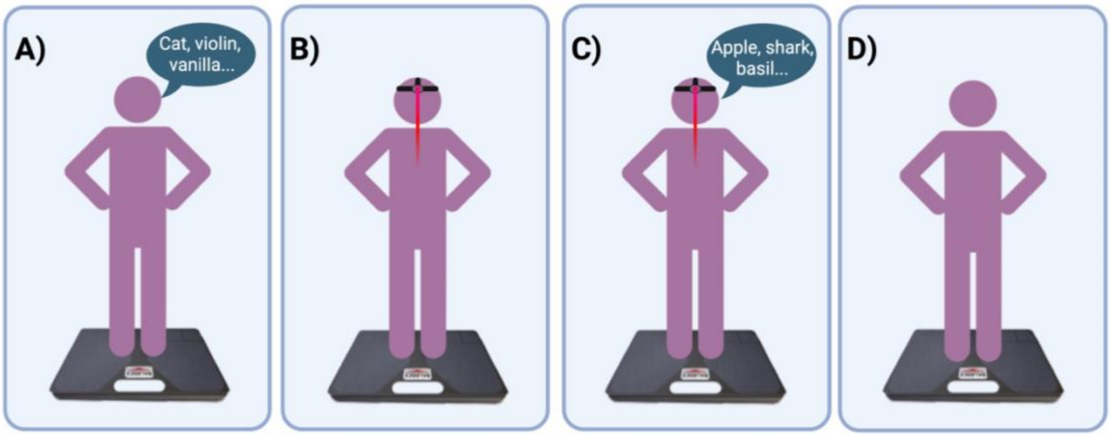

Figure 3. Representative figures of the tests on a stable surface. A) Cognitive dual-task, B) Proprioceptive (motor) dual-task, C) Multitask, and D) Balance single-task.

Step 7. Unstable surface block (4 conditions in randomized order).

Participants will be asked to perform the same single, task, dual-task, and multitask conditions explained above while standing on a foam surface placed on top of the force plate **(Figure 4A-D)**.

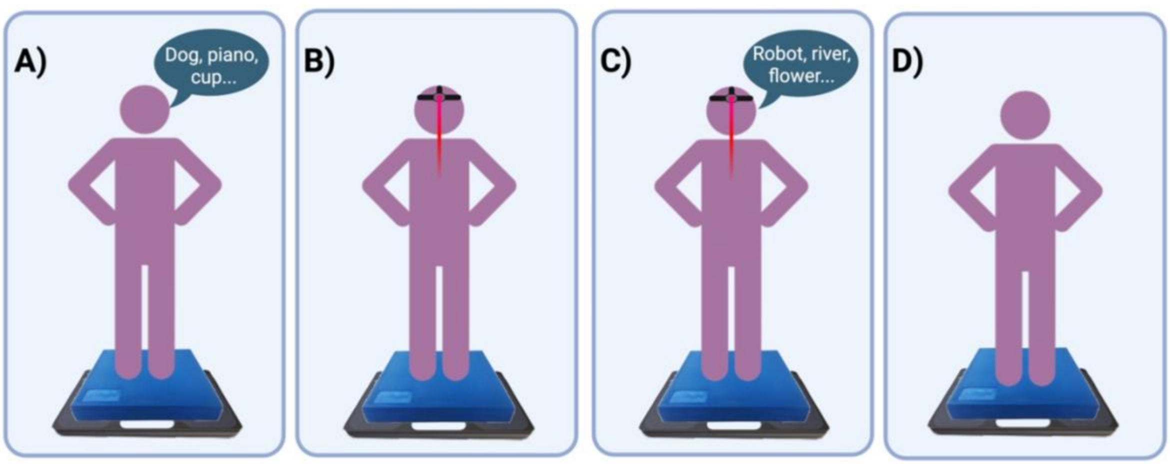

Figure 4. Representative figures of the tests on an unstable surface. A) Cognitive dual-task, B) Proprioceptive (motor) dual-task, C) Multitask, and D) Balance single-task.

Step 7. Seated cognitive control task.

This control condition isolates cognitive performance without balance demands, allowing us to compare their cognitive task accuracy when they are just sitting versus when they are maintaining balance (dual-task condition).

While participants are comfortably seated in a chair, 5 words will be presented to them during the first 10 seconds of the test, followed by 10 seconds of silence. After the test, they will be asked to recall the words in the order they were presented **(Figure 5)**.

Figure 5. Representative figure of the seated cognitive task (single-task).

Step 8. Removal of safety equipment and conclusion of the protocol.

4.2 Provide a description of all research procedures being performed and when they are performed, including procedures being performed to monitor participants for safety or minimize risks.

Section 4.1 provides a description and explanation of the study design, as well as a description of all research procedures being performed, including the timing of these procedures and the methods used to monitor participants for safety or minimize risks.

4.3 Describe procedures or methods in place to lessen the probability or magnitude of risks.

Risk of ground-level falls: The risk associated with this study is minimal, not greater than those of daily life activities. However, participants may potentially have a ground-level fall. To minimize this risk, participants will wear a gait belt, and at least one trained staff member will be standing next to the participant throughout the entire testing process with immediate intervention capabilities.

Breach of confidentiality: Participants may potentially experience a breach of confidentiality in the unlikely event of a security breach. To mitigate this risk, participants will be assigned ID numbers (e.g., SUB01). The only form that will contain identifiable information linking the participant's name to their ID number will be the demographic questionnaire. All other data collection forms and electronic data files will use only the participant ID number, ensuring that there is no direct link between identifiable information and research data. Notwithstanding, we will take extra precautions to ensure these forms are protected. First, a single folder will be allocated to contain all participant-signed IRB forms and the demographic questionnaire. These folders will be stored in a locked filing cabinet in Dr. Baweja's office in the School of Kinesiology, Room #221. This is a key-locked office, located behind a key-locked door. These two security-locked doors will ensure that the folders are not accessible to the general public. Likewise, the IRB forms will be retained in this office for a 3-year period. After this period, Dr. Baweja will personally destroy these forms using a double-pane shredder. Finally, electronic data entered into the force plate software, Microsoft Excel, or SPSS will only use the subject ID number. Thus, there will be no way to link these data to a participant. We will protect this data by entering it only into computers in the laboratory room #136. These computers are password-protected in accordance with Auburn University IRB protocols and will be located behind a one-key-card-locked door.

4.4 Describe all drugs and devices used in the research and the purpose of their use, as well as their regulatory approval status.

Force plate: Force plate technology is one of the most sensitive and objective means for assessing postural sway in clinical settings and research. Force plates measure postural sway based on a metric called the Center of Pressure (COP), which represents the weighted average of forces generated while standing on a force plate. We will use an FDA-approved portable force plate (BTrackS Balance Plate^{TM}) in accordance with its intended use for balance assessments as approved by the FDA. This device has been previously used in another IRB-approved protocol study at Auburn University (*24-758 EP 2405).*

Headband laser: A lightweight headband with a small laser pointer attached, similar to laser pointers commonly used in presentations. The laser pointer is a standard, low-power device (of the same type sold in stores) that poses no risk to participants. The headband allows us to measure how well participants can control precise head movements while maintaining balance.

4.5 Describe the source records that will be used to collect data about participants. Uploaded to the local site documents.

4.6 What data will be collected during the study, and how will that data be obtained?

All data will be obtained by trained research personnel during a single testing session. The following data will be obtained:

- Participants' demographics: An appendix entitled "*Demographic Questionnaire*" has been attached to this IRB.
- Balance and fall risk data: The software of the force plate automatically records the trial's results, enabling assessment of balance under different single and dual-task conditions.
- Cognitive task performance: Cognitive task accuracy will be recorded online in a secure computer-based system, based on participants' accuracy in memorizing and recalling words while maintaining balance on the force plate.
- Motor task performance: Laser targeting accuracy will be recorded online in a secure computer-based system, assessing whether the laser dot stays within the target circle while participants maintain balance.

Data source(s): ☒New Data ☐Existing Data	**Will recorded data directly or indirectly identify participants?** ☒Yes ☐No
Data collection will involve the use of: ☐ Educational Tests (cognitive diagnostic, aptitude, etc.) ☒ Internet / Electronic ☐ Interview ☐ Audio ☐ Observation ☐ Video	**Will study data be stored within a HIPAA covered facility?** ☐Yes ☒No If yes, which facility(ies)? (To determine AU HIPAA covered entities, please refer to Auburn University's HIPAA page):

☐ Locations or Tracking Measures ☐ Photos ☒ Physical / Physiological Measures or Specimens ☐ Digital Images ☒ Surveys / Questionnaires ☐ Private records or files ☐ Other (please specify):	

4.7 If there are plans for long-term follow-up (once all research-related procedures are complete), what data will be collected during this period?

No further data will be collected once all research-related procedures are complete

5.0 Data and Specimen Banking*

5.1 If data or specimens will be banked for future use, describe where the specimens will be stored, how long they will be stored, how the specimens will be accessed, and who will have access to the specimens. N/A

5.2 List the data to be stored or associated with each specimen. N/A

5.3 Describe the procedures to release data or specimens, including: the process to request a release, approvals required for release, who can obtain data or specimens, and the data to be provided with specimens. N/A

6.0 Sharing of Results with Participants

6.1 Describe whether results (study results or individual participant results, such as results of investigational diagnostic tests, genetic tests, or incidental findings) will be shared with participants or others (e.g., the participant's primary care physicians) and, if so, describe how the results will be shared. Upon request, de-identified results can be shared with the participants. Participants will be reminded that these are research-grade tests and that we cannot interpret the results; however, they are free to share their test results with their physicians or physical therapists.

7.0 Study Timelines*

7.1 Describe:

- **The duration of an individual participant's participation in the study.** Each participant will visit the lab for one testing session of ~45 minutes, including all consent procedures and balance tests.
- **The duration anticipated to enroll all study participants.** ~4 months following the approval of this protocol.
- **The estimated date for the investigators to complete this study (complete primary analyses).** July 2026

8.0 Study Endpoints*

8.1 Describe the primary and secondary endpoint.

Primary study points: Postural sway (Center of Pressure displacement) will be obtained from the force plate recording during all standing conditions.

Secondary study points:

1. Cognitive task accuracy (percentage of words correctly recalled during the test).
2. Motor task accuracy (off the target = 0 points, on the target = 1 point).
3. Fall risk classification scores from the Better Balance Test, using the same force plate.

8.2 Describe any primary or secondary safety endpoints. No safety endpoints are anticipated, given the low-risk nature of the study. However, safety procedures include a rest period of ~10 seconds (or as long as needed for the participant) after each trial, the use of a gait belt, trained staff supervision, and immediate discontinuation of the testing if safety concerns arise.

9.0 Inclusion and Exclusion Criteria

9.1 Describe the targeted population. Healthy young (18-35 years old) and older adults (more than 60 years old).

9.2 Describe how individuals will be screened for eligibility. Interested individuals will report to KINE Room #136 at the School of Kinesiology and will receive a verbal study description by a member of the research team (~10 minutes). If they consent to participate and are deemed safe and eligible for all testing, they will be asked to sign the consent form and complete the demographic questionnaire.

9.3 Describe the criteria that define who will be included or excluded in your final study sample. Participants should meet the following exclusion/inclusion criteria to be included in the study:

Inclusion criteria: 1) Healthy young adults aged 18-35 or older adults aged 60+ years; 2) no history or diagnosis of neurological or musculoskeletal conditions; 3) no acute injuries affecting their ability to stand within the last six months; and 4) ability to perform simple motor and cognitive tasks.

Exclusion criteria: 1) Difficulty understanding and/or following simple verbal instructions; 2) inability to complete standing tasks safely; 3) any medical conditions that could compromise safety during the balance testing; and 4) current pregnancy, as pregnancy-associated physiological changes can affect postural control.

9.4 Indicate specifically whether you will include or exclude each of the following special populations.

☐Pregnant people/fetuses EXCLUDE	☒Known interpersonal relationships	☐At risk for/Experiencing substance use disorder EXLUDE	☒ LBGTQIA+

☐ Minors EXCLUDE	☒ At risk of/Experiencing homelessness	☒ Refugees	☒ American Indian/Alaskan Native
☐ Prisoners/Justice-Involved EXCLUDE	☒ Persons with economic disadvantages	☐ Disabled people/People with disabilities EXCLUDE	☒ AU faculty, staff, students
☒ Persons with educational disadvantages	☐ Decisionally or intellectually impaired EXCLUDE	☒ Unauthorized immigrants	☒ Non-AU Students

10.0 Local Number of Participants

10.1 Indicate the total number of participants to be accrued locally. All participants (n= 50).

10.2 If applicable, distinguish between the number of participants who are expected to be enrolled and screened, and the number of participants needed to complete the research procedures (i.e., numbers of participants excluding screen failures.) We expect to enroll 50 participants (25 younger adults aged 18-35 and 25 older adults aged 60+). We estimate that screening approximately 55-60 individuals will achieve our target enrollment, taking into account potential screen failures. Interested individuals will report to KINE Room #136 at the School of Kinesiology and will receive a verbal study description by a member of the research team. As part of the consent process, research staff identified in this protocol will screen participants against inclusion/exclusion criteria by verbally reviewing: age (18-35 or 60+ years), absence of neurological or musculoskeletal conditions, recent injuries affecting standing balance, ability to understand and follow simple verbal instructions, absence of any medical conditions compromising safety during balance testing, and pregnancy status. Only participants who meet all inclusion criteria and have no exclusion criteria will be eligible for enrollment. If they are deemed safe and eligible to participate, they will be asked to read and sign the consent form and fill out the demographic questionnaire.

11.0 Vulnerable Populations*

11.1 If the research involves individuals who are vulnerable to coercion or undue influence, describe additional safeguards included to protect their rights and welfare. N/A

12.0 Recruitment Methods

12.1 Describe when, where, and how potential participants will be recruited.

We will initiate contact with potential participants through flyers placed in multiple visible locations across the Auburn-Opelika area and on social media platforms (e.g., Facebook, Instagram), using IRB-approved language. We will also contact participants who have previously participated in our lab studies and consented to being contacted for future studies via email or phone.

For recruitment, we will contact potential participants no more than 3 times and no more than once a week. All potential participants will be instructed to contact the Sensorimotor and Rehab Technology (SMaRT) Neuroscience Lab team by phone (334 844 1926) or email (mzm0403@auburn.edu) to schedule their consent and screening visit.

During the consenting and screening visit, a laboratory team member will verbally review the consent form and describe the research study using clear explanations and pictures. If potential participants verbally agree to be enrolled, they will be asked to read and sign the informed consent form and complete the demographic questionnaire.

12.2 Describe the source of participants. Potential participants will come mainly from the Auburn and Opelika community areas.

12.3 Describe the methods that will be used to identify potential participants.

All lab personnel conducting this study (identified in this IRB) will recruit potential participants from the Auburn and Opelika areas through the following methods: 1) Distributing flyers in several locations; 2) Posting the flyer on social media platforms (An appendix entitled "*Flyer*" has been attached to this IRB); 3) contacting previous participants who consented to be contacted for future studies; and 4) verbal recruitment using the verbal script attached to this document. All recruitment will be conducted by trained research staff using IRB-approved materials and procedures.

12.4 Describe materials that will be used to recruit participants.

IRB-approved recruitment flyer and verbal script will be used (these documents are attached to this IRB document). The flyer will provide concise details about the study, including its purpose, eligibility criteria, and contact information for those interested in participating.

12.5 Describe plans to compensate participants, keeping in mind the institutional policies set forth by Procurement and Business Services. Be sure to include the amount and timing of any payments to participants. Participants will not be compensated.

13.0 Withdrawal of Participants*

13.1 Describe anticipated circumstances under which participants will be withdrawn from the research without their consent. Participants will be withdrawn without consent if safety concerns arise during balance testing that prevent safe completion (see the attached "*Emergency Action Plan*" document for more details).

13.2 Describe any procedures for orderly termination. Testing will be immediately stopped, participants will be seated safely, and any necessary safety equipment (such as a gait belt) will be removed.

13.3 Describe procedures that will be followed when participants withdraw from the research, including partial withdrawal from procedures with continued data collection. Participants may withdraw from the study at any time. Their participation is completely voluntary. For participants who withdraw before completing all tasks, partial data will be retained unless the participant requests data deletion. All data from withdrawn participants will be stored using the same confidentiality procedures as completed participants. Participants who request data deletion will have their data permanently removed from all study records.

14.0 Risk to Participants*

14.1 List the reasonably foreseeable risks, discomforts, hazards, or inconveniences to the participants related the participants' participation in the research.

Risk of ground-level falls: The risk associated with this study is minimal, not greater than those of daily life activities. However, participants may potentially have a ground-level fall. To minimize this risk, participants will wear a gait belt, and at least one trained staff member will be standing next to the participant throughout the entire testing process with immediate intervention capabilities.

Breach of confidentiality: Participants may potentially experience a breach of confidentiality in the unlikely event of a security breach. To mitigate this risk, participants will be assigned ID numbers (e.g., SUB01). The only form that will contain identifiable information linking the participant's name to their ID number will be the demographic questionnaire. All other data collection forms and electronic data files will use only the participant ID number, ensuring that there is no direct link between identifiable information and research data. Notwithstanding, we will take extra precautions to ensure these forms are protected. First, a single folder will be allocated to contain all participant-signed IRB forms and the demographic questionnaire. These folders will be stored in a locked filing cabinet in Dr. Baweja's office in the School of Kinesiology, Room #221. This is a key-locked office, which is also behind a key-locked door. These two security-locked doors will ensure that the folders are not accessible to the general public. Likewise, the IRB forms will be retained in this office for a 3-year period. After this period, Dr. Baweja will personally destroy these forms using a double-pane shredder. Finally, electronic data entered into the force plate software, Microsoft Excel, or SPSS will only use the subject ID number. Thus, there will be no way to link these data to a participant. We will protect this data by entering it only into computers in the laboratory room #136. These computers are password-protected in accordance with Auburn University IRB protocols and will be located behind a one-key-card-locked door.

14.2 If applicable, indicate which procedures may have risks to the participants that are currently unforeseeable. N/A

14.3 If applicable, indicate which procedures may have risks to an embryo or fetus should the participants be or become pregnant. N/A

14.4 If applicable, describe risks to others who are not participants (e.g., risks to ethnic or cultural groups, risks to sexual partners of participants, etc.). N/A

15.0 Potential Benefits to Participants*

15.1 Describe the potential benefits that individual participants may experience from taking part in the research. There will be no direct benefits for the participants. However, their participation will benefit the scientific community**.**

16.0 Data Management* and Confidentiality

Data will be collected:

☐	Anonymously with no direct or indirect coding, link, or awareness by key personnel of who participated in the study
☐	Confidentially, but without a link to participant's data to any identifying information (collected as "confidential" but recorded and analyzed "anonymous")

☒	Confidentially with collection and protection of linkages to identifiable information.

16.1 Describe the data analysis plan, including any statistical procedures. Provide a power analysis as necessary.

Prior to data analysis, data will be screened for univariate and multivariate outliers using box plots and Mahalanobis distance. Normality will be assessed using the Shapiro-Wilk test and Q-Q plots. For repeated measures ANOVA, sphericity will be evaluated using Mauchly's test, with Greenhouse-Geisser or Huynh-Feldt corrections applied when violated. Homogeneity of variance will be assessed using Levene's test.
Primary analyses: All variables will be statistically analyzed using independent sample t-tests, one-way and two-way ANOVA with repeated measures, along with regression analyses as appropriate.
Secondary analyses: Task accuracy will be compared using two-way ANOVA (standing vs. seated conditions).
Descriptive statistics (mean, SEM, and SD) will be calculated for all variables.

Data analysis will be conducted using Microsoft Excel, SPSS, and MATLAB.

16.2 Describe the steps that will be taken to secure the data (e.g., training authorization of access, password protection, encryption, physical controls, certificates of confidentiality, and separation of identifiers and data) during storage, use, and transmission.

Participants will be assigned ID numbers (e.g., SUB01). The only form that will contain identifiable information linking the participant's name to their ID number will be the demographic questionnaire. All other data collection forms and electronic data files will use only the participant ID number, ensuring no direct link between identifiable information and research data. Notwithstanding, we will take extra precautions to ensure these forms are protected. First, a single folder will be allocated to contain all participant-signed IRB forms and the demographic questionnaire. These folders will be stored in a locked filing cabinet in Dr. Baweja's office in the School of Kinesiology, Room #221. This is a key-locked office, located behind a key-locked door. These two security-locked doors will ensure that the folders are not accessible to the general public. Likewise, the IRB forms will be retained in this office for a 3-year period. After this period, Dr. Baweja will personally destroy these forms using a double-pane shredder. Finally, electronic data entered into the force plate software, Microsoft Excel, or SPSS will only use the subject ID number. Thus, there will be no way to link these data to a participant. We will protect this data by entering it only into computers in the laboratory room #136. These computers are password-protected in accordance with Auburn University IRB protocols and will be located behind a one-key-card-locked door. Only personnel identified in this protocol will have access to the data.

Unidentifiable data will be transferred to Microsoft Excel for subsequent export to SPSS and MATLAB for statistical analysis, and Sigma Plot for creating figures.

16.3 Describe any procedures that will be used for quality control of collected data.

Several quality control measures will be implemented:

Equipment calibration: The force plate will be calibrated before each testing session according to manufacturer protocols to ensure accurate center of pressure measurements.

Staff training: All research personnel will be trained on standardized testing protocols, data collection procedures, and equipment operation to minimize variability between testers.

Data backup: All data will be backed up to secure, password-protected storage immediately after collection to prevent data loss.

Standardize protocols: Written protocols of step-by-step instructions will be followed for all procedures to ensure consistency across participants and testing sessions.

16.4 Describe how data or specimens will be handled study-wide.

Data will be password-protected and encrypted. Only key study personnel identified in this IRB form will have access to the data. A single folder will be allocated to contain all participant-signed IRB forms and the demographic questionnaire. These folders will be stored in a locked filing cabinet in Dr. Baweja's office in the School of Kinesiology, Room #221. This is a key-locked office, located behind a key-locked door. These two security-locked doors will ensure that the folders are not accessible to the general public. Likewise, the IRB forms will be retained in this office for a 3-year period. After this period, Dr. Baweja will personally destroy these forms using a double-pane shredder. Finally, electronic data entered into the force plate software, Microsoft Excel, or SPSS will only use the subject ID number. Thus, there will be no way to link these data to a participant. We will protect this data by entering it only into computers in the laboratory room #136. These computers are password-protected in accordance with Auburn University IRB protocols and will be located behind a one-key-card-locked door. Electronic data will be regularly backed up to secure, encrypted storage accessible only to authorized study personnel.

Unidentifiable data will be transferred to Microsoft Excel for subsequent export to SPSS and MATLAB for statistical analysis, and Sigma Plot for creating figures.

16.5 Describe the steps that will be taken to protect participants' privacy interests.

Recruitment and contact:

- Potential participants will be contacted no more than 3 times and no more than once per week during recruitment.
- Participants self-select into the study by voluntarily responding to recruitment flyers via phone or email.

During study participation:

- Testing will be conducted in a private laboratory space (KINE Room #136) with only authorized research personnel identified in this study present.
- Participants may decline to answer any questions on the demographic questionnaire.
- Participants may withdraw from the study at any time without penalty or consequence.

16.6 If data are collected with identifiers and coded or linked to identifying information, describe the identifies and how the identifiers are linked to participants' data. Provide the rationale for coding or linking the data with identifying information.

Participants will be assigned unique ID numbers (e.g., SUB01, SUB02) that will be used on all data collection forms and demographic questionnaires. Only the demographic questionnaire will contain the identifying information and the assigned ID number. ID numbers are necessary to organize and track multiple data files generated during the testing while maintaining participant confidentiality. Using ID numbers instead of names on data files protects participants' confidentiality during data analysis and reduces the risk of confidentiality breaches. All identifying information (informed consent and demographic questionnaire) will be retained for 3 years after the completion of the study, as required by IRB policy. However, de-identified data will be stored indefinitely for potential future analyses. Digital files containing only coded data are stored on password-protected files on OneDrive (requiring 2-factor authentication).

16.7 Describe how and where identifying data and/or code lists will be stored. Be specific (building, room number, AU Box, etc.) describe how the location where the data is stored will be secured. For electronic data, describe security measures. If applicable, describe where IRB-approved and participant-signed consent documents will be kept on campus for 3 years after the study ends.

Participants will be assigned ID numbers (e.g., SUB01). The only forms that will contain identifiable information linking the participant's name to their ID number will be the demographic questionnaire. All other data collection forms and electronic data files will use only the participant's ID number, ensuring no direct link between identifiable information and research data. Notwithstanding, we will take extra precautions to ensure these forms are protected. First, a single folder will be allocated to contain all participant-signed IRB forms and the demographic questionnaire. These folders will be stored in a locked filing cabinet in Dr. Baweja's office in the School of Kinesiology, Room #221. This is a key-locked office, located behind a key-locked door. These two security-locked doors will ensure that the folders are not accessible to the general public. Likewise, the IRB forms will be retained in this office for a 3-year period. After this period, Dr. Baweja will personally destroy these forms using a double-pane shredder.

16.8 Describe how and where data will be stored (e.g., hard copy, audio/visual files, electronic data, etc.) and how the location where data is stored is secured. If data is separated from identifying data, please indicate that. For electronic data, describe data security.

Electronic Data Storage: All de-identified research data (force plate data) will be stored electronically in Excel, SPSS, MATLAB, and SigmaPlot files on OneDrive, utilizing two-factor authentication, and will be accessible only to authorized research personnel listed in this protocol. These files will contain only participant ID numbers (e.g., SUB01) with no identifying information. Per Auburn University protocols, raw data will be entered on a password-protected computer located in Laboratory Room #136, which is secured behind a key-card-locked door.

Hard Copy Storage (Identifiable Information): Only two forms will contain identifiable information: (1) the informed consent form (which includes the participant's name and signature), and (2) the demographic questionnaire (which links the participant's name to their assigned ID number). These forms will be stored in a locked cabinet in Dr. Baweja's office (School of Kinesiology, Room #221), which is a key-locked office behind a key-card-locked door. These forms will be retained for 3 years, after which Dr. Baweja will personally destroy them using a double-pane shredder.

16.9 Indicate the latest date that identifying information will be retained and how the information or links will be destroyed.

All IRB forms will remain in Dr. Baweja's office (School of Kinesiology, Room #221) for a 3-year retention period. After this period, Dr. Baweja will personally destroy these physical forms using a double-pane shredder.

17.0 Provisions to Monitor the Data to Ensure the Safety of Participants*

17.1 Describe:

- **The plan to periodically evaluate the data collected regarding both harms and benefits to determine whether participants remain safe. The plan might include establishing a data monitoring committee and a plan for reporting data monitoring committee findings to the IRB and the sponsor.** Data monitoring safety program is not necessary for this study.
- **What data are reviewed, including safety data, untoward events, and efficacy data.** Any adverse events will be reported immediately.
- **How the safety information will be collected (e.g., with case report forms, at study visits, by telephone calls with participants).** N/A
- **The frequency of data collection, including when safety data collection starts.** N/A
- **Who will review the data.** N/A
- **The frequency or periodicity of review of cumulative data.** N/A
- **The statistical tests for analyzing the safety data to determine whether harm is occurring.** N/A
- **Any conditions that trigger an immediate suspension of the research.** N/A

18.0 Compensation for Research-Related Injury

18.1 If the research involves more than Minimal Risk to participants, describe the available compensation in the event of research-related injury

The risk associated with this study is minimal, not greater than those of daily life activities. However, as described in the informed consent document (An appendix entitled "*Informed Consent Document*" has been attached to this IRB), participants will be informed that: "if you decide to participate, you will not be monetarily charged for anything. In the unlikely event that you sustain an injury from participating in this study, the investigators have no current plans to provide funds for any medical expenses or other costs you may incur."

18.2 Provide a copy of contract language, if any, relevant to compensation for research-related injury.

Verbiage from the informed consent document: "If you decide to participate, you will not be monetarily charged for anything. In the unlikely event that you sustain an injury from participating in this study, the investigators have no current plans to provide funds for any medical expenses or other costs you may incur."

19.0 Economic Burden to Participants

19.1 Describe any costs that participants may be responsible for because of participation in the research.

Verbiage from the informed consent document: "If you decide to participate, you will not be monetarily charged for anything."

20.0 Consent Process

20.1 Indicate whether you will be obtaining consent, and if so, describe the consent process.

Any potential participant interested in the study will be instructed to contact the SMaRT Laboratory by phone (334 844 1926*)* or via email (mzm0403@auburn.edu) through recruitment flyers to schedule the consenting and screening visit. We will respond to the e-mail or call using the verbal script. If potential participants meet the eligibility criteria, they will be instructed to meet with IRB-approved personnel in the School of Kinesiology (KINE #136).

During the screening and consent visit, a laboratory team member will verbally review the consent form (~10 minutes), describing the research study in lay language, using illustrations and step-by-step guidance. If potential participants verbally agree to participate, they will be instructed to read the informed consent, initial each page, and sign it, thereby accepting their willingness to participate in the study. Dr. Baweja will then sign the informed consent document. Participants will then complete the demographic questionnaire. If there are no precluding conditions for participation, the participant will begin the testing protocol.

21.0 Process to Document Consent in Writing

21.1 Describe whether you will be following HRP-091 – SOP – Written Documentation of Consent. If not, describe whether and how the consent of the participant will be documented in writing. Yes, we will be following the HRP-091-SOP Documentation Consent.

21.2 Will participants be asked to sign the consent document? ☒ Yes ☐ No

21.3 Will you use an electronic consent document? ☐ Yes ☒ No

Please complete the table below:

☐	Waiver of Consent (Including existing de-identified data)
☐	Waiver of Documentation of Consent (Use of Information Letter, rather than consent form requiring signatures)

☐	Waiver of Parental Permission (in Alabama, 18 years-olds may be considered adults for research purposes)

22.0 Setting

22.1 Describe the sites or locations where your research team will conduct the research.

Data collection will take place in Room #136 of the School of Kinesiology at Auburn University, located on the Entry floor at 301 Wire Road, Auburn, AL 36849. This laboratory is equipped with the necessary technology and provides a controlled environment suitable for balance testing procedures.

23.0 Resources Available

23.1 Describe the resources available to conduct the research.

Personnel: All laboratory staff members identified in this form have expertise in balance assessments and postural control research. All personnel will be trained on study protocols and safety procedures.

Participant pool: The Auburn and Opelika community areas provide access to a sufficient number of potential participants who can meet the study's inclusion criteria.

Facilities and equipment: The School of Kinesiology provides a dedicated laboratory space (SMaRT Lab, room #136) equipped for balance testing with controlled environmental conditions. The SMaRT Lab has access to FDA-approved BTrackS Balance Plate^{TM}, headband laser systems, and necessary computer hardware/software for data collection and analysis.

Timeline: We plan to commit a year’s worth of time to conducting and completing the research.

24.0 Multi-Site Research* N/A

24.1 Study-Wide Number of Participants N/A

24.2 Study-Wide Recruitment Methods N/A

24.3 Describe the method for communicating with engaged participating sites. N/A

24.4 If this is a multicenter study where you are a participating site/investigator, describe the local procedures for maintenance of confidentiality. N/A